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THREE ESSAYS ON HEALTH-RELATED PRODUCT ATTRIBUTES AND CONSUMER PURCHASING BEHAVIOR: AN APPLICATION TO READY-TO-EAT BREAKFAST CEREAL MARKET

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Abstract

This dissertation focuses on exploring the relationship between health-related product characteristics and consumers' purchase behaviors in the ready-to-eat breakfast cereal market. Chapter one introduces all the three essays. Chapter two studies the relation between health-related product attributes and consumers' purchase choices by incorporating the distance metric method into a censored demand system. Based on the demand estimation in chapter two, chapter three extends to evaluate the welfare changes due to the product reformulations in the cereal market. Chapter four investigates the impact of consumers' preference of variety in choosing breakfast cereals by developing a different model that consumers' utility depends on both their direct preference for product characteristics and their preference for variety. Chapter five concludes. Here is a brief introduction of all the three essays:

Chapter Two: Demand for Ready-to-Eat Cereals with Household-level Censored Purchase Data and Nutrition Label Information: A Distance Metric Approach

In this essay, we investigate the demand for ready-to-eat breakfast cereals in the U.S. using censored, household-level purchase data matched with product-level nutrition data. Instead of using a multi-equation based approach, we propose an alternative approach that relies on Pinkse, Slade, and Bretts (2002) distance metric method, which is highly practical and less burdensome computationally than some multiple-equation methods. Among other results, we find that households with children are less price sensitive to cereals with whole grain as the first ingredient and to cereals that contain a higher number of fortified vitamins. Additionally, we find that households tend to switch between products with similar fiber content and whole grain content profiles.

Chapter Three: Quantifying the Welfare Effect of Changing Healthy Attributes in the Ready-to-Eat Cereal Market

This essay quantifies the welfare impact of changing healthy attributes of ready-to-eat cereal products. We develop a equilibrium model of production and demand, incorporating the optimal demand choice of consumers facing multiple products in the market and optimal pricing strategy for multi-product firms. We use this model to evaluate how changing healthy attributes in the RTE cereal market affects consumer welfare, producer surplus, and total welfare, taking into account that product prices and consumer demand are endogenous in the equilibrium. We find that improving healthy product attributes has a substantial impact on consumer welfare, producer surplus, and total welfare, but these changes may not necessarily be positive. The results reflect how consumer demand and production costs change when nutritional content changes.

Chapter Four: How Important is Preference for Variety in Consumer Demand: Evidence from Ready-to-Eat Cereal Market

In this essay, we investigate the role preference for variety plays in shaping consumer demand and how the preference for variety varies by household characteristics, by estimating a model of heterogeneous consumers' demand. The model allows consumers to choose a subset of products to consume, and if any, by how much for each product, based on their interdependent direct preferences for product attributes and their preferences for variety. The purchasing record of ready-to-eat breakfast cereal at the household level from Nielsen Homescan data provides a natural field to quantify the effect of preference for variety. Estimation results show that preference for variety is important for understanding consumer demand. Removing consumer preference for variety would leads to a loss of market size by about 26%. The effect is heterogeneous on different products.

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Chapter 1

Introduction and Motivation

Chronic health problems, such as diabetes, hypertension, and heart disease have become major health concerns in the United States in recent decades. According to National Health and Nutrition Examination Surveys (NHANES), more than one third of U.S. adults, and around 17% of children aged 2-19 were obese in 2010. The Centers for Disease Control and Prevention (CDC) also report that 20% of adults in U.S. have heart disease and 25% have hypertension. According to most medical and health studies, diet is strongly linked to these chronic health problems. In the key recommendations listed in the Dietary Guidelines for Americans since 2005, The U.S. Department of Health and Human Services (HHS) and the U.S. Department of Agriculture (USDA) continuously suggest that people in U.S. should increase intake of whole grain, dietary fiber, and reduce consumption of refined grains, added sugar, solid fats and sodium (USDA/HHS, 2005, 2010, 2015). Many of the food components mentioned, especially fiber and whole grain, are key attributes of ready-to-eat (RTE) breakfast cereal, which is a popular breakfast option in the U.S. As a result, the increasing emphasis on these food components calls for knowledge of the relationship between these heath-related attributes and consumer choices in this market.

Economists have already shown strong interest in the impact of nutrition and a healthy diet on demand and choice in the market place. Early research focuses on the impact of consumers' general health concerns on purchase decisions and consumption patterns, and confirms that health concerns play a significant role in changing consumer food choices (Brown and Schrader, 1990; Kim and Chern, 1995; Variyam, Blaylock, and Smallwood, 1996; Kinnucan, Xiao, Hsia, and Jackson, 1997; Binkley and Eales, 2000). Studies explicitly investigating diet and nutrition find that existence of healthy attributes in food products increase consumers' willingness to pay (Kim and Chern, 1995; Khknen, Tuorila, and Rita, 1996), but that valuations of healthy attributes differ across consumers once demographic information is considered (Huffman and Jensen, 2004; Muth, Zhen, Taylor, Cates, Kosa, Zorn, and Choiniere, 2013).

While there is ample research on health and consumers' purchase behaviors, the data used are basically limited to three major types. Early research most commonly use aggregated level data due to lack of more detailed micro-level datasets. An obvious disadvantage of these data is that they miss detailed product information and consumer demographics, both of which are important factors determining consumer demand. As a result, survey data, such as Continuing Surveys of Food Intakes by Individuals (CSFII), have become a better choice and performs better by considering consumer heterogeneity. The advantages of these survey data are that they allow investigations into the relationship between food intake and consumer health outcome, or the influence of consumer demographics on the evaluation of some nutrients (e.g., the varying impact that education or gender may have on fat and sugar, Variyam, Blaylock, and Smallwood, 1996; Variyam, Blaylock, Lin, Ralston, and Smallwood, 1999; Shi and Price, 1998; Ranney and McNamara, 2002). However, an important disadvantage of these data is their product-level, rather than brand level, aggregation.

With the advent of scanner data and other more comprehensive data sets of food purchase and product attributes, such as Nielsen Homescan data, researchers are able to investigate and estimate the purchasing process with more information. This dissertation uses Nielsen Homescan data to analyze the relationship between health-related product attributes in ready-to-eat breakfast cereals and consumer purchasing behaviors. Moreover, we match this micro-level data set with a list of product level attributes and our final dataset is comprehensively composed of purchasing records, household demographics and product characteristics. The first part investigates the impact of health and non-health related product attributes on consumers' purchase decisions, and characterizes the importance of these determinants. In the second part, we use the results from first part to implement several experimental analyses to examine hypothetical policies designed to mimic General Mills' (GM) decision to convert all of its Big G cereal products to whole grain in the late 2004. Finally, in the third part, we further consider the impact of consumers preference for variety, defined in part by product attributes, and examine how the preference for variety shape consumers purchasing decisions, as well as how their preference for variety varies with different social-demographic factors.

This study differs from previous research in several aspects. First, it is one of a few studies to analyze consumer choice based on product and brand-level data reformatted to reflect how close or far apart products are in product-attribute space. This line of research (which includes only a handful of published papers) is called the Distance Metric approach, which is initially developed by Pinkse, Slade, and Brett (2002) with application to market-level data. As mentioned above, most studies about health and consumer purchasing behavior relies on product level aggregation. Also, previous estimation methods used in this line of research are often limited to simply use hedonic price models, Rotterdam demand systems, Almost Ideal Demand System (AIDS) models, or different logit models. By using Nielsen Homescan data and detailed brand-level product attributes, the research in this dissertation will be one of the few studies uses of the Distance Metric approach to examine consumers' choices and substitution patterns between health-related and other product attributes.

A second major difference is that this study will be the first study, as far as we know, to incorporate the Distance Metric approach into a censored regression model to analyze micro-level data. This approach is highly practical and less burdensome computationally than the traditional multiple-equation methods. Until now, almost all of the studies that use Distance Metric method analyze aggregated market level data and these studies do not consider the impact of observed consumer heterogeneity on demand due to the limitation of the data. By using micro-level Nielsen Homescan data, this study will be the first try to adopt the Distance Metric method to analyze individual consumer purchasing behavior and also incorporate consumer heterogeneity in investigating preference for healthy attributes in cereals and responsiveness to the changes of key nutrients.

Once consumers' purchasing behavior is completely characterized and estimated using the mentioned model, the results are used to evaluate the welfare effects from hypothetical firms' product reformulation in the cereal market. In our study, we examine consumers' welfare change due to a hypothetical competition strategy meant to be a stylized version of General Mills' actual shift to whole grains. In addition to evaluating consumers' welfare, we also measure the benefit to cereal manufacturers from the product reformulations, which contribute to better understanding whether or not this competition strategy is profitable and how much benefit exactly could be gained by each cereal manufacturer.

Finally, a third major difference is that this research further investigates how consumers' preferences for variety affect their purchasing decisions, besides acknowledging that consumers have preference on the healthy attributes. This research extends existing research to explicitly model consumers' preferences for variety by building a model where their utility is derived from consuming a vector of product characteristics. A consumer's utility of consuming cereals depends not only on absolute amount of product characteristics, such as fiber or sugar content, more importantly it also depends on the variety of their purchase set. Inspired by the Distance Metric approach, the level of variety is captured by using the pair-wise distances among cereal products in each consumer's purchase set, which further extends the application of this method as well.

There are several reasons why we choose ready-to-eat breakfast cereals. RTE cereal is one of the largest grocery categories. We are able to obtain more purchase observations from this product than from the others. Also, due to its wide variety of brands and convenience, it is one of major breakfast choices in the United States. More importantly, it can be rich in fiber and whole grain, which are increasingly of interest to consumers as they are key components in preventing heart disease and obesity. The level of sugar content is also an important determinant of consumer choice since it is acknowledged that sugar is a major factor in obesity and diabetes.

In addition, the cereal sector has a rich history, first as the focus of pricing investigation and industry concentration, and more recently as a continually reformulated product in the forefront of health-related trends. Strategic competition between 100-year old cereal companies and newer private label cereals has led to tactics based on promotions (such as trade promotions, coupons, and advertising) and new product innovation and product reformulation. Recently, some of these tactics have centered on health-related product formulations. For example, in late

2004 General Mills switched all its Big G cereals to whole-grain, and in 2006 announced that every Big G cereal brand would contain at least 8 grams of whole grain per serving. Since 2007, General Mills has reduced sugar in its Big G kid cereals by 16%. In 2010, General Mills further reduced sugar content to single-digit level per serving while keeping a high level of whole grain. In the same year, they announced another plan to reduce sodium, on average, by 20% in its top 10 categories. As the largest competitor to General Mills, Kellogg implemented similar tactics. In 2005, Kellogg introduced Tiger Power as a delicious whole grain kids cereal, meant to be a good source of fiber, protein and calcium. In 2009, Kellogg introduced two new kids cereals, Mini-Wheats Little Bites in two flavors, which contains whole grain and 6 gram of fiber in each serving. As of 2012, Kellogg has announced that more of its cereal products will be both a better source of fiber (3 grams) and contain more whole grain (at least 8 grams) than any other U.S. food company. Collectively, all of these cereal reformulations aimed at increasing whole grain and fiber or decreasing sugar suggest that the cereal sector is at the forefront of consumer interest in diet and health.

Objective

The main objective of this dissertation is to analyze the effect of health-related product attributes in ready-to-eat breakfast cereal on consumer purchasing decisions. Three elements constitute the core of this research question: health, demand, and variety. Since consumers have increasing health concerns about consumption of health-related product attributes, such as dietary fiber, whole grain, or sugar content, the impact of these attributes on product choice will be investigated first. Another interesting data fact shows that consumers in the cereal market would commonly purchase at least two different brands in each shopping trip, which indicates that preference for variety also play an important role in shaping consumers purchasing behaviors. Therefore, the impact of a wide range of factors, including a list of health-related attributes, relative differences between products, and consumers' preference for variety will be examined in this research.

As a result, we approach the main research question by using three essays that build on and relate to each other. The first essay focuses on a new application of Distance Metric method that accommodates censored data. The second essay uses the demand results developed from the first essay and conducts several experimental case studies about the impact of a widespread change in product attributes. Finally, the third essay is a extended version of essay one that considers the impact of consumers preference for variety when choosing cereal products.

In the first essay, the objective is to evaluate the impact of health-related product attributes on consumer purchasing behavior and to further characterize the importance of these attributes in the RTE breakfast cereal industry. By following Pinkse, Slade, and Brett (2002) and Pinkse and Slade (2004), we use a measure of the relative distance between each pair of cereal products in product attribute space to approximate the closeness of competition among different brands. We then incorporate this Distance Matric method into a censored regression model to estimate consumer demand in a simplified way, using disaggregated consumer level data. The impact of demographic factors on consumer preferences for health-related product attributes is also considered. Finally, this essay provides a evaluation of conditional/unconditional own- and cross-price elasticities, after the demand model is estimated.

In essay two, we use the results from essay one to implement an experimental analysis to measure the impact of a business strategy of product reformulation in cereal market, which is similar to General Mills' conversion of all its Big G cereal products to whole grain in late 2004. Specifically, we design eight counterfactual experiments where all brands owned by each major cereal manufacturer change their primary ingredient to whole grain, or all manufacturers in the cereal market change the content of fiber, sugar, or fat by certain amount. Then we will evaluate: (1) how consumers could benefit from a company-based strategy that improves one or more health-related product attributes; and (2) whether this competition activity would end up being a successful strategy by increasing the target company's profit. Using counterfactual analysis, we calculate the new price and consumption shares for each brand under the market equilibrium as if the reformulation of cereal products occurs as we design. Once we have the market outcome under the assumed scenarios, we are able to measure the change of surplus for both consumers and producers.

Finally, in the last essay, we investigate the impact of preference for variety on consumers purchasing decisions by estimating a model of heterogeneous consumers' demand and evaluate how the preference for variety varies by household social-demographic factors. Observing the data, we find that consumers are very likely to purchase several different brands at a single purchase trip, which calls for further research on consumer demand behavior by including the factors of variety. Compared to the first two essays, this part relates to and further extends them in two major aspects. First, we a build model to explicitly characterize consumers' purchasing behavior, which is determined by both their direct preference for product attributes and their satisfaction from enjoying varied cereal products. Second, we continue to include a list of health-related product attributes, such as fiber, sugar, and grain type and we use the same method, the Distance Metric method, to measure the variety of each consumer's purchase. After we estimate consumers' demand using the newly built model, we use the result to further conduct a counterfactual analysis to quantify the money-valued impact of consumers' preference for variety in the breakfast cereal market.

Chapter 2

Demand for Ready-to-Eat Cereals with Household-level Censored Purchase Data and Nutrition Label Information: A Distance Metric Approach

2.1 Introduction

Because scanner data at the Universal Product Code (UPC) level allow for information from a product's nutrition label to be matched with actual consumer purchases, recent research has been able to investigate how nutrition levels and price interact in consumers' purchase decisions. For example, after matching scanner data on cereal purchases to data obtained by visually inspecting cereal boxes and nutrition labels, Nevo (2001) recovers quality-change information from an estimated demand system that includes product-specific information on fat, sugar, and fiber content. Chidmi and Lopez (2007) also add cereal box nutrition label information to scanner data from Boston-area supermarkets before estimating a cereal demand model. Among other results, they find that households with lower income have a stronger preference for sugary cereals. Binkley and Golub (2011) combine nutrition information from both U.S. Department of Agriculture databases and cereal boxes with consumers' cereal purchases from scanner data to construct a measure of purchased cereal healthfulness, which they regress on various household characteristics and prices. They find that, controlling for prices, education and income are positively linked to more healthful choices. Finally, Wang, Rojas, and Bauner (2015) combine weekly scanner data with long-term data on cereals' nutrition profiles to show that cereals' nutritional quality has generally improved since 2001 even though it is below nutritional levels in the 1980s. These four studies, chosen for illustrative purposes, are just a few of the many consumer studies on cereals and other products that can address consumer behavior and health because they combine product nutrition information and scanner data.

The same four studies also illustrate another intriguing element of this line of research: While Nevo (2001), Chidmi and Lopez (2007), and Wang, Rojas, and Bauner (2015) use scanner data collected at the retailer level or market level, Binkley and Golub (2011) use scanner data collected at the household level. Both types have advantages. Within a particular market, the retailer-level data may be more complete. On the other hand, the household-level data come with a long list of socioeconomic attributes, a benefit for studying how household structure affects consumer decisions. However, one of the empirical problems of working with household-level data on food purchases is censoring, which occurs because most households purchase only a small subset of available products or brands. Censoring is not much of a problem for demand systems that fit well in a discrete choice framework where households buy only one brand at a time (for example, Shum, 2004; Thunstrm, 2010; Szymanowski and Gijsbrechts, 2012; Guadagni and Little, 1983; Chintagunta, 1992). However, when households routinely purchase multiple quantities of a single brand, then a demand system that relies on continuous quantities might be more appropriate. Simultaneous estimation of share equations for multiple brands in the continuous-quantities framework presents some empirical difficulties that researchers have been confronting for over 30 years (Wales and Woodland, 1983). Kasteridis, Yen, and Fang (2011) provide background of cases when demand is continuous but censored at zero, including a taxonomy of models inspired by Kuhn-Tucker (Lee and Pitt, 1986), Tobit (Wales and Woodland, 1983; Dong, Gould, and Kaiser, 2004; Yen, Lin, and Smallwood, 2003), and sample selection (Shonkwiler and Yen, 1999; Yen and Lin, 2006; Jonas and Roosen, 2008; Hailu, Vyn, and Ma, 2014) methods.[1] Kasteridis, Yen, and Fang (2011) note that the two-step sample selection method becomes increasingly computationally burdensome as each additional demand equation doubles the number of equations to be estimated and adds an integral to the sample likelihood function.

Researchers have attempted to overcome this issue in different ways. Richards, Yonezawa, and Winter (2015) and Richards and Mancino (2013) follow Dub (2004), Hanemann (1984), Bhat (2005, 2008), and others to blend discrete and continuous choice to estimate cross-category effects in the market of cereals and other products using a Kuhn-Tucker method. These multiple-discrete/continuous models share a trait with the censored-continuous models in that they are computationally difficult

[1] This is not the only method to overcome censoring. For example, a few papers use a "pseudo panel approach" where household-level purchase data are aggregated to obtain pseudo-cohorts from the population that can be used to estimate "representative consumer" demand models. For examples, see Allais, Bertail, and Nichle (2010) and Gardes, Duncan, Gaubert, Gurgand, and Starzec (2005).

to apply. By assuming the error terms to be IID extreme value distributed, the joint probability function in their method collapses to a closed form, which helps to avoid the calculation of multiple integrals as in Kim, Allenby, and Rossi (2002). However, their method does not explicitly model the impact of the differences between products in attributes on the substitution patterns.

In this paper, we propose an alternative approach to the estimation of a censored-continuous demand system using household-level purchase data matched with product-level nutrition data, and we use it to investigate the demand for ready-to-eat (RTE) breakfast cereals in the US. Instead of using a multi-equation based approach, we propose an alternative approach that relies on Pinkse, Slade, and Brett (2002)'s distance-metric (DM) method. Our approach follows Rojas (2005, 2008), Rojas and Peterson (2008), and Bonanno (2013) and uses a modified linear approximate almost ideal demand system (LA/AIDS) model that incorporates the DM method in a single equation. Pinkse, Slade, and Brett (2002)'s DM method, proposed originally as a way to assess price competition, assumes that the level of product differentiation and substitutability can be captured by the relative distance in attribute space between products in such a way that (1) cross-price parameters are functions of relative product distance in attribute space and (2) own-price parameters are functions of product characteristics. When applied to demand analysis (see Pinkse and Slade, 2004), this method reduces the estimation of any large system of demand equations to the estimation of a stacked, single equation. If zero-purchase events are prevalent in the data, then the post-stacked demand equation can be easily estimated via a Tobit estimator or an instrumental Tobit estimator to accommodate price endogeneity. Because, to our knowledge, all previous applications of the DM method (Pinkse and Slade, 2004; Slade, 2004; Rojas, 2008; Rojas and Peterson, 2008; Pofahl and Richards, 2009; Bonanno, 2013; Brissette and Ruff, 2014) use market-level data, this paper represents the first application of the DM method in demand estimation using micro-level, censored purchase data.

We apply the DM method to cereal purchase information on the 20 top cereal brands in the Nielsen Homescan dataset, and we match these data to nutrition information from USDA's National Nutrient Database for Standard Reference databases as well as label inspection. Once the censored demand equations are stacked, the Tobit estimation is straightforward. Among other results, we find that households with children are less price sensitive to cereals with whole grain as the first ingredient and to cereals with a higher number of fortified vitamins. Additionally, we find that households tend to switch between products with similar fiber content and whole grain content profiles. Based on the estimated demand, we also calculate conditional and unconditional own- and cross-price elasticities.

2.2 Cereal Attributes and Consumer Choice

Because of prolonged competition coupled with intense brand proliferation and product reformulations among top cereal manufacturers, the breakfast cereal industry has long been the focus of economic and marketing research (as examples, see Schmalensee, 1978; Scherer, 1979; Cotterill and Franklin, 1999; Nevo, 2000, 2001; Price and Connor, 2003). In the last decade or so, cereal manufacturers have competed by means of improving the nutrition profiles of their brands. For example, from 2006 to 2012, cereal manufacturers have engaged in product reformulations by reducing sugar and sodium and increasing fiber content. These changes resulted in an improvement in the nutritional quality of existing cereal brands by 14 percent for children's cereals, 12 percent for family cereals, and 5 percent for adult cereals (Harris, Schwartz, Brownell, Sarda, Dembek, , Munsell, Shin, Ustjanauskas, and Weinberg, 2012) and were due mostly to competition among large breakfast cereal companies.[2] In addition, cereal sales experienced significant growth around this time: Annual reports from the top two cereal companies, General Mills and Kellogg's, state that total net sales of breakfast cereals increased by about 36 percent, from \$3.9 billion to \$5.3 billion from 2002 to 2010 (General Mills and Kellogg's Annual Report to Shareholders, 2003-2010).

A number of studies focus on the nutrition profiles of breakfast cereals and their relation to consumer choices. Ippolito and Mathios (1989) and Binkley and Eales (2000) find that fiber content is an important factor in consumers' breakfast cereal purchase decisions. Other studies find that while households with children purchase cereals with more sugar, households with teenagers value energy more than other nutrients (Binkley and Golub, 2011; Thunstrm, 2010). Also, on average, households with higher income, education, or age make more healthful cereal choices (Shi and Price, 1998; Golub and Binkley, 2005). However, taste and habits may deter consumers from choosing healthful cereals: Golub and Binkley (2005) show that households with children tend to purchase cereal with relatively less fiber because of the taste. Thunstrm (2010) finds that breakfast cereal consumers demonstrate highly persistent habits, some of which are unhealthful.

2.3 An Application of the DM Demand Model to Censored Data

In this section, we illustrate the empirical approach that we propose to assess the role of nutrients on the demand for RTE breakfast cereals in the U.S. using

[2]Harris, Schwartz, Brownell, Sarda, Dembek, , Munsell, Shin, Ustjanauskas, and Weinberg (2012) evaluate nutritional quality by using the Nutrition Profiling Index (NPI) score based on the nutrition profiling system adopted in the United Kingdom. The NPI evaluates the overall nutrition of cereal products based on total calories, fiber, sugar, sodium, and other components.

household-level data. First, we discuss how Pinkse and Slade (2004)'s demand model, which uses the DM method, has been used to adapt the LA/AIDS model. Then we show how this model can be used in the context of censored household-level data. Last, we present caveats and formulas for the calculation of different types of elasticities.

2.3.1 The LA/AIDS DM Demand Model

Lancaster (1966, 1979) posits that consumers derive utility from the attributes of the products they consume. As a result, consumers' choices can be transferred from a product space framework into one based on a product-attribute space, where consumers maximize utility by choosing the level of product attributes within their budget constraint. Using this theoretical framework, (Pinkse, Slade, and Brett, 2002, p. 1113) introduce the DM method, claiming that it can be preferred to other demand analysis methods in markets with a large number of differentiated products, as it is tractable while allowing for flexible substitution patterns.

We follow Rojas and Peterson (2008)'s approach by incorporating the DM method into Deaton and Muellbauer (1980) LA/AIDS model. Let $i \in \{1, 2, ..., I\}$ denote consumers in market $t \in \{1, 2, ..., T\}$ and $j \in \{1, 2, ..., J\}$ represent the set of cereal brands. The expenditure share function for consumer i who purchases brand j in market t is

$$w_{ijt} = \alpha_{jt} + \sum_{k=1}^{J} b_{ijk} logp_{ikt} + c_{ij} log \frac{x_{it}}{P_{it}^{L}} + e_{ijt}. \tag{2.1}$$

where $w_{ijt} = q_{ijt}p_{ijt}/x_{it}$ is the expenditure share for consumer i, purchasing brand j in market t. q_{ijt} and p_{ijt} are the corresponding purchase quantities and price for consumer i, and $x_{it} = \sum_j q_{ijt}p_{ijt}$ is the total expenditure for consumer i for all products in market t. The term $logP_{it}^{L}$ is an approximated log-linear analogue of the Laspeyeres Price index (Moschini, 1995), where $logP_{it}^{L} \approx \sum_{j=1}^{J} w_{ij}^{0} logp_{ijt}$ and w_{ij}^{0} denotes brand j's base share for consumer i with $w_{ij}^{0} = Y^{-1} \sum_{y=1}^{Y} w_{ijy}$ and $y \in (1, ..., Y)$ represents the year. α_{jt}, b_{ijk}, and c_{ij} are parameters to be estimated and e_{ijt} is the error term. After imposing all of the restrictions dictated by theory on the parameters of equation 2.1, J-1 seemingly unrelated equations need to be estimated to obtain a total of (J-1)∗(3+J/2) parameters.[3] However, if one's analysis focuses on a market with a large number of products, such as the different brands in the breakfast cereal market, the problem becomes hardly tractable. This hurdle can be overcome by the DM method. Following Pinkse and Slade (2004) one can specify each cross-price coefficient b_{ijk} as a function

[3]To guarantee that the LA/AIDS demand estimates are consistent with economic theory, three restrictions should be satisfied: (1) Slutsky symmetry; (2) the adding-up restriction; and (3) homogeneity of degree zero.

of the attribute-space distance δ_{jk} between brands j and k, $b_{ijk} = g(\delta_{jk})$, which reflects the notion that substitutability is impacted by the relative position of the products in characteristics space. The distance measures can be either continuous, δ^c_{jk} , that is, constructed from continuous characteristics (e.g., grams of dietary fiber, fat, or sugar per 100 grams of cereal) or discrete, δ^d_{jk} , constructed from discrete characteristics (e.g., whole grain listed as the first ingredient, or a cereal targeted to children).

The distance measure δ^c_{jk} is computed using continuous product attributes (z^c_j), and, as in Rojas (2008), is obtained using a function of the inverse of the Euclidean distance between products j and k in one-dimensional space for each continuous product attribute considered:

$$\delta^c_{jk} = \frac{1}{1 + 2\sqrt{\left(z^c_j - z^c_k\right)^2}}, \tag{2.2}$$

where z^c_j represents the c-th continuous attribute. Increased "closeness" in continuous attribute space leads to a larger value of δ^c_{jk}, meaning that the products are more likely to be substitutes. We consider three continuous attributes in our estimation: sugar, fiber, and fat.

The second type of closeness measure, δ^d_{jk} , is constructed based on discrete (binary) product attributes (z^d_j). Unlike δ^c_{jk}, the discrete distance measure captures substitutability among products within the same type since only products belong to the same group type will have positive distance measure. As a result, discrete distance measures capture local substitution while continuous ones capture global substitution. The distance measure for each discrete product characteristic is defined as:

$$\delta^d_{jk} = \begin{cases} 1 & if \ |z^d_j - z^d_k| = 0, \\ 0 & if \ |z^d_j - z^d_k| \neq 0. \end{cases} \tag{2.3}$$

We use four binary attributes: whole-grain, added flavor, manufacturer, and whether a product is targeted to children. The distance between brand j and k for each discrete attribute is one if they belong to the same product type (e.g., both are whole-grain or are produced by the same manufacturer), and zero otherwise. The cross-price parameters, b_{ijk}, are therefore defined as a linear combination of distance measures:

$$b_{ijk} = \begin{cases} \sum_{c=1}^{C} \lambda^c_{ij}\delta^c_{jk} & for \ continuous \ distance, \\ \sum_{d=1}^{D} \lambda^d_{ij}\delta^d_{jk} & for \ discrete \ distance. \end{cases} \tag{2.4}$$

To satisfy Slutsky symmetry ($b_{ijk} = b_{ikj}$), λ^c_{ij} and λ^d_{ij} are assumed to be the same across equations ($\lambda^c_{i1} = \lambda^c_{i2} = \cdots = \lambda^c_{iJ} = \lambda^c_i$ and $\lambda^d_{i1} = \lambda^d_{i2} = \cdots = \lambda^d_{iJ} = \lambda^d_i$)

and consumers ($\lambda_1^c = \lambda_2^c = \cdots = \lambda_J^c = \lambda_c$ and $\lambda_1^d = \lambda_2^d = \cdots = \lambda_J^d = \lambda_d$); since distance is symmetric by definition, Slutsky symmetry is ensured.

The number of equations to be estimated can then be reduced to one, assuming that the constant term α_{jt}, the own-price coefficient b_{ijj} , and the coefficient of total expenditure c_{ij} , are linear functions of product characteristics:$\alpha_{jt} = \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha}$, $b_{ijj} = b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta}$, and $c_{ij} = c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma}$, where z_{jl}^{α}, z_{jm}^{β}, and z_{jn}^{γ} represent brand j's characteristics. In order to avoid multicollinearity, each z_{jl}^{α}, z_{jm}^{β}, and z_{jn}^{γ} may be a separate subset of j's characteristics. Imposing these restrictions, equation 2.1 can be rewritten as:

$$\begin{aligned} w_{ijt} &= \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \left(b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta} \right) logp_{ijt} \\ &\quad + \sum_{c=1}^{C} \left(\lambda_c \sum_{j \neq k} \delta_{jk}^{c} logp_{ikt} \right) + \sum_{d=1}^{D} \left(\lambda_d \sum_{j \neq k} \delta_{jk}^{d} logp_{ikt} \right) \\ &\quad + \left(c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma} \right) log \frac{x_{it}}{P_{it}^{L}} + e_{ijt}. \end{aligned} \tag{2.5}$$

As mentioned above, consumers' purchasing decisions can also be affected by socio-demographic factors, particularly in a differentiated product market, where heterogeneity in consumers' preferences plays a major role. Let h_{hit} be the h-th demographic variable for consumer i in market t, with demographic $h \in \{1, 2, ..., H\}$. We include demographic variables as intercept shifters in the LA/AIDS model as follows:

$$\alpha_{jt} = \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit} \tag{2.6}$$

The demographic variables capture information about both the household head (age and education) and the household in general (income, household size, marital status, and race).

2.3.2 Extending the LA/AIDS DM to Censored Dependent Variables

Because the ready-to-eat cereal market contains numerous alternatives, each household will purchase only a limited number of products; thus, the number of non-purchase observations will be numerous.[4] Given that the dependent variable is restricted to be non-negative, the presence of zeros might lead to underestimating the impact of product attributes (or the distance of attributes) on consumer purchase decisions if the censored nature of the data is not taken into account.[5]

The Tobit model (Tobin, 1958) has been widely used to deal with zero purchases in demand estimation. Let latent share, w^*_{ijt} , represent the potentially unobserved purchase behavior for consumer i choosing brand j in market t. The observed share w_{ijt} is assumed to be equal to the latent share w^*_{ijt} whenever the latent share is above zero:

$$w^*_{ijt} = \begin{cases} w_{ijt} & if\ w^*_{ijt} > 0, \\ 0 & if\ w^*_{ijt} \leq 0. \end{cases} \tag{2.7}$$

so that:

$$\begin{aligned} w^*_{ijt} \quad = \quad & \alpha_0 + \sum_{l=1}^{L} a_l z^{\alpha}_{jl} + \sum_{h=1}^{H} a_h h_{hit} + \left(b_0 + \sum_{m=1}^{M} b_m z^{\beta}_{jm} \right) log p_{ijt} \\ & + \sum_{c=1}^{C} \left(\lambda_c \sum_{j \neq k} \delta^c_{jk} log p_{ikt} \right) + \sum_{d=1}^{D} \left(\lambda_d \sum_{j \neq k} \delta^d_{jk} log p_{ikt} \right) \\ & + \left(c_0 + \sum_{n=1}^{N} c_n z^{\gamma}_{jn} \right) log \frac{x_{it}}{P^L_{it}} + \epsilon_{ijt}. \end{aligned} \tag{2.8}$$

where $\epsilon_{ijt} \sim N(0, \sigma^2)$. Under this specification, the zero-purchase outcomes are assumed to represent a corner solution from a utility maximization process.

Given the potential endogeneity of prices, the parameters of the model can be consistently estimated using Newey's two-step estimator (Newey, 1987). The final specification given by 2.7 and 2.8 allows us to easily estimate demand for a large number of alternatives and to account for censoring, as it requires the calculation of only a single integral instead of multiple integrals.

[4]There are several reasons (both empirical and theoretical) why we observe zero purchases of a specific brand. First, empirical selection of a time period may cause an observation of zero purchases for a specific product. Second, some argue that a zero purchase outcome is the result of a utility-maximization process, and is caused by a relatively high price, unattractive product attributes, or different preferences of consumers. We generally assume that the second reason fits our case.

[5]Underestimation of demand by ignoring the impact of zero observations is discussed by Tobin (1958) and Lee, Kwon, and Chung (2010).

2.3.3 Conditional and unconditional elasticities

Conditional and unconditional price elasticities can be obtained using the estimated coefficients from equation 2.8. Conditional price elasticities reflect responsiveness to price changes for consumers who have already purchased a given product. Following Yen and Huang (2002), we derive conditional elasticities by differentiating the conditional expectation of expenditure share:

$$E\left(w_j/w_j>0\right)=f_j\left(\theta\right)+\sigma_j\phi\left[f_j\left(\theta\right)/\sigma_j\right]/\Phi\left[f_j\left(\theta\right)/\sigma_j\right] \tag{2.9}$$

with respect to prices. In equation 2.9, $E\left(w_j/w_j>0\right)$ is the conditional expenditure share for product j;[6] θ represents the estimated parameters in equation 2.8; $f_j\left(\theta\right)$ is the expenditure share function defined in equation 2.8; σ_j is the standard deviation of the errors; and λ_j is the inverse Mill's ratio calculated as $\lambda_j=\phi\left[f_j\left(\theta\right)/\sigma_j\right]/\Phi\left[f_j\left(\theta\right)/\sigma_j\right]$, where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density function (PDF) and cumulative distribution function (CDF).

Considering that $f_j\left(\theta\right)$ includes product attributes as shifters of the own-price and expenditure parameters, and cross-price parameters are function of attributes' distance (as in Bonanno, 2013), the conditional elasticities can be represented as:

$$\eta_{jk}^{C}=\begin{cases}-1+\Gamma\left[\left(b_0+\sum_{m=1}^{M}b_m z_{jm}^{\beta}\right)-\left(c_0+\sum_{n=1}^{N}c_n z_{jn}^{\gamma}\right)w_j\right] & if\ j=k,\\ \Gamma\left[\left(\sum_{c=1}^{C}\lambda_c\delta_{jk}^{c}+\sum_{d=1}^{D}\lambda_d\delta_{jk}^{d}\right)-\left(c_0+\sum_{n=1}^{N}c_n z_{jn}^{\gamma}\right)w_k\right] & if\ j\neq k.\end{cases} \tag{2.10}$$

where $\Gamma=\left[\frac{1}{E(w_j/w_j>0)}-\frac{\lambda_j}{\sigma_j}\right]$ The expenditure share (w) is taken at the sample average.

The unconditional price elasticity, η_{jk}^{U}, measures the overall response of purchased quantity to price changes, and is also calculated following Yen and Huang (2002). The unconditional own- and cross-price elasticities are calculated by summing the probability elasticity, η_{jk}^{P}, and conditional elasticity, η_{jk}^{C}:

$$\eta_{jk}^{U}=\eta_{jk}^{P}+\eta_{jk}^{C} \tag{2.11}$$

The probability elasticity η_{jk}^{P} represents the percentage change in the probability of consumers purchasing brand j with respect to the percentage change of price for product k, and is obtained by differentiating the probability of purchasing product j, $Pr\left(w_j>0\right)=\Phi\left[f_j\left(\theta\right)/\sigma_j\right]$, with respect to price k:

$$\eta_{jk}^{P}=\begin{cases}\sigma_j^{-1}\lambda_j\left[\left(b_0+\sum_{m=1}^{M}b_m z_{jm}^{\beta}\right)-\left(c_0+\sum_{n=1}^{N}c_n z_{jn}^{\gamma}\right)w_j\right] & if\ j=k,\\ \sigma_j^{-1}\lambda_j\left[\left(\sum_{c=1}^{C}\lambda_c\delta_{jk}^{c}+\sum_{d=1}^{D}\lambda_d\delta_{jk}^{d}\right)-\left(c_0+\sum_{n=1}^{N}c_n z_{jn}^{\gamma}\right)w_k\right] & if\ j\neq k.\end{cases} \tag{2.12}$$

[6] In order to simplify the notation, we remove the consumer (i) and market (t) subscripts.

2.4 Data and variables

The data used to estimate equation 2.8 come mainly from three sources. The first source is the Nielsen Homescan dataset, which provides the purchase information and household-level demographics. The second source is the USDA's National Nutrient Database for Standard Reference, which provides the nutritional composition of various food products sold in the United States. Also, we collected some non-nutrient related product information from web pages archived on the World Wide Web, using the Wayback Machine website that archives many prominent websites.

The Homescan database contains three product modules for cereals: granola and natural cereals, hot cereals, and RTE breakfast cereals. Focusing on RTE cereal, we isolate an initial sample of 723,849 purchase records from 36,664 households in 2004. We focus on this year because it covers the period leading up to important product reformulations, which began in late 2004. In order to reduce the scope of the analysis, we select the 20 brands with the highest number of observed purchase records, accounting for about 40 percent of total market sales for RTE breakfast cereal in this year. We exclude other brands and private labels, because of difficulties in collecting the full set of these brands' attributes. Because a number of the top brands are targeted to children or to both children and adults, we further filter our sample to include only households that have at least one child aged less than 18 years. Finally, to further reduce the percentage of observations with zero purchases, we focus on households that show at least 15 purchases of RTE cereals over a three-year period.[7]

According to the selection criteria, our households-with-kids sample contains data on the cereal purchases of 3,269 households. The data are aggregated across all purchases of a given product by each household during the year, so that each observation represents household i's yearly purchase of RTE cereal brand j. Because we only observe purchased cereals, we construct a balanced panel by setting the household-specific purchase amount to zero for those brands that were not purchased in 2004.

A cereal brand's price ($/oz) is calculated by dividing the total dollars paid by the total number of ounces of a given brand bought by a household in each year. However, because the Nielsen Homescan database only reports prices for purchased products, we imputed the missing prices for the non-purchased products by using the average scantrack market price (Arnade, Gopinath, and Pick, 2008).

The Nielsen Homescan data also contain detailed demographic information for

[7]Even though this study uses only one year of data for estimation, this criterion allows us to focus on households who are consistently in the cereal market.

each household and household head.[8] We control for the following demographic variables: household size (HHSIZE), household income (HHINC), marital status (MARRIED), highest educational attainment (high school, HIGHSC; some college, SOMECOL) of a household head (or the maximum if there is more than one head), highest age (AGEHIGH) of a household head (or the maximum if there is more than one head), and a binary indicator for ethnicity of the household (WHITE, HISPANIC). Table 3.1 presents summary statistics of all the socio-demographics used.

From the USDA National Nutrient Database for Standard Reference, we collect cereal nutrition profiles for the top 20 brands. Consistent with previous research (e.g. Nevo, 2000; Golub and Binkley, 2005), we consider the following nutrients: total sugar (SUGAR), total fat (FAT), total dietary fiber (FIBER), and the number of vitamins added to fortify the product (NVF). The content of the first three nutrients is measured as grams per 100 grams of cereal. We construct the variable NVF by summing five binary vitamin-fortification variables: vitamin A, vitamin D, vitamin E (total ascorbic acid), vitamin B-6, and vitamin B-12.[9] For each vitamin considered, a binary variable is given the value one if the brand is enriched with an extra amount of this vitamin according to the reference value from the Recommended Dietary Allowances (RDAs) from the U.S. Food and Drug Administration (USDA/ARS, 2012).

Because cereal manufacturers disclose product labels and descriptions on their websites, we collected non-nutrient-related product attributes from archived web pages, using the Wayback Machine (a service provided by the Internet Archive) to collect old product information from archived webpages for the year 2004. Using the Wayback Machine, we are able to create the following binary variables: whole-grain cereals (WG), identifying products whose first ingredient in the ingredients list is whole grain; added flavors (ADFLAVOR), capturing products that report added flavors in the ingredient list; and colors added (ADCOLOR), indicating products that report artificial coloring ingredients in the ingredient list. Also, according to the cereal facts report by Yale University's Rudd Center for Food Policy and Obesity (Harris, Schwartz, and Brownell, 2009), we create the binary variable KIDS, which identifies products targeted to children. In addition, we construct another variable average package size (AVESIZE), by using Homescan's information on package size for each product.

We use these product attribute variables to construct the distance measures described above, which are then used to obtain weighted averages of the log prices

[8] The head of household is identified by the survey participant, and can be a single person or two persons, regardless of gender, or marital or employment statuses. In our sample, 87.46% of households have both a female and male household head, 11.10% only have a female household head, and the remaining 1.43% only have a male household head.

[9] Although there are other vitamins, we focus on these five vitamins that are generally listed on the cereal box and can be easily recognized by the consumers.

in equation 2.8. As illustrated in the previous section, we use two types of distance measures, continuous and discrete. The continuous distance measures are defined as the inverse of the Euclidean distance for each nutrient variable: fiber (DM_FIBER), sugar (DM_SUGAR), and fat (DM_FAT). The discrete measures take into account whole-grain type (DM_WG), whether a product targets children (DM_KIDS), added flavors (DM_FLAVOR), and manufacturer (DM_MAKER). For example, if two cereal brands are produced by the same manufacturer, or both feature whole grains as the first ingredient, then the measure of the distance between these two products would equal one. Also, product attributes are used as shifters of the own-price and expenditure parameters. The variables fat (FAT), sugar (SUGAR), number of vitamins fortified (NVF), whole-grain type (WG), and added color (ADCOLOR) are interacted with the log form of the own-price term (LNP), while only whole-grain type, number of vitamins fortified, and fat are interacted with the expenditure term (LNEP). Finally, we add dummy variables to capture unobserved heterogeneity in geographic markets and cereal manufacturers.

2.5 Identification and Model Specifications

To proceed with the estimation of equation 2.8, two empirical issues need to be addressed. The first issue involves price endogeneity. We test for and then attempt to correct for price endogeneity using Hausman-type price instruments, i.e., prices from other markets picking up the same cost shock but not affected by the same demand shocks.

We propose a random-draw method to construct the Hausman-type price instruments.[10] First, we divide all the Nielsen scantrack markets according to the four macro regions used by the United States Census Bureau: Northeast, Midwest, South and West. For each market, we randomly draw two outside macro regions. Then we randomly draw one market from each chosen outside macro region as the source of our price instrument. Finally, we calculate the yearly average price of the products in the selected instrument markets as the price instruments. The validity of this random-draw version of Hausman-type price instruments is based on the assumption that two markets from two different regions that are far enough apart have no common demand shocks. The performance of these random-draw Hausman-type price instruments, which will be discussed in the results section, is evaluated based on 600 random draws.

A second empirical issue is model specification, i.e., choosing the exact variables constituting the z^{β} and z^{γ} vectors. We select our preferred model specification from

[10] To choose a proper outside market, our first attempt selected an outside market farthest away from the target market. However, only a very few outside markets are chosen as instrument markets with this method, and most of these outside markets are located on the east or west coast of the United States. This first attempt results in a low variation of price instruments and poor performance of estimation.

50 different model specifications and a series of robustness checks comparing estimation results. These specifications vary in two ways: the interactions between product attributes and the log form of price or the interactions between product attributes and the expenditure term. More specifically, we explore adding or removing interactions between different nutrients and prices (or expenditures), and then evaluate each specification's performance.

Three model specification criteria are used. The first one is a Wald test for model selection between nested models. The null hypothesis is that the parameters for the added independent variables are simultaneously equal to zero. Rejecting the null indicates that the additional independent variables could help to increase the goodness of fit of the model in a statistically significant way.[11]

Second, due to the potential risk of multicollinearity arising from using the same attributes as own-price and expenditure parameter shifters (as well as in the distance measures), the average variance inflation factor (VIF) is used as a second model specification criterion. An informal rule of thumb is that a VIF above 20 signals a problem (Greene, 2012, p. 90). We therefore eliminate model specifications with a VIF value above 20.

The third criterion involves instrumental variable tests. Given the chosen price instruments above, we use three tests to justify the validity of instruments among different model specifications. An F-test is used to evaluate the joint significance of parameters for excluded instruments, which helps to rule out weak instruments. According to Staiger and Stock (1997), a test statistic larger than 10 indicates that the instruments have enough explanatory power. The Wald test of endogeneity is used to verify whether correcting for price endogeneity is necessary. We choose 1% as the critical value for this test, and rejecting the null indicates the existence of endogeneity. Finally, to verify whether the overidentifying restrictions are satisfied, we rely on the Amemiya-Lee-Newey (ALN) minimum distance statistic. We use a 10% threshold for the ALN test statistic, where failure to reject the null hypothesis casts doubt on the validity of the instruments.

Using these criteria, the model specification follows the following procedure: we first identify specifications that pass all three instrumental tests; second, we rule out the specifications that fail the pair-wise Wald tests; finally, among the remaining specifications, we choose the one with the smallest VIFs. Results of these tests and procedures are discussed in the next section.

[11] We choose 5% as the critical value for rejecting the null for this Wald test.

2.6 Empirical results

2.6.1 Performance of price instrument

Before presenting the estimation results for our preferred specification, we first evaluate the performance of random-draw Hausman-type price instruments. We also examine parameters estimated under each trial of the price instruments used. All 600 random draws pass the weak instrument tests by a wide margin (with F-statistics averaging over 2000); 558 out of 600 draws pass the Wald endogeneity test; 358 draws pass the ALN test; and 337 passing all three tests. Model estimations for these 337 draws all yield parameter estimates satisfying basic economic rationales such that estimated own-price coefficients are negative and statistically significant, and estimated total expenditure coefficients are positive and significant. As a result, we can see that our random-drawn Hausman-type price instrument works well on average, with a 56.17% success rate of passing all instrument tests, which is much higher than the alternative procedure that chooses outside-markets using a farthest-distance rule.[12]

2.6.2 Selection of model specification

As mentioned above, we compare 50 model specifications that vary by interactions between own-price term (or expenditure term) and product attributes. To select the best specification, we first test instrument validity. All of these specifications pass the weak instrument test with F-statistics in the range of [32.07, 8184.16] and with an average value of 2728.47. Only seven specifications fail the Wald endogeneity test (indicating that they have an endogeneity issue) and 19 specifications fail the ALN test (indicating that they fail to satisfy the overidentification restriction). By jointly considering these three instrumental tests, 25 models remain, all of which satisfy the economic rationale of negative own-price terms and positive total expenditure terms.

Among the remaining specifications, we generally encounter a tradeoff between goodness of fit, as indicated by pairwise Wald tests, and potential multicolinearity, as indicated by VIF calculations. We can eliminate 14 specifications that lead to VIFs above 20. Among the remainders, we find our preferred model, which has

[12] We have not yet justified the choice of using two outside market price instruments. Our reasoning goes as follows: (1) To guarantee that the demand shock is uncorrelated, we choose a price instrument from the maximum for each product estimated, given the fact that there are four macro regions in the United States. (2) We then compare instrument performance by using one, two, or three price instruments and find that using two price instruments has virtually no difference compared with using three. Moreover, both of these options have much better performance than using only one price instrument, which we measure by examining the success rate of passing all three instrumental tests. As a result, price instruments from markets in two outside regions are used in our final estimation.

a VIF of 20 and the best Wald test results. Empirical results in the next section are based on this model in which five product attributes are interacted with price, including whole-grain type (WG), fat (FAT), sugar (SUGAR), number of vitamin fortifications (NVF), and added artificial color (ADCOLOR), and three product attributes are interacted with the total expenditure term, including WG, FAT, and NVF.

2.6.3 Results for our preferred specification

Given the discussion above, we report the empirical results of the preferred specification in this section. We employ Newey's two-step estimator for instrumental-variable (IV) Tobit models. The average VIF value for this specification is 20, which is comparable to previous research using the DM method (Bonanno, 2013). The p-value of Wald endogeneity test is 0, which indicates the existence of endogeneity in the estimation. The F-statistic for the weak instrument test is 2854.50, which suggests sufficient explanatory power of the random-draw Hausman-type price instrument. Furthermore, the p-value for the ALN statistic is 0.2359, which indicates the validity of the instruments used in this paper.

Table 3.4 shows the estimated parameters for the IV Tobit. The own-price coefficient (LNP) is negative and significant (-0.3516) at the 1% level. Estimated coefficients for price-attribute interactions that are positive (and significant) indicate less price sensitivity to those attributes, while negative (and significant) estimates indicate greater price sensitivity. Our results show that households in our sample become less price sensitive if cereal products have whole grain as first ingredient (LNP$*$WG = 0.0567), have higher levels of fat (LNP$*$FAT = 0.0160) and sugar (LNP$*$SUGAR = 0.0027), and have additional vitamin fortifications (LNP$*$NVF = 0.0133). On the other hand, households become more price sensitive if a cereal product contains artificial color (LNP$*$ADCOLOR = -0.0833). For some of these results, preferences on health and taste may be intertwined; however, the results for vitamin fortifications and artificial color are arguably centered only on health.

The interpretation of results in table 3.4 that feature the DM coefficients require the notion of closeness in attribute space, and generally show how consumers respond to the price changes of products that are closer substitutes. The positive and significant estimated parameter for DM_FIBER (0.0011) indicates that, in response to price increases households in our sample are more likely to switch to another cereal product that has similar fiber content. Similarly, the positive and significant coefficient of DM_WG (0.0123) suggests that these households are more likely to move to products that also use whole grain as first ingredient in response to a price increase. In other words, households that prefer whole-grain cereals will likely switch to other whole-grain cereals. On the other hand, for sugar and fat, which are generally understood to be unhealthful attributes, the estimated coefficients show different substitution patterns (DM_SUGAR = -0.0322; DM_FAT = -0.0203). Given a price increase, households are less likely to switch to another cereal product with similar sugar or fat content, and therefore they are more likely to turn to cereals that are farther away in the attribute space of these two nutrients. One possible explanation for this result is that consumers are making tradeoffs between good taste and healthful eating. Given a price increase, consumers who favor cereals with higher levels of sugar or fat (perhaps tastier cereals) are induced to switch to more healthful cereals by price increases. The converse is also true: consumers who favor more healthful cereals with lower sugar or fat can be induced by a price increase to switch to less healthful cereals. The positive and significant coefficient of DM_KIDS (0.0098) indicates that households that buy cereals targeted to children tend to switch to other kids' cereals, while households that buy adult or family cereals tend to switch to other adult or family cereals. Finally, a DM for manufacturers (DM_MAKER) and added artificial flavor (DM_ADFLAVOR) show no statistical effect on households' substitution patterns among these 20 cereal brands.

The estimated parameter for the expenditure term (LNEP) is positive and significant at the 1% level (0.0903). Estimated coefficients for expenditure-attribute interactions that are positive (and significant) indicate greater expenditure sensitivity to those attributes, while negative (and significant) estimates indicate less expenditure sensitivity. Our results show that households become more expenditure sensitive if cereal products have whole grain as the first ingredient (LNEP$*$WG = 0.0085). The opposite result is found for products with more fat (LNEP$*$FAT = -0.0063) or fortified with vitamins (LNEP$*$NVF = -0.007). Overall, these results indicate that demand for whole-grain cereals expands the most as the cereal category expands, while demand for vitamin-fortified or higher fat content cereals contracts as the category expands.

Our preferred model also has intercept shifter terms, only some of which are statistically significant. Larger households (HHSIZE) tend to purchase more cereal (0.0051), as do households identified as white (WHITE) (0.0072). On the other hand, households with higher age for the household head (AGEHIGH) tend to purchase less cereal on average (-0.0021). Package size (AVESIZE) also has a negative impact on cereal purchases (-0.0017). Neither marriage status, education, household income, nor Hispanic shifters show evidence of affecting household purchasing decisions on breakfast cereal.

Using the estimated demand parameters, we calculate and present the own- and cross-price elasticities in tables 2.4 and 2.5. All of the unconditional and conditional own-price elasticities are negative and significant at the 1% level. The unconditional elasticities are slightly larger than the conditional elasticities in absolute value (with average values of -2.024 and -1.707, respectively), indicating that existing consumers tend to be less price-sensitive than those who have not purchased the products before. These findings also indicate that, for our sample of households with children, demand for cereal is quite elastic. Compared to previous analyses of the U.S. cereal market (e.g., Hausman, 1996; Nevo, 2001; Chidmi and Lopez, 2007), our own-price elasticities (both conditional and unconditional ones) are smaller;[13] however, their elasticities are obtained using market-level purchase data, while we use more disaggregated data.

Both the conditional and unconditional cross-price elasticities show similar substitution (or complementarity) patterns. Among the 380 conditional cross-price elasticities, 260 are statistically different than zero: 203 at the 1% level, 32 at the 5% level, and 25 at the 10% level. With respect to the 380 unconditional cross-price elasticities, 261 are statistically different from zero: 204 are significant at the 1% level, 31 at the 5% level, and 26 at the 10% level. These results also show that if two cereal products are targeted to children (or to family/adults), they tend to be closer substitutes in most cases (for example, 67 out of 90 conditional cross-price elasticities between two children's cereals are positive, and 67 out of 90 conditional cross-price elasticities between two family/adult cereals are positive). By contrast, children's cereals are more likely to be complements with family/adult cereals: 131 of 200 conditional cross-price elasticities between a children's cereal and a family/adult cereal are negative. These findings suggest that households may buy a portfolio of cereals from either children's cereals or family/adult cereals to satisfy each family member's preference.

2.6.4 Robustness check of conditional own-price elasticity

As mentioned above, we investigated 50 specifications before arriving at our preferred model. In this section, we utilize the results of those 50 specifications to investigate the robustness of own-price elasticity calculations for the preferred specification. In table 2.6, the average values of own-price elasticity are calculated for all 50 specifications and for the 25 specifications that pass all three instrumental tests and thus are valid IV specifications. The own-price elasticities for our preferred model are also listed for comparison. The own-price elasticities are negative and significant across all 50 specifications. The mean value of own-price elasticity is -1.843 for all the specifications and -1.604 for the valid IV specifications. We find that the average value of own-price elasticities for our preferred specification (-1.707) is quite close to the average value across specifications, either compared with the full set of specifications or the valid-IV specifications. Moreover, after we exclude the specifications that fail any of those three instrument tests above, the difference between the average own-price elasticity for our preferred model and the passable specifications becomes even smaller, a result that demonstrates

[13] The average unconditional own-price elasticities derived by using market level data are -2.32 from Hausman (1996), -3.04 from Nevo (2001), and -4.1822 from Chidmi and Lopez (2007). However, the brands and markets chosen in their papers are quite different from the ones chosen in our paper.

robustness of the own-price elasticity in our preferred model.

2.6.5 Comparison with a two-step procedure

For a comparison, we also estimated the full demand system for the 20 cereal products using a two-step estimation method by following Shonkwiler and Yen (1999). On one hand, the estimated results from this method confirm the need for an appropriate correction for the zero purchases. However, the final results from this method often run counter to economic intuition. For example, estimated own-price coefficients are often not statistically significant and sometimes positive. In addition, about half of the estimated coefficients for the expenditure terms are negative and significant, which is again in conflict with standard economic outcomes. We conclude that DM method performs very well against this alternative.

2.7 Conclusion

This paper investigates the impact and importance of health-related product attributes on consumers' purchasing behaviors in the RTE cereal market, and illustrates how a relatively simple method, Pinkse, Slade, and Brett (2002)'s DM method, can be used to assess demand for a large number of product alternatives using micro-level, censored, purchase data. Three major benefits of using the DM method were shown in this paper. First, the DM method solves the dimensionality problem in terms of both the number of parameters and equations to be estimated. Second, the DM method can be easily incorporated into a censored demand system, avoiding the calculation of multiple integrals when dealing with zero purchases in a continuous-quantity framework. Finally, the DM method explicitly models the impact of the differences between products in attributes on the substitution patterns among cereal products.

The sensitivity analyses conducted to support our preferred model choice support the extreme practicality of our approach. With very little computational burden, we estimated hundreds of versions of a censored demand system for 20 brands of breakfast cereal. This task might seem achingly tedious, if not virtually impossible, in other estimation frameworks. However, despite the computational ease, our results correspond quite closely to results from previous research.

Our results show that, in the context of RTE breakfast cereals, health-related attributes do impact consumer purchase decisions. When prices change, products with similar fiber content or products containing whole grain as the first ingredient tend to be strong substitutes. For our sample of households with children, we observe that households are likely to switch within the kids or adult cereal categories in response to a price increase. Also, households on average are less responsive to price changes for cereals with whole grain listed as the first ingredient; however, they are also less responsive to price changes for cereals with higher content of sugar and fat. These findings suggest that attitudes towards healthful and unhealthful product attributes do not generate behavioral responses explained purely by health concerns. Rather, the results suggest that preferences for taste and health are intertwined with price concerns in a more complicated fashion, and substitutability reflect cereal's entire attribute space.

Tables and Figures

Table 2.1. Summary statistics of purchase data and demographics

Variable	Description	Mean	Std.
Purchase			
SH	Individual expenditure share for each brand	0.05	0.12
LNP	Average purchase price (cents), in log form	2.71	0.27
Demographics			
Continuous			
HHSIZE	Number of individuals in the household	4.12	1.12
HHINC	Household annual income	21.17	5.26
AGEHIGH	Max age category of household head(s)	5.60	1.51
Discrete		Frequency of one	
WHITE	Race is white for the household		0.77
MARRIED	Marital Status of household head(s)		0.85
HISPANIC	Hispanic origin for the household		0.10
HIGHSC	Max edu. attainment for household head(s): high school		0.15
SOMECOL	Max edu. attainment for household head(s): some college		0.26

Table 2.2. Summary statistics of health/non-health related product attributes

Variable	Description	Mean	Std.
Continuous			
FAT	Total fat (g/100 g)	2.92	2.39
SUGAR	Total sugars (g/100 g)	27.35	13.30
FIBER	Total dietary fiber (g/100 g)	5.46	3.81
NVF	Number of vitamin fortified	2.85	1.88
AVESIZE	Average package size (oz)	18.54	4.68
MAKER	Manufacturer for the RTE breakfast cereal	2.05	0.80
Discrete		Frequency of one	
WG	Product has whole grain as first ingredient		0.35
KIDS	Target to children		0.50
ADFLAVOR	Other flavor ingredient added		0.45
ADCOLOR	Other artificial color added		0.40

Table 2.3. Estimated parameters for preferred model specification

Variables	Coefficient		Standard errors
HHSIZE	0.0051	* * *	0.0015
WHITE	0.0072	*	0.0044
MARRIED	-0.0018		0.0050
HISPANIC	-0.0054		0.0060
AGEHIGH	-0.0021	*	0.0011
HIGHSC	0.0035		0.0049
SOMECOL	0.0063		0.0039
HHINC	-0.0002		0.0004
AVESIZE	-0.0017	* * *	0.0002
LNP	-0.3516	* * *	0.0486
LNP∗WG	0.0567	* * *	0.0192
LNP∗FAT	0.0160	* * *	0.0026
LNP∗NVF	0.0133	* * *	0.0051
LNP∗SUGAR	0.0027	* * *	0.0001
LNP∗ADCOLOR	-0.0833	* * *	0.0053
DM_SUGAR	-0.0322	* * *	0.0028
DM_FAT	-0.0203	* * *	0.0012
DM_FIBER	0.0011	**	0.0006
DM_WG	0.0123	* * *	0.0024
DM_KIDS	0.0098	* * *	0.0027
DM_MAKER	-0.0007		0.0032
DM_ADFLAVOR	0.0016		0.0015
LNEP	0.0903	* * *	0.0095
LNEP∗WG	0.0085	*	0.0044
LNEP∗FAT	-0.0063	* * *	0.0009
LNEP∗NVF	-0.0070	* * *	0.0023
COMPANY A	-0.0703	* * *	0.0258
COMPANY B	-0.0926	* * *	0.0395
COMPANY C	-0.0359		0.0782
CONSTANT	0.2208	**	0.1013
VIF	20.00		
F-test	2854.51		
Endog(p-value)	0.0000		
ALN Test(p-value)	0.2359		

[1] *, **, and * * *represent 10%, 5% and 1% significance levels, respectively.

Table 2.4. Conditional Own- and Cross-price elasticity

		Kids Cereal										Family/Adult Cereal									
		Company A	Company B			Company C						Company A			Company B		Company C				Company D
		K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	FA1	FA2	FA3	FA4	FA5	FA6	FA7	FA8	FA9	FA10
Company A	K1	-1.642	0.024	0.023	-0.014	0.006	0.028	0.016	-0.025	-0.001	0.022	-0.030	-0.033	0.012	-0.020	-0.014	0.013	-0.009	0.002	0.003	-0.013
Company B	K2	0.025	-1.123	0.025	-0.002	0.028	0.027	0.027	0.024	0.012	0.027	-0.002	0.000	0.013	0.000	-0.001	0.014	0.007	0.014	0.006	0.000
	K3	0.025	0.026	-1.416	-0.007	0.015	0.019	-0.001	0.025	0.007	0.031	-0.020	-0.013	0.016	-0.018	-0.042	0.019	0.005	0.016	0.015	-0.016
	K4	0.000	-0.007	0.000	-1.078	0.003	0.004	-0.003	0.000	0.018	0.006	0.004	0.008	-0.006	0.003	0.003	-0.003	-0.010	-0.004	-0.008	-0.001
Company C	K5	0.005	0.021	0.010	0.000	-1.253	0.015	0.015	0.013	-0.002	0.014	-0.013	-0.020	0.010	-0.007	-0.007	0.007	-0.001	0.000	0.005	-0.005
	K6	0.018	0.019	0.011	-0.001	0.014	-1.310	0.015	-0.002	0.002	0.008	-0.006	-0.007	0.010	-0.008	-0.004	-0.007	0.005	0.003	-0.005	-0.005
	K7	0.005	0.007	0.000	-0.002	0.006	0.006	-1.107	0.004	0.002	0.006	-0.005	-0.003	0.003	-0.003	-0.008	0.003	-0.001	0.003	0.002	-0.003
	K8	-0.003	0.009	0.012	-0.001	0.010	0.002	0.007	-1.126	0.001	0.007	-0.005	-0.005	0.007	-0.005	-0.003	-0.004	0.003	0.003	0.000	-0.004
	K9	-0.013	0.007	0.004	0.056	-0.024	-0.003	-0.005	-0.040	-2.084	-0.041	0.017	-0.010	-0.075	0.017	0.037	-0.061	-0.068	-0.134	-0.077	-0.037
	K10	0.012	0.013	0.015	0.001	0.011	0.007	0.011	0.005	-0.003	-1.249	-0.007	-0.019	0.008	-0.010	-0.009	-0.012	0.004	-0.006	-0.006	-0.006
Company A	FA1	-0.057	-0.042	-0.052	-0.014	-0.049	-0.028	-0.058	-0.059	0.015	-0.043	-1.702	0.044	0.005	0.047	0.050	0.011	-0.064	-0.002	-0.005	0.055
	FA2	-0.171	-0.093	-0.103	-0.013	-0.190	-0.085	-0.114	-0.159	-0.014	-0.242	0.106	-3.320	0.023	0.098	0.103	-0.057	-0.033	-0.159	-0.009	0.148
	FA3	0.025	0.015	0.028	-0.041	0.029	0.030	0.016	0.019	-0.045	0.028	0.010	0.016	-2.162	-0.034	0.013	0.077	0.069	0.073	0.075	-0.020
Company B	FA4	-0.003	-0.007	-0.007	0.003	-0.003	-0.003	-0.006	-0.008	0.012	-0.008	0.023	0.021	-0.004	-1.170	0.020	0.005	0.007	0.005	0.007	0.018
	FA5	-0.057	-0.048	-0.195	-0.012	-0.054	-0.034	-0.158	-0.073	0.059	-0.092	0.109	0.091	0.023	0.111	-2.154	0.013	-0.008	-0.051	0.032	0.109
Company C	FA6	0.018	0.011	0.026	-0.032	0.012	-0.026	0.012	-0.046	-0.034	-0.055	0.010	-0.018	0.063	-0.009	0.005	-2.002	0.053	0.032	0.032	0.010
	FA7	-0.007	0.000	0.005	-0.030	-0.003	0.009	-0.007	0.003	-0.023	0.010	-0.034	-0.002	0.042	0.006	0.000	0.040	-1.407	0.032	-0.015	0.006
	FA8	0.006	0.030	0.041	-0.047	-0.007	0.009	0.018	0.001	-0.127	-0.043	0.003	-0.085	0.105	0.000	-0.034	0.059	0.077	-2.399	0.065	0.014
	FA9	0.013	-0.008	0.043	-0.077	0.018	-0.032	0.014	-0.034	-0.076	-0.050	-0.001	0.005	0.121	0.009	0.028	0.066	-0.047	0.073	-2.273	0.024
Company D	FA10	-0.024	-0.038	-0.046	-0.033	-0.024	-0.020	-0.046	-0.052	-0.020	-0.039	0.072	0.078	-0.022	0.045	0.063	0.019	0.008	0.012	0.018	-2.171

Table 2.5. Unconditional Own- and Cross-price elasticity

		Kids Cereal										Family/Adult Cereal									
		Company A	Company B		Company C							Company A		Company B			Company C				Company D
		K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	FA1	FA2	FA3	FA4	FA5	FA6	FA7	FA8	FA9	FA10
Company A	K1	-2.217	0.046	0.044	-0.027	0.011	0.053	0.030	-0.046	-0.002	0.042	-0.056	-0.063	0.023	-0.038	-0.027	0.025	-0.017	0.003	0.006	-0.024
Company B	K2	0.045	-1.224	0.045	-0.003	0.051	0.050	0.049	0.044	0.021	0.048	-0.004	0.000	0.023	0.000	-0.002	0.026	0.012	0.025	0.012	0.000
	K3	0.045	0.048	-1.749	-0.012	0.028	0.034	-0.001	0.046	0.013	0.057	-0.036	-0.024	0.028	-0.033	-0.076	0.034	0.009	0.028	0.027	-0.029
	K4	0.000	-0.015	-0.001	-1.160	0.007	0.009	-0.006	0.000	0.037	0.012	0.009	0.016	-0.012	0.006	0.005	-0.005	-0.021	-0.008	-0.016	-0.003
Company C	K5	0.014	0.057	0.026	0.001	-1.671	0.039	0.039	0.036	-0.005	0.037	-0.034	-0.054	0.026	-0.018	-0.018	0.018	-0.003	-0.001	0.012	-0.013
	K6	0.047	0.050	0.030	-0.001	0.037	-1.816	0.038	-0.005	0.006	0.021	-0.017	-0.020	0.026	-0.022	-0.011	-0.019	0.012	0.007	-0.014	-0.012
	K7	0.025	0.033	0.002	-0.011	0.029	0.030	-1.517	0.018	0.009	0.030	-0.022	-0.013	0.014	-0.016	-0.036	0.017	-0.002	0.012	0.011	-0.015
	K8	-0.008	0.024	0.032	-0.002	0.026	0.006	0.019	-1.343	0.002	0.019	-0.013	-0.013	0.018	-0.015	-0.009	-0.011	0.009	0.009	-0.001	-0.010
	K9	-0.019	0.011	0.006	0.083	-0.035	-0.004	-0.007	-0.058	-2.598	-0.061	0.026	-0.015	-0.110	0.025	0.055	-0.090	-0.100	-0.197	-0.114	-0.055
	K10	0.034	0.037	0.044	0.003	0.031	0.019	0.033	0.016	-0.009	-1.720	-0.021	-0.055	0.023	-0.030	-0.026	-0.035	0.013	-0.016	-0.017	-0.019
Company A	FA1	-0.084	-0.061	-0.075	-0.020	-0.071	-0.041	-0.085	-0.086	0.022	-0.063	-2.021	0.064	0.007	0.069	0.073	0.016	-0.093	-0.003	-0.007	0.080
	FA2	-0.185	-0.101	-0.111	-0.014	-0.206	-0.092	-0.123	-0.173	-0.015	-0.262	0.115	-3.512	0.025	0.106	0.112	-0.061	-0.036	-0.172	-0.009	0.160
	FA3	0.034	0.021	0.038	-0.055	0.039	0.040	0.021	0.026	-0.061	0.038	0.014	0.022	-2.566	-0.045	0.018	0.104	0.093	0.098	0.101	-0.027
Company B	FA4	-0.006	-0.013	-0.014	0.006	-0.006	-0.005	-0.011	-0.015	0.023	-0.016	0.045	0.041	-0.008	-1.334	0.039	0.009	0.014	0.010	0.014	0.035
	FA5	-0.063	-0.052	-0.215	-0.013	-0.059	-0.038	-0.174	-0.081	0.065	-0.102	0.120	0.101	0.026	0.122	-2.271	0.014	-0.009	-0.056	0.035	0.120
Company C	FA6	0.030	0.018	0.042	-0.052	0.019	-0.043	0.019	-0.076	-0.056	-0.090	0.017	-0.029	0.104	-0.015	0.007	-2.647	0.087	0.053	0.053	0.016
	FA7	-0.012	-0.001	0.008	-0.051	-0.005	0.016	-0.011	0.005	-0.038	0.017	-0.058	-0.004	0.071	0.011	0.000	0.068	-1.689	0.055	-0.026	0.010
	FA8	0.008	0.035	0.048	-0.054	-0.008	0.010	0.021	0.001	-0.149	-0.051	0.003	-0.099	0.123	0.000	-0.040	0.069	0.090	-2.635	0.076	0.016
	FA9	0.014	-0.009	0.048	-0.085	0.020	-0.035	0.016	-0.037	-0.084	-0.055	-0.001	0.006	0.133	0.010	0.030	0.073	-0.051	0.081	-2.405	0.027
Company D	FA10	-0.029	-0.045	-0.054	-0.039	-0.028	-0.024	-0.055	-0.061	-0.023	-0.047	0.086	0.092	-0.026	0.054	0.074	0.023	0.009	0.014	0.021	-2.392

Table 2.6. Robustness checks: own-price elasticity across specifications

Brands	Preferred Model	25 Valid IV Specifications			All 50 Specifications		
		Mean	Min	Max	Mean	Min	Max
K1	-1.642	-1.496	-1.820	-0.603	-1.763	-3.365	-0.603
K2	-1.078	-1.066	-1.149	-0.958	-1.030	-1.149	-0.834
K3	-1.253	-1.212	-1.298	-0.943	-1.257	-1.633	-0.943
K4	-1.310	-1.259	-1.371	-0.919	-1.340	-1.869	-0.919
K5	-1.126	-1.106	-1.181	-0.941	-1.154	-1.382	-0.941
K6	-1.249	-1.200	-1.283	-0.846	-1.331	-2.412	-0.846
K7	-1.702	-1.579	-2.093	-0.913	-1.795	-3.394	-0.913
K8	-3.320	-2.913	-4.414	-0.820	-3.669	-8.069	-0.820
K9	-2.162	-2.003	-2.445	-0.880	-2.442	-4.920	-0.880
K10	-2.154	-2.064	-2.761	-1.502	-2.107	-3.059	-0.762
FA1	-2.273	-2.087	-2.532	-0.687	-2.646	-5.451	-0.687
FA2	-2.171	-1.993	-2.635	-1.241	-2.546	-20.551	-1.241
FA3	-1.123	-1.140	-1.272	-0.981	-1.129	-1.272	-0.981
FA4	-1.416	-1.337	-1.523	-0.830	-1.449	-2.098	-0.830
FA5	-1.107	-1.090	-1.125	-0.970	-1.118	-1.338	-0.970
FA6	-2.084	-1.946	-2.621	-0.934	-2.184	-3.928	0.684
FA7	-1.170	-1.161	-1.253	-1.046	-1.174	-1.387	-0.884
FA8	-2.002	-1.845	-2.167	-0.654	-2.390	-6.221	-0.654
FA9	-1.407	-1.356	-1.584	-0.816	-1.528	-2.404	-0.816
FA10	-2.399	-2.229	-2.625	-0.798	-2.807	-6.429	-0.798

Chapter 3

Quantifying the Welfare Effect of Changing Healthy Attributes in the Ready-to-Eat Cereal Market

3.1 Introduction

Since 2005, the Dietary Guidelines for Americans recommend that people in the United States should increase their intake of whole grains and dietary fiber and decrease consumption of refined grains, added sugars, solid fats, and sodium to reduce the risk of heart disease, diabetes, and other chronic health conditions (USDA/HHS, 2005, 2010, 2015). Recent research confirms that U.S. consumers have become increasingly aware of what constitutes a healthy diet (Gregory, Smith, and Wendt, 2011; Variyam and Smith, 2010; Mancino, Kuchler, and Leibtag, 2008). To appeal to a more health-conscious consumer base, cereal manufacturers have improved the nutritional profiles of their products. From 2006 to 2012, ready-to-eat (RTE) breakfast cereals manufacturers engaged in product reformulations by reducing sugar and sodium and increasing fiber content. These changes, according to Harris, Schwartz, Brownell, Sarda, Dembek, , Munsell, Shin, Ustjanauskas, and Weinberg (2012), resulted in an improvement in the nutritional quality of existing cereal brands by 14 percent for kids cereals, 12 percent for family cereals, and 5 percent for adult cereals, with large RTE breakfast cereal companies contributing the most to this change. Thomas, Pehrsson, Ahuja, Smieja, and Miller (2013) also confirm these nutritional changes by examining the nutrition data of RTE breakfast cereal products from the two major cereal manufacturers, General Mills and Kellogg, which account for about 62% of the whole RTE cereal market. They find that from 2005 to 2011 the fiber content increased by about 13.4%, and the sugar and sodium levels decreased by about 7.6% and 11.2% respectively. Whole grain ingredients were found in at least two thirds of the cereals in 2011. Coincidentally RTE cereal sales experienced significant growth around the same time: the two leading firms, General Mills and Kellogg, experienced a strong sales growth of about 36% in total, from $3.9 billion to $5.3 billion from 2002 to 2010 (General Mills and Kellogg Annual Report to Shareholders, 2003-2010).

In this paper, we evaluate the welfare effect to consumers and manufactures of nutritional improvements to RTE cereals due to the resulting change of consumer demand and associated production costs. More specifically, we quantify the impacts of the nutritional improvement on consumer surplus, producer surplus, and total surplus, taking into account that market prices and consumer demand are endogenous in equilibrium. To do so, we extend the demand model of Li, Jaenicke, Anekwe, and Bonanno (2016) to an equilibrium model by incorporating manufacturers' optimal pricing strategy. The model captures how the nutritional improvement influences the equilibrium prices for each cereal products and accordingly the consumer demand at the new prices.

In order to quantify the effect of the nutritional improvement of the RTE cereals, we first estimate a censored demand system, which is derived from a modified linear approximate almost idea demand system(LA/AIDS) model, using micro-level data following Li, Jaenicke, Anekwe, and Bonanno (2016). The demand estimation applies the distance metric (DM) approach following Pinkse, Slade, and Brett (2002), Pinkse and Slade (2004), Rojas (2008), and Bonanno (2013), which contributes to a simplified estimation of a demand system and accounting for the impact of product differences in the key attributes. Specifically, estimating a demand system with numerous products would encounter a large computational burden due to a dimensionality problem. Using micro-level data, which has become increasingly popular due to its comprehensive information, can substantially aggravate this problem because micro-level data are usually censored with many zero purchases.[1] The distance metric approach simplifies the censored demand system into a stacked, single equation, which is much easier to estimate when dealing with many-zero-purchase issues in micro-level data such as Nielsen Homescan data set.

We then aggregate the individual consumer demand to market demand and, following Nevo (2001), solve firms' optimal pricing strategies to recover the marginal production costs for each product using information on observed consumer demand, prices, and other observed factors shifting consumer demand and production costs, without actually observing the production data following Nevo (2001). Equipped with the demand and cost functions, we then conduct a series of counterfactual experiments to evaluate how nutritional improvements to RTE cereal products affect consumer surplus, producer surplus, and total surplus, through the channels of resulting equilibrium prices and demand.

The empirical results show that improving the health quality of product at-

[1] For more literature review on solving both dimensionality problem and censoring issue, and a review of distance metric method, please refer to chapter two (essay one).

tributes has a substantial impact on consumer welfare, producer surplus, and total welfare through their effect on consumer demand, production costs, and the resulting equilibrium prices. However, these effects may not necessarily be positive. We find that changing the first ingredient to whole grain increases consumer welfare, producer surplus, and total welfare. In contrast, reducing fat and/or sugar actually lowers welfare. This outcome arises as a new equilibrium because consumers actually prefer cereal products with high content of sugar and fat, although they are treated as unhealthy, probably because the taste is better or because many consumers do not fully realize the health risk associated with high intake of sugar and fat. The effect of changing fiber content has but a small effect on consumer welfare, producer surplus, and total welfare. These welfare effects reflect the equilibrium results from consumer demand and production costs, associated with the change of nutritional contents.

This paper is related to several papers trying to quantify the impact of product reformulations. For example, Feenstra (1993) find that after quality upgrading of the imported Japanese cars in the United States, the deadweight loss becomes very large. Beatty, Lin, and Smith (2014) find that changes in food formulation account for a substantially large percentage of the dietary improvement among adults in the United States. Griffith, OConnell, and Smith (2014) find that consumers' recent decline of intake of dietary salt in UK is entirely attributable to product reformulation by firms. Several studies focus on the RTE cereal market: Nevo (2003) conducts a welfare analysis due to the quality change and new product introduction in the ready-to-eat breakfast cereal industry during the year from 1988 to 1992. His results are mostly negative, probably due to few major reformulations in that period or because a very small set of products is considered in his research. In contrast, Mancino, Kuchler, and Leibtag (2008) track the trend of consumers purchase of five whole-grain food products from 1998 to 2006, including RTE breakfast cereal, and find that consumers' dietary changes to meet the recommended dietary guideline can be attributed to food manufacturers' new product introductions or product reformulations by increasing the content of whole grain in these products led by the 2005 U.S. dietary guidelines.

The rest of this paper is organized as follows: next we first introduce the data and variable definitions used in the estimation. In section three, we discuss the demand model, and the counterfactual setups by constructing manufacturers' profit optimization. Section four shows the estimated results as well as the changes of consumer and manufacturers' surplus. The last section concludes.

3.2 Data and Variable Definition

3.2.1 Data

Since the data used in this paper is from the same source as that in chapter two, we only briefly review the data and summarize the main variables used in this chapter. The first data source is the Nielsen Homescan dataset, which contains detailed information for household level purchases, including the quantity, price, and other product information for each purchase trip. It also contains detailed social demographics for each household which can be matched to each household-level purchase record. This dataset encompasses households living in all 48 contiguous states and the District of Columbia; the households are grouped into 52 metropolitan market areas, plus an additional area that covers the rest of the United States.

Following chapter two, we focus on the top 20 national cereal brands with the highest number of observed purchase records and sales in this data sets. The total annual sales of these brands account for about 40 percent of the total RTE cereal market in this year. Because a number of cereal brands are targeted to children, we further filter our sample to focus on households with at least one child aged less than 18 years old. Finally, to further reduce the percentage of observed zero purchases, we limit our sample to those household who have at least 15 purchases of RTE cereals over a three-year period. As a result, our data sample extracted from the Nielsen Homescan dataset is constituted by the purchase records from 3,269 households with kids over the top 20 national-brand breakfast cereals in 2004. All the purchase records are yearly aggregated by household and brand.

Next, we match this dataset with brand level product characteristics based on two additional data sources. The first is the USDA National Nutrient Database for Standard Reference. It contains information on over 100 different nutrients and detailed description for each food product. All the nutrient values in this dataset are recorded based on a 100g edible portion. For the purpose of this research, we use several nutrients that are key components for the RTE breakfast cereals, including fiber, sugar, fat, etc. Since cereal manufacturers usually add extra content for some minerals to attract more consumers, we also include the number of vitamins added to fortify the cereal products, which is calculated by using the product description information of the five vitamin components in this dataset.[2]

In addition, since whole grain is commonly accepted as a healthy ingredient in the RTE breakfast cereals, we collected the information of whole-grain type for each cereal product from the official website of each manufacturer. To assist this data collection, we use the "Wayback Machine" website that archives many prominent websites including the main page of RTE cereal manufacturers. Another

[2]The five vitamin components are vitamin A, vitamin D, vitamin E (total ascorbic acid), vitamin B-6, and vitamin B-12.

two attributes, extra flavor added and artificial color added, are also collected by reading the nutrition labels collected in this method. Finally, these three datasets are matched together using each product name and the UPC descriptions.

3.2.2 Variables for Estimation

Price ($/oz) is calculated by dividing the total dollars paid by the total number of ounces of a given brand bought by a household in each year. However, because the Nielsen Homescan database only reports prices for purchased products, we impute the missing prices for the non-purchased products by using the average scantrack market price (Arnade, Gopinath, and Pick, 2008). The quantity used in calculating each household's expenditure share is converted to total ounce purchased by each household in a year.

We control for several demographic variables constructed by using the Nielsen Homescan dataset: household size (HHSIZE), household income (HHINC), marital status (MARRIED), highest educational attainment (high school, HIGHSC; some college, SOMECOL) of a household head (or the maximum if there is more than one head), highest age (AGEHIGH) of a household head (or the maximum if there is more than one head), and a binary indicator for ethnicity of the household (WHITE, HISPANIC). Summary statistics of these variables are listed in table 3.1

Following chapter one, we focus on these nutrients: total sugar (SUGAR), total fat (FAT), total dietary fiber (FIBER), and the number of vitamins added to fortify the product (NVF). The content of the first three nutrients is measured as grams per 100 grams of cereal. We construct the variable NVF by summing five binary vitamin-fortification variables: vitamin A, vitamin D, vitamin E (total ascorbic acid), vitamin B-6, and vitamin B-12. For each vitamin considered, a binary variable is given the value one if the brand is enriched with an extra amount of this vitamin according to the reference value from the Recommended Dietary Allowances (RDAs) from the U.S. Food and Drug Administration (USDA/ARS, 2012).

By using the information collected from the Wayback Machine, we are able to create the following binary variables: whole-grain cereals (WG), identifying products whose first ingredient in the ingredients list is whole grain; added flavors (ADFLAVOR), capturing products that report added flavors in the ingredient list; and colors added (ADCOLOR), indicating products that report artificial coloring ingredients in the ingredient list. Also, according to the cereal facts report by Yale University's Rudd Center for Food Policy and Obesity (Harris, Schwartz, and Brownell, 2009), we create another binary variable, KIDS, which identifies products targeted to children. Finally, we construct another variable reflecting the average package size (AVESIZE) by using Homescans information on package size for each product.

All the product attributes mentioned above are considered to affect consumers' choices, and therefore are incorporated in the demand estimation. On the other hand, when considering the production process from the view of cereal manufacturers, all the product characteristics , not only the factors that affect consumers' purchase decisions, will play a role in affecting the marginal cost for breakfast cereals. As a result, besides the product attributes mentioned above, we also control several extra factors affecting cost including the nutrition levels for sodium(SODIUM), folate(FOLATE), calcium(Calcium), protein(PROTEIN), carbohydrate(CARB). Besides that, we also include the binary variable identifying whether or not the cereal product has fruit added (FRUIT). In order to approximate the operation cost for each cereal brand, the average package size (AVESIZE) is used to serve a different purpose here as an approximate of stock cost, which could also affect the production cost due to packaging. Finally, to reflect market coverage, we also include the number of unique stores that selling that cereal product (UNISTORE).

3.2.3 Distance Metric Measure

Consumers' purchase decisions for cereal products are not only determined by the characteristics of the product itself, but also by the relative position to other brands. Therefore, consumers' purchase could vary depending on the relative distance among the cereal options. Following Pinkse, Slade, and Brett (2002), Pinkse and Slade (2004) and Rojas (2008), we construct two distance measures in attributes space to quantify the dissimilarity of each unique product relative to the rest products when the consumer is making a choice.

The first one is the continuous distance measure (δ^c_{jk}), which is calculated using continuous product attributes (z^c_j) such as fiber and sugar by following Rojas (2008). It is defined as a function of the inverse Euclidean distance between any pair of products (j and k) in one-dimensional continuous attribute space. In this paper, we focus on three continuous attributes: fiber, sugar and fat. The measure is defined as follows

$$\delta^c_{jk} = \frac{1}{1 + 2\sqrt{\left(z^c_j - z^c_k\right)^2}}, \tag{3.1}$$

where $c = \{1, \ldots, C\}$ represents the index of the three continuous product attributes. z^c_j and z^c_k represent the content of attribute c for product j and k respectively. By construction, this continuous distance measure is positive between 0 and 1. It is smaller when the attribute-space difference between these two products is large.

The second distance measure is (δ^d_{jk}), is constructed based on discrete (binary) product attributes. If both products j and k belong to the same product type (e.g., both are whole-grain or both are produced by the same manufacturer), the distance between these two products for that attribute will be one. It equals zero otherwise.

$$\delta^d_{jk} = \begin{cases} 1 & if\ |z^d_j - z^d_k| = 0, \\ 0 & if\ |z^d_j - z^d_k| \neq 0. \end{cases} \tag{3.2}$$

Similar to the definition for continuous distance measure, $d = \{1, \ldots, D\}$ represents the discrete product attributes, and z^d_j and z^d_k are the attribute type for product j and k accordingly. Smaller value of δ^d_{jk}, which means $\delta^d_{jk} = 0$, indicates the two products are located far away from each other in this (binary) attribute space. Four binary attributes are considered in constructing the discrete distance measures: whole-grain, added flavor, manufacturer, and whether a product is targeted to children.

Using these distance measures, we further construct the weighted averages of the log form of cross prices in the estimation ($\sum_{j\neq k} \delta^c_{jk} logp_{ikt}$ for continuous attributes; $\sum_{j\neq k} \delta^d_{jk} logp_{ikt}$ for discrete attributes). The constructed variables are named as DM_FIBER, DM_SUGAR and DM_FAT, using the continuous distance measure for the continuous attribute mentioned above. Using the discrete distance measures, we construct another four weighted average variables to take into account of whole-grain type (DM_WG), whether a product targets children (DM_KIDS), adds flavors (DM_FLAVOR), and is produced by the same manufacturer (DM_MAKER).

3.3 A Model of Demand and Optimal Pricing

3.3.1 Consumer Demand

Since the demand estimation in this paper is based on the one in chapter two, we briefly review the demand model in this subsection. Following Lancaster (1979), consumers are assumed to maximize their utility by choosing the level of product attributes within their budget constraint. Under this framework, we follow Rojas and Peterson (2008) to apply the DM method into Deaton and Muellbauer (1980) LA/AIDS model. Consumer $i \in \{1, 2, ..., I\}$ spends a share of her expenditure w_{ijt} on product $j \in \{1, 2, ..., J\}$ in market $t \in \{1, 2, ..., T\}$, which is specified in the same way as chapter two as follows,

$$w_{ijt} = \alpha_{jt} + \sum_{k=1}^{J} b_{ijk} logp_{ikt} + c_{ij} log\frac{x_{it}}{P^L_{it}} + e_{ijt}. \tag{3.3}$$

where $w_{ijt} = q_{ijt}p_{ijt}/x_{it}$ is the expenditure share for consumer i, purchasing product j in market t. p_{ijt} is the unit price for product j and q_{ijt} is the total purchase quantity for consumer i in a year. $x_{it} = \sum_j q_{ijt}p_{ijt}$ is consumer i's total expenditure of all cereal products at market t. The term $logP^L_{it}$ is an approximated log-linear analogue of the Laspeyeres Price index (Moschini, 1995), where $logP_{it}^L \approx \sum_{j=1}^{J} w_{ij}^0 logp_{ijt}$ and w_{ij}^0 denotes brand j's base share for consumer i with $w_{ij}^0 = Y^{-1}\sum_{y=1}^{Y} w_{ijy}$ and $y \in (1, ..., Y)$ represents the year. α_{jt}, b_{ijk}, and c_{ij} are demand parameters to be estimated. The unobserved demand shocks e_{ijt} is assumed to be iid over i, j and t.

To further simplify the estimation and overcome the hurdle of dimensionality issue, we follow Pinkse, Slade, and Brett (2002), Pinkse and Slade (2004), Rojas (2008), and Bonanno (2013) to modify equation 3.3 by defining each cross-price coefficient $b_{ijk}(j \neq k)$ as a linear function of the relative distance in attribute space between product j and k, $b_{ijk} = g(\delta_{jk})$, which reflects the notion that substitutability is impacted by the relative position of the products in characteristics space. The distance measures can be either continuous, δ_{jk}^c, which is constructed from continuous attributes (e.g., grams of dietary fiber, fat, or sugar per 100 grams of cereal) or discrete, δ_{jk}^d , constructed from discrete characteristics (e.g., whole grain listed as the first ingredient, or a cereal targeted to children). Both of these two distances are constructed following equation 3.1 and equation 3.2. Specifically, the cross-price coefficient $b_{ijk}(j \neq k)$ can be defined as:

$$b_{ijk} = \begin{cases} \sum_{c=1}^{C} \lambda_{ij}^c \delta_{jk}^c & for\ continuous\ distance, \\ \sum_{d=1}^{D} \lambda_{ij}^d \delta_{jk}^d & for\ discrete\ distance. \end{cases} \tag{3.4}$$

Here, both λ_{ij}^c and λ_{ij}^d are assumed to be the same across product equations and consumers, which means $\lambda_{ij}^c = \lambda_c$ and $\lambda_{ij}^d = \lambda_d$. Since the constructed distance measures, shown in equation 3.1 and equation 3.2, are symmetric, the Slutsky symmetry restrictions are satisfied, which means $b_{ijk} = b_{ikj}$.

To further assist the simplification of the estimated demand model, we define the constant term (α_{jt}), the own-price coefficient (b_{ijj}), and the coefficient of total expenditure (c_{ij}) to be linear functions of product characteristics (z). Besides that, to capture consumers' heterogeneous preferences over cereal products, consumers purchase decisions are also allowed to vary depending on their socio-demographic factors, which are modeled as a demand shifter in this paper. As a result, these three terms are defined as: $\alpha_{jt} = \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit}$, where h_{hit} is the h-th demographic variable for consumer i at market t; $b_{ijj} = b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta}$; and $c_{ij} = c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma}$. All the z variables, z_{jl}^{α}, z_{jm}^{β}, and z_{jn}^{γ}, represent the characteristics for product j. In order to avoid the multicollinearity, each z_{jl}^{α}, z_{jm}^{β}, and z_{jn}^{γ} may be a separate subset of j's characteristics. Up to this point, the estimated demand system are reduced to a single equation based on all the restrictions imposed. Replacing all these modifications of equation 3.3, our estimated demand model is shown:

$$
\begin{aligned}
w_{ijt} &= \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit} + \left(b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta} \right) logp_{ijt} \\
&+ \sum_{c=1}^{C} \left(\lambda_c \sum_{k \neq j} \delta_{jk}^{c} logp_{ikt} \right) + \sum_{d=1}^{D} \left(\lambda_d \sum_{k \neq j} \delta_{jk}^{d} logp_{ikt} \right) \\
&+ \left(c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma} \right) log \frac{x_{it}}{P_{it}^{L}} + e_{ijt}. \qquad (3.5)
\end{aligned}
$$

Since each household could only purchase a small subset among all the cereal products, leaving zero-purchases for most of the rest, the expenditure share (w_{ijt}) as defined above are restricted to be non-negative. To take account of this censored nature of our data, the Tobit model (Tobin, 1958) is used in our empirical estimation. Let latent share, w_{ijt}^*, represent the unobserved purchase behavior for consumer i choosing product j in market t. The observed share (w_{ijt}) is assumed to be equal to the latent share (w_{ijt}^*) whenever the latent share is above zero:

$$
w_{ijt}^* = \begin{cases} w_{ijt} & if \ w_{ijt}^* > 0, \\ 0 & if \ w_{ijt}^* \leq 0. \end{cases} \qquad (3.6)
$$

The latent share (w_{ijt}^*) is defined by following equation 3.5:

$$
\begin{aligned}
w_{ijt}^* &= \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit} + \left(b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta} \right) logp_{ijt} \\
&+ \sum_{c=1}^{C} \left(\lambda_c \sum_{k \neq j} \delta_{jk}^{c} logp_{ikt} \right) + \sum_{d=1}^{D} \left(\lambda_d \sum_{k \neq j} \delta_{jk}^{d} logp_{ikt} \right) \\
&+ \left(c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma} \right) log \frac{x_{it}}{P_{it}^{L}} + \epsilon_{ijt}. \qquad (3.7)
\end{aligned}
$$

where $\epsilon_{ijt} \sim N(0, \sigma^2)$. Under this specification, the zero-purchase outcomes are assumed to represent a corner solution from a utility maximization process.[3] Given the potential endogeneity of prices, the parameters of this model can be consistently estimated using Newey's two-step estimator (Newey, 1987). The final specification

[3]There are several reasons (both empirical and theoretical) why we observe zero purchases of a specific brand. First, empirical selection of a time period may cause an observation of zero purchases for a specific product. Second, some argue that a zero purchase outcome is the result of a utility-maximization process, and is caused by a relatively high price, unattractive product attributes, or different preferences of consumers. We generally assume that the second reason fits our case.

given by 3.6 and 3.7 allows us to easily estimate demand for a large number of alternatives and account for censoring data fact as well, as it requires the calculation of only a single integral instead of multiple integrals.[4]

3.3.2 Firms' Optimal Pricing

Following Nevo (2001), there are F cereal manufacturers in the market and each manufacturer produces a subset of differentiated RTE breakfast cereal products ($\mathscr{F}_f$). Each firm chooses the prices for each one of their products to maximize their total profit over all their produced cereals in each market. The profit maximization problem for each manufacturer f at market t is:

$$\pi_{ft} = \max_{p_{jt}, j \in \mathscr{F}_f} \sum_{j \in \mathscr{F}_f} \left(p_{jt} - mc_{jt}\right) q_{jt}\left(p\right) - C_{jt}, \tag{3.8}$$

where p_{jt} is the price of product j in market t, mc_{jt} is the marginal cost to supply j in market t, and $q_{jt}(p)$ is the quantity sold in market t for product j. Note that we allow the marginal cost (mc_{jt}) to vary in both product and market to capture the idea of potential market-specific costs to supply the same product, such as heterogeneous wage rate and transportation costs in different markets. The total quantity for product j at market t, $q_{jt}(p)$, is recovered by using the estimated expenditure share as defined in the demand model in last section, $w_{ijt}\left(p\right)$. Given that, we first calculate each consumer i's purchasing quantity for product j in market t:

$$q_{ijt}\left(p\right) = \frac{w_{ijt}\left(p\right) * x_{it}}{p_{ijt}}. \tag{3.9}$$

Then the total quantity of product j sold in market t is the sum of individual purchase quantity from consumers who are in market t:

$$q_{jt}\left(p\right) = \sum_{i=1}^{I^t} q_{ijt}\left(p\right), \tag{3.10}$$

where I^t represents the total population in market t. Again, following Nevo (2001), we assume that the prices are the outcome of Nash-Bertrand equilibrium, where each firm maximizes their total profit over all its products in each market t. Then the set of first-order conditions of profit maximization for each product j for man-

[4]Since the demand estimation are the same as in chapter one, here for easy reference we recap the estimation results. For more details about specification and estimation, please refer to chapter two.

ufacturer f at market t becomes:

$$q_{jt}(p) + \sum_{j \in \mathscr{F}_f} (p_{jt} - mc_{jt}) \frac{\partial q_{jt}}{\partial p_{kt}} = 0 \tag{3.11}$$

Under Nash-Bertrand competition for multiple-product manufacturers, the ownership matrix Ω^*_{jk} can be defined:

$$\Omega^*_{jk} = \begin{cases} 1 & if \;\; k, j \in \mathscr{F}_f, \\ 0 & if \;\; otherwise. \end{cases} \tag{3.12}$$

Also, define $\Delta_{jt} = \partial q_{jt}/\partial p_{kt}$, and replacing q_{jt} using equation 3.9 and equation 3.10, we can get:

$$\Delta_{jk} = \begin{cases} \sum_{i=1}^{I^t} \frac{x_{it}}{p_{jt}^2} \left[\frac{w_{ijt}(p)}{logp_{jt}} - w_{ijt}(p) \right] & if \;\; k = j, \\ \sum_{i=1}^{I^t} \frac{x_{it}}{p_{kt}^2} \left[\frac{w_{ijt}(p)}{logp_{kt}} \right] & if \;\; k \neq j. \end{cases} \tag{3.13}$$

Then define the matrix $\Omega_{jk} = \Omega^*_{jk} * \Delta_{jk}$ and the first order condition from equation 3.11 can be rewritten in the vector notation as:

$$p - mc = -\Omega^{-1} q(p) \tag{3.14}$$

where all variables are vectors for all products j. Given the knowledge of prices, ownership matrix, and demand, we can solve out the vector of marginal costs for all products as

$$mc = p + \Omega^{-1} q(p). \tag{3.15}$$

Marginal Cost Estimation

We first solve for the marginal costs for all products in all markets using equation 3.15 given the prices, ownership matrix, and demand observed in the data. Because in the data consumer prices varies due to different reasons, such as using coupon or retailer promotion, we approximate the market prices set by the firms as the average prices in each market. Specifically, the market price for product j at market t, p_{jt}, is calculated using the total expenditure for product j at market t divided by total quantity of product j at market t (q_{jt}):

$$p_{jt} = \frac{x_{jt}}{q_{jt}(p)} = \frac{\sum_{i=1}^{I^t} x_{ijt}}{q_{jt}(p)} \tag{3.16}$$

where the market-level quantity $q_{jt}(p)$ can be calculated using equation (3.10), based on the estimated demand function.

We further assume that marginal costs of production is affected by the characteristics of that product (z_j) and related operational cost factors (o_{jt}).

$$mc_{jt} = f\left(z_j, o_{jt}\right) \tag{3.17}$$

In this paper we consider a list of cost-shifting continuous product characteristics including fiber, sugar, fat, sodium, folate, calcium, protein, carbohydrates, and number of vitamin fortifications. We also consider the discrete product characteristics including whether the product is made of whole grain as first ingredient, targeting to children, whether the product has added fruit, and whether or not the product use artificial colors or add extra flavors. Besides including these detailed list of product characteristics, we also consider the average package size as well as the approximate of retailing coverage, e.g. total number of unique stores, to capture the operational cost for each product j at market t. We assume that the marginal cost is a linear function of all these cost-shifting factors mentioned above.

Then, using the estimated marginal cost function, we are able to predict the new marginal cost given any change of the product characteristics, which will be used in the counterfactual analysis in the next subsection.

3.3.3 Counterfactual Setup

In this research, we discuss how consumer welfare, producer surplus, and total welfare will change if some or all firms change some of their product attributes. For this purpose, we consider a series of counterfactual scenarios in each of which we allow some or all firms change some of important product attributes to the cereal products they produce. Specifically, we consider eight counterfactual scenarios. In the first two, we allow two major cereal manufacturers, Firm A and Firm B,[5] to change all their own products to be made using whole grain as primary ingredient, respectively. In the next three counterfactuals, we allow all firms to increase fiber, reduce sugar, or reduce fat by 10% in each of the experiments, respectively.[6] For

[5]Due to the agreement of using this dataset, we are not able to disclose the name of firm and products. As a result, we use "Firm A" and "Firm B" to represent the two major cereal manufacturers. Since products in this research come from four cereal manufacturers, the other two are name as "Firm Three" and "Firm Four" accordingly.

[6]Although the USDA has confirmed that the amount of fiber in breakfast cereal products from the top two manufacturers increased 32% in the United States from 2005 to 2011, and the amount of sugar and sodium decrease by about 10% and 14% respectively, Williams (2014) found that there is no significant reduce of intake of sodium for consumers who eat breakfast cereals after a systematic review of over two hundreds published scientific literature from all dates until October 2013 in the Scopus and Medline databases. Besides that, Williams (2014) found that consumers who regularly eat breakfast cereal will have higher percentage of intake of fiber and sugar, and lower percentage of intake of fat. As a result, our counterfactual scenarios will focus on these product characteristics: fiber, sugar, fat, and whole grain.

the last three scenarios, we consider a combination of increasing fiber, and reducing sugar and/or fat, all by 10%. In all these experiments, we assume that the change of product attributes would lead to a increase of product healthy quality of some or all products.

In each of the counterfactual, given the proposed change of product attributes we calculate the welfare change using the following procedures:

- Predict the new marginal cost for each product j in each market t using cost equation 3.17.
- Based on firms' optimal pricing rule in each market, calculate the new prices for each product in each market following equation 3.15.
- Calculate the new demand (expenditure share) using the new equilibrium price for each individual calculated in last step. Then compute the aggregate demand in each market.
- Given the new prices and new demand, calculate the new consumer surplus for individual consumer i for each product j, which is the triangle area underneath the demand curve and above the line of price actually paid:

$$\begin{aligned} CS_{ijt} = \; & x_{it}\left(\alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit}\right)(p_{q_{jt}=0} - p_{new}^{jt}) \\ & + \frac{1}{2}\left\{\left[b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta} - \left(c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma}\right) w_{ij}^0\right]\right. \\ & \left. * \left[\left(logp_{q_{jt}=0}\right)^2 - (logp_{new}^{jt})^2\right]\right\} \end{aligned} \tag{3.18}$$

  $p_{q_j=0}$ indicates a corner solution for price when the purchase quantity is zero.[7] Then the aggregate consumer surplus is calculated by summing over all the consumers across all the products and all the markets, $CS = \sum_j^J \sum_i^I CS_{ijt}$.

- Given the new prices and marginal costs, calculate the new producer surplus for each firm F. Then calculate the new aggregate producer surplus for all

[7] In order to calculate the price when $q_j = 0$, we solve for the following equation by assuming the price for all the other products unchanged:

$$p_{q_{jt}=0} = exp\left\{\left(\frac{1}{B - Cw_{ij}^0}\right)\left[-(A+D) - C\left(logx_{it} - \sum_{j\neq k} w_{ik}^0 logp_{ikt}\right)\right]\right\} \tag{3.19}$$

where $A = \alpha_0 + \sum_{l=1}^{L} a_l z_{jl}^{\alpha} + \sum_{h=1}^{H} a_h h_{hit}$, $B = b_0 + \sum_{m=1}^{M} b_m z_{jm}^{\beta}$, $C = c_0 + \sum_{n=1}^{N} c_n z_{jn}^{\gamma}$, and $D = \sum_{c=1}^{C}\left(\lambda_c \sum_{j\neq k} \delta_{jk}^c logp_{ikt}\right) + \sum_{d=1}^{D}\left(\lambda_d \sum_{j\neq k} \delta_{jk}^d logp_{ikt}\right)$. For simplification of notation, here we remove the sub-index of i for $p_{q_j=0}$. Similar simplification is done for p_{new}^{jt}. However, we should clarify that the p_{new}^{jt} for each consumer is actually used by the new average market price based on our calculated new equilibrium price.

firms:

$$PS = \sum_{f}^{F} \sum_{j \in \mathscr{F}_f} \sum_{t}^{T} (p_{new}^{jt} - mc_{new}^{jt}) \frac{\sum_i^{I^t} x_{ijt}}{p_{new}^{jt}} \tag{3.20}$$

where I^t represents all the consumers who are in market t and $\frac{\sum_i^{I^t} x_{ijt}}{p_{new}^{j}}$ is the total quantity sold for product j at market t.

- Compare the consumer surplus, producer surplus, and total surplus (the sum of the consumer surplus and producer surplus) with their counterpart computed in the data.[8] Due to the filtering of our data, focusing on the purchases from households with at least one kid over the top 20 national cereal brands, we report the percentage change of welfare for proper measurements.

3.4 Empirical Results

In this section, we first recap the demand estimation result from chapter two and the marginal cost estimation. Next, we will focus on the results of counterfactual experiments, looking at the change of product prices and welfare after firms change some or all of their product attributes in the eight counterfactual experiments.

3.4.1 Demand Parameters

The estimated demand parameters from the estimated instrumental-variable (IV) Tobit models are shown in table 3.4.[9]

The own-price coefficient (LNP) is negative and significant (-0.3516) at the 1% level. Estimated coefficients for interactions between price and product attribute show that households in our sample become less price sensitive if cereal products use whole grain as first ingredient (LNP∗WG = 0.0567), have higher levels of fat (LNP∗FAT = 0.0160) and sugar (LNP∗SUGAR = 0.0027), and have more vitamins fortified (LNP∗NVF = 0.0133). While, households become more price sensitive if a cereal product contains artificial color (LNP∗ADCOLOR = -0.0833). For the results for sugar and fat, consumers show a stronger preferences of taste over health, since reducing the content of sugar and fat will lead to a more sensitive to the price, which is consistent to our result of welfare analysis in the following subsection.

[8]Following equation 3.18 and equation 3.20, we calculate the consumer surplus and producer suplus from the data. Note that, the subscript for price (p_{new}^{jt}) should change to p_{data} for clear notation.

[9]For more detail about the selection of model specification and price instrument, please refer chapter two.

The estimated results for the distance metric terms (DM) reflect how consumers substitute between products, which are closer in attribute space, given the changes of price. The positive and significant coefficient for DM_FIBER (0.0011) and DM_WG(0.0123) indicate that, in response to price increases households in our sample are more likely to switch to another cereal product that has similar fiber content or to anther cereal that is also made with whole grain as primary ingredient. On the other hand, for sugar and fat, which are generally advised as unhealthy food elements, the estimated coefficients are negative and significant (DM_SUGAR = -0.0322; DM_FAT = -0.0203). It can be interpreted that households are more likely to switch to cereals that are farther away in the attribute space of sugar or fat when facing a increase of product price. Again, the reason could be that consumers are making tradeoffs between good taste and healthy diet. For example, given a price increase, consumers who are in favor of more healthful cereals with low level of sugar or fat can be induced to switch to cereals that are less healthy but have much better taste. The positive and significant coefficient of DM_KIDS (0.0098) indicates that households with kids tend to switch to other kids' cereals for their children.

The estimated parameter for the expenditure term (LNEP) is positive and significant at the 1% level (0.0903), showing a positive income effect. The result of interaction terms between expenditure and product attributes show that households become more expenditure sensitive if cereal products use whole grain as the first ingredient (LNEP∗WG = 0.0085). Otherwise, household in our sample become less expenditure sensitive for products with more fat (LNEP∗FAT = -0.0063) or fortified with more vitamins (LNEP∗NVF = -0.007). Overall, these results indicate that demand for whole-grain cereals expands the most as the cereal category expands, while demand for vitamin-fortified or higher fat content cereals contracts as the category expands.

Finally, considering the impact of consumers heterogeneous preference, our results show that households that are white in race (WHITE=0.0072) or are larger in size (HHSIZE=0.0051) tend to purchase more cereal. While households with household head who is higher in age (AGEHIGH) tend to purchase less cereal on average (-0.0021). Package size (AVESIZE) also shows a negative impact on cereal purchases (-0.0017). However, neither marriage status, education, household income, nor Hispanic shifters show evidence of affecting household purchasing decisions on breakfast cereal.

3.4.2 Marginal cost parameters

We estimate the marginal cost function (3.17) using observed data on product characteristics (z_j) and operational cost factors (o_{jt}) and the recovered marginal cost of production from equation (3.15). The estimation results are reported in table 3.5. We find that the marginal cost increases if the firm adds fruit, color, flavor or protein to the product. Switching the product to be whole grain, or to targeting kids food also increase marginal costs. Similarly, reducing the product contents of sugar, fat, fiber, calcium, sodium, folate, carbohydrate actually increases production costs, probably because the firm needs to introduce extra producing procedures in order to reduce these contents. We also find that increasing package size also help to reduce the marginal cost per ounce. Finally, if a firm increases its retailing coverage, the marginal cost also get reduced.

3.4.3 Counterfactual results

Based on the estimated results of consumer demand, we are able to proceed to conduct counterfactual experiments under eight different scenarios, which capture the impact of major nutrients of the RTE breakfast cereals on the welfare for both consumers and producers. In this subsection, we first report the results of new equilibrium price under each counterfactual scenario and then the welfare change for consumer and producer are reported accordingly.

3.4.3.1 Counterfactual Price

The price changes in the counterfactual experiments are reported in table 3.6. Compared with the data, the new prices in the counterfactual experiments are mostly higher except the case when only reducing fiber by 10%. The change of prices (except the fiber only case) ranges from 0.32% to 1.80%. This implies that, in general, improving healthy attributes leads to higher firm prices. The price increases is justified because the production costs rise in order to improve healthy attributes, and/or the consumer demand increases in healthy attributes. For example, switching to whole grain on one hand increases consumer demand, and on the other hand it increases production costs. As a result, manufacturers' optimal prices rise when they switch to produce whole grain products. When Firm A switches all of its products to whole gain, the average market price increases by 0.77%; when Firm B switches all its products to whole grain, the market average price increases by 1.35%. In contrast, when reducing sugar or fat content, the average market price also rises but due to different reasons. When reducing sugar and fat, consumer demand actually decreases as shown in table 3.4. At the same time, the production cost rises. These two competing forces shape the final price change. The resulting higher price (1.80% for sugar and 1.29% for fat) suggests that the cost changes dominates the demand changes. However, when increasing fiber content, the market average prices actually decreases slightly. The major reason is that the production costs decrease when increasing fiber content. The price change, though, is quite minimal.

3.4.3.2 Consumer Welfare

We measure consumer welfare as consumer surplus, and use it to evaluate the change of benefit for consumers when some or all healthy attributes are changed by the manufacturers in the RTE cereal market. When some or all manufacturer improve the healthy attributes of their products, as shown in the eight counterfactual experiments, the prices generally increase. At the same time, the demand may also change. These two forces together lead to a change of consumer welfare in the counterfactual experiments.

We report the results in table 3.7. The change of consumer surplus in each of the counterfactual experiments are reported in column 1. Because consumers have heterogeneous demand, some new or existing consumers may start or stop purchasing this reformulated product when prices and healthy attributes are changed. For this reason, we report the number of purchases in each counterfactual experiment in column 2. In column 3, we also report the change of average consumer surplus per actual purchase.

First we observe that a reformulation that makes whole grain first ingredient has an positive impact on consumer welfare. When Firm A changes the first ingredient of its cereal products to be whole grain, the aggregate consumer welfare increases by 13.22%. This mainly come from the positive effect on consumer demand. Despite the price increases shown in table 3.6, the increased number of purchases leads to the increase in consumer welfare shown in table 3.7. Similarly, when Firm B changes the first ingredient of its cereal products to be whole grain, the aggregate consumer welfare is improved by about 12.55%.

Second, when reducing sugar or fat, or increasing fiber—which in fact improves healthy quality of the products—the measured consumer welfare actually decreases. For example, when decreases sugar by 10% for all products in the market, aggregate consumer welfare drops by about 20%. This reflects that, although less sugar is good for health, consumers like it, and will purchase fewer units when the level drops. In column 2 and 3 of table 3.7, we see that this drop of aggregate consumer welfare is mainly due to the reduced number of consumers actually purchase cereal products. However, if we calculate the average consumer surplus per actual purchase, as reported in column 3, consumers who continue to purchase the products after reducing fat and sugar actually get a welfare improvement. These consumers may be those who have healthier eating habit and care about their health conditions a lot, as reflected in their demographic variables. Finally, if we look at the changes of two or more health-related nutrients, consumers would benefit more if manufacturers could increase the health quality of cereal products by improving more kinds of nutrients at the same time.

3.4.3.3 Producer Surplus

The change of production costs and prices due to the change of healthy attributes affect producer surplus directly. The impact on producer surplus is very important because eventually it is the manufacturers that determine if the health quality of product attributes will be improved. We report the counterfactual results on producer surplus in table 3.8. We find that the aggregate producer surplus is improved if either Firm A or Firm B changes the first ingredient of their products to be whole grain. When Firm A makes this change, aggregate producer surplus for all firms on average increases by 17.98%. This number is 12.15% when Firm B changes the first ingredient of its products to be whole grain. This result also supports the current stylized fact that many cereal manufacturers are focusing on whole grain; that is, this strategy is profitable. When all firms increases fiber by 10%, the aggregate welfare also increases slightly at 1.82%, mainly due to the reduced prices in the conterfactual.

In contrast, after reducing sugar or fat alone or in combination with increasing fiber, there is a large drop of producer surplus, ranging from -12.75% to -25.11%. Two reasons may be responsible for this decrease: First, reducing sugar and fat has a negative impact on consumer demand due to the negative change of taste; Second, it also increases production costs according to the estimation of marginal cost function. Both of them lead to the reduction of producer surplus. This explains why in the market, many cereal products still contain high level of sugar and fat. Although government agencies or health policy makers recommend that consumers reduce sugar or fat for health reasons, it is seemingly not a profitable business strategy.

Changing product attributes also changes the competition advantage among different cereal manufacturers, thus it may have different impacts on individual firms. In table 3.9, we calculate the change of producer surplus for each firm in each counterfactual scenario, compared with the observed data. It shows very heterogeneous effects for individual firms. First, while switching to whole grain cereal increases aggregate producer surplus, it has very different effect on different firms. For example, if Firm A switches all of its products to whole grain products, it actually loses some producer surplus. This may happen because it rises the production costs for Firm A, and meanwhile Firm A may lose some consumers to other firms because its prices increase due to higher production cost. However, when Firm B switches all its products to whole gain, it has large gains of producer surplus, while all other firms hurt. The different effects on Firm A and Firm B's producer surplus may come from the different product attributes, the similarity among their own products, and the differences between their products to other products available in the market.

When the sugar and/or fat content of all products in the market are reduced, or a combination with rising fiber, the producer surplus for all firms are reduced. This is because all firms might bear similar change of production costs, and that the relative difference of product attributes does not change much from consumer's perspective, while only observing a increase of price. As a result, all firms suffer a loss of producer surplus in these counterfactual experiments, though the magnitude of the changes differ across firms presumably depending on the product attributes in the data.

3.4.3.4 Total Welfare

The effect on total welfare is also an important indicator for policy makers. We also calculate the total welfare as the sum of aggregate consumer surplus and producer surplus and we report these results in table 3.10. First, we find that whole grain has a substantial positive impact on total welfare. If Firm A alone changes the first ingredient of all its cereal products to whole grain, the total welfare can be improved by 14.23%, even thought the production costs and prices will be higher. Similarly, if Firm B changes the first ingredient of all its cereal products to whole grain, the total welfare can be improved by 12.47%. This suggests that policy makers should encourage firms to do so.

In contrast, increasing fiber or reducing sugar and/or fat in fact reduces the measured total welfare, although these changes in fact can help improve health. For example, increasing fiber content in all cereal products in the market by 10% reduces total welfare by about 1.03%. Reducing sugar and fat by 10% in the fourth and fifth counterfactuals reduces total welfare substantially by 19.84% and 17.07%, because both firms and consumers lose after these changes. However, the large drop of total welfare may well come from the fact that most consumers either love sweet cereals so much so that they do not care about health, or they are not aware of the health risk resulting from high intake of sugar or fat. The policy implication is that policy makers should strengthen education about food health, by helping more people realizes the risk of high sugar and fat in the food, and to encourage manufacturers to use more healthy substitutes to replace sugar and fat.

3.5 Conclusion

This paper quantifies the welfare effect of changing healthy attributes in the RTE cereal market based on a equilibrium model of demand and production. We find that improving health quality of product attributes has a substantial impact on consumer welfare, producer surplus, and total welfare. But the changes may not necessarily be positive. This reflects the joint results from consumer demand and production costs, associated with the change of nutritional contents. There are two important policy implications from this study. First, policy makers should encourage more cereal manufacturers to use whole grain as the first ingredient of their products. Second, policy makers should also provide more education to consumer about the health risk associated with high intake of sugar and fat, and encourage cereal manufacturers to develop substitutes of sugar and fat.

We admit that the results shown in this paper still have limitations. First, the impact might be overestimated compared to the actions in the real market of the 20 cereals since we assume a change of some nutritional characteristics, for example increase fiber by 10%, for all the 20 cereals. Second, reformulation for cereal industry is a complex process and it might not be the case that manufacturer only change one nutrition at a time. Our results only approximate a few scenarios interested which might not reflect the whole reformulation cases in this industry. However, our research still provide useful insight from these simulated scenarios that consumers do benefit from these reformulation like changing to whole grain, increasing fiber content. With this purpose in mind, our results will also be instructive to the implementation of health related food policies.

Tables and Figures

Table 3.1. Summary statistics of purchase data and demographics

Variable	Description	Mean	Std.
Purchase			
SH	Individual expenditure share for each brand	0.05	0.12
LNP	Average purchase price (cents), in log form	2.71	0.27
Demographics			
Continuous			
HHSIZE	Number of individuals in the household	4.12	1.12
HHINC	Household annual income	21.17	5.26
AGEHIGH	Max age category of household head(s)	5.60	1.51
Discrete		Frequency of one	
WHITE	Race is white for the household		0.77
MARRIED	Marital Status of household head(s)		0.85
HISPANIC	Hispanic origin for the household		0.10
HIGHSC	Max edu. attainment for household head(s): high school		0.15
SOMECOL	Max edu. attainment for household head(s): some college		0.26

Table 3.2. Summary statistics of health/non-health related product attributes

Variable	Description	Mean	Std.
Continuous			
FAT	Total fat (g/100 g)	2.92	2.39
SUGAR	Total sugars (g/100 g)	27.35	13.30
FIBER	Total dietary fiber (g/100 g)	5.46	3.81
NVF	Number of vitamin fortified	2.85	1.88
AVESIZE	Average package size (oz)	18.54	4.68
MAKER	Manufacturer for the RTE breakfast cereal	2.05	0.80
Discrete		Frequency of one	
WG	Product has whole grain as first ingredient		0.35
KIDS	Target to children		0.50
ADFLAVOR	Other flavor ingredient added		0.45
ADCOLOR	Other artificial color added		0.40

Table 3.3. Statistics of recovered marginal cost and independent variables for cost estimation

Variable	Description	Mean	Std.
Marginal Cost			
MC	Recovered marginal cost	12.33	3.55
Product Characteristics			
Continuous			
FAT	Total fat (g/100 g)	2.92	2.39
SUGAR	Total sugars (g/100 g)	27.35	13.30
FIBER	Total dietary fiber (g/100 g)	5.46	3.81
NVF	Number of vitamin fortified	2.85	1.88
SODIUM	Sodium (mg$*$0.01/100 g)	6.08	1.97
FOLATE	Folate, total (g$*$0.01/100 g)	4.76	3.08
CALCIUM	Calcium (mg$*$0.01/100 g)	1.06	1.43
PROTEIN	Protein (g/100 g)	8.21	4.38
CARB	Carbohydrate, by difference (g/100 g)	82.44	5.64
UNISTORE	Number of unique stores selling product $j*0.01$	2.97	0.42
AVESIZE	Average package size (oz)	18.54	4.68
Discrete		Frequency of one	
WG	Product has whole grain as first ingredient		0.35
KIDS	Target to children		0.50
FRUIT	Add fruit in cereal		0.30
ADFLAVOR	Other flavor ingredient added		0.45
ADCOLOR	Other artificial color added		0.40

Table 3.4. Parameter estimates of consumer preference

Variables	Coefficient		Standard errors
HHSIZE	0.0051	* * *	0.0015
WHITE	0.0072	* * *	0.0044
MARRIED	-0.0018		0.0050
HISPANIC	-0.0054		0.0060
AGEHIGH	-0.0021	*	0.0011
HIGHSC	0.0035		0.0049
SOMECOL	0.0063		0.0039
HHINC	-0.0002		0.0004
AVESIZE	-0.0017	* * *	0.0002
LNP	-0.3516	* * *	0.0486
LNP∗WG	0.0567	* * *	0.0192
LNP∗FAT	0.0160	* * *	0.0026
LNP∗NVF	0.0133	* * *	0.0051
LNP∗SUGAR	0.0027	* * *	0.0001
LNP∗ADCOLOR	-0.0833	* * *	0.0053
DM_SUGAR	-0.0322	* * *	0.0028
DM_FAT	-0.0203	* * *	0.0012
DM_FIBER	0.0011	**	0.0006
DM_WG	0.0123	* * *	0.0024
DM_KIDS	0.0098	* * *	0.0027
DM_MAKER	-0.0007		0.0032
DM_ADFLAVOR	0.0016		0.0015
LNEP	0.0903	* * *	0.0095
LNEP∗WG	0.0085	*	0.0044
LNEP∗FAT	-0.0063	* * *	0.0009
LNEP∗NVF	-0.0070	* * *	0.0023
FIRM A	-0.0926	**	0.0395
FIRM B	-0.0359		0.0782
FIRM C	-0.0703	* * *	0.0258
CONSTANT	0.2208	**	0.1013
VIF	20.00		
F-test	2854.51		
Endog(p-value)	0.0000		
ALN Test(p-value)	0.2359		

[1] *, **, and * * *represent 10%, 5% and 1% significance levels, respectively.

Table 3.5. Estimated parameters for marginal cost equation

Variables	Coefficient		Standard errors
WG	1.0261	* * *	0.3977
FIBER	-0.3405	* * *	0.0580
SUGAR	-0.0634	* * *	0.0132
FAT	-0.1853	**	0.0761
SODIUM	-0.6870	* * *	0.0488
FOLATE	-0.2099	* * *	0.0507
CALCIUM	-0.2733	* * *	0.0881
KIDS	0.5961	**	0.2732
NVF	-0.5510	* * *	0.0813
PROTEIN	0.0344		0.0561
CARB	-0.2469	* * *	0.0558
FRUIT	0.9723	* * *	0.2793
ADCOLOR	0.1323		0.5177
ADFLAVOR	1.2830	* * *	0.2286
UNISTORE	-4.0071	* * *	0.2284
AVESIZE	-0.0545	* * *	0.0037
CONSTANT	65.1889	* * *	5.7250

[1] *, **, and * * *represent 10%, 5% and 1% significance levels, respectively.

Table 3.6. Average market price under each counterfactual scenarios [1]

Counterfactual Scenarios	Average Price (cent/oz)		
	Before	After	Changes (%△)
Convert to whole grain for Firm A products	15.53	15.65	0.77
Convert to whole grain for Firm B products		15.74	1.35
Fiber 10% ↑		15.52	-0.06
Sugar 10% ↓		15.81	1.80
Fat 10% ↓		15.73	1.29
Fiber 10% ↑ & Sugar 10% ↓		15.66	0.84
Fiber 10% ↑ & Fat 10% ↓		15.58	0.32
Fiber 10% ↑ & Sugar 10% ↓ & Fat 10% ↓		15.72	1.22

[1] The first and second row means Firm A or Firm B changes all their products to be made with whole grain as first ingredient.

Table 3.7. Percentage changes of consumer welfare under each counterfactual scenario

Counterfactual Scenarios	Consumer Surplus (%△)	No.of Purchase Before	No.of Purchase After	Ave.Surplus /Purch.(%△)
Convert to whole grain for Firm A products	13.22	116060	154828	-15.13
Convert to whole grain for Firm B products	12.55		110777	17.92
Fiber 10% ↑	-1.79		119375	-4.52
Sugar 10% ↓	-20.03		47327	96.10
Fat 10% ↓	-17.59		56096	70.49
Fiber 10% ↑ & Sugar 10% ↓	-19.36		48549	92.77
Fiber 10% ↑ & Fat 10% ↓	-16.88		58493	64.92
Fiber 10% ↑ & Sugar 10% ↓ & Fat 10% ↓	-31.08		35863	123.04

Table 3.8. Percentage change of producer surplus under each counterfactual scenario

Counterfactual Scenarios	Producer Surplus (%△)
Convert to whole grain for Firm A products	17.98
Convert to whole grain for Firm B products	12.15
Fiber 10% ↑	1.82
Sugar 10% ↓	-19.11
Fat 10% ↓	-15.11
Fiber 10% ↑ & Sugar 10% ↓	-16.88
Fiber 10% ↑ & Fat 10% ↓	-12.75
Fiber 10% ↑ & Sugar 10% ↓ & Fat 10% ↓	-25.11

Table 3.9. Changes of producer surplus by firm under each counterfactual scenario

Counterfactual Scenarios	Producer Surplus (%△) Firm A	Firm B	Firm C	Firm D
Convert to whole grain for Firm A products	-24.71	82.05	182.86	205.52
Convert to whole grain for Firm B products	-35.37	131.32	-40.79	-31.79
Fiber 10% ↑	0.55	6.93	-12.90	0.96
Sugar 10% ↓	-16.24	-21.51	-45.14	-27.36
Fat 10% ↓	-14.19	-13.17	-39.81	-23.80
Fiber 10% ↑ & Sugar 10% ↓	-14.51	-19.26	-35.67	-23.07
Fiber 10% ↑ & Fat 10% ↓	-12.48	-10.58	-29.65	-19.20
Fiber 10% ↑ & Sugar 10% ↓ & Fat 10% ↓	-22.47	-28.03	-44.18	-32.40

Table 3.10. Percentage change of total surplus under each counterfactual scenario

Counterfactual Scenarios	Total Surplus (%△)
Convert to whole grain for Firm A products	14.23
Convert to whole grain for Firm B products	12.47
Fiber 10% ↑	-1.03
Sugar 10% ↓	-19.84
Fat 10% ↓	-17.07
Fiber 10% ↑ & Sugar 10% ↓	-18.83
Fiber 10% ↑ & Fat 10% ↓	-16.01
Fiber 10% ↑ & Sugar 10% ↓ & Fat 10% ↓	-29.81

Chapter 4

How Important is Preference for Variety in Consumer Demand: Evidence from Ready-to-Eat Cereal Market

4.1 Introduction

Product proliferation and near saturation of the product-attribute space has been well documented in the ready-to-eat (RTE) breakfast cereal market for over three decades. On the supply side, Scherer (1979) and Schmalensee (1978) suggested that entry deterrence was one rationale for product-attribute space saturation. On the demand side, heterogeneous preferences as well as preferences for variety are reasons that support product proliferation. In this paper, we examine the specific role that preference for variety plays in shaping consumer demand, especially in the RTE cereal market. Our main research questions focus on estimating consumers' variety preferences and investigating how these estimates vary with income, household size, the presence of children in the household, and other household characteristics.

Allender, Richards, Park, and Hamilton (2013, p.2) note that "researchers rarely model the preference for variety in an explicit way", but we intend to extend some recent research to develop a utility-based model that incorporates variety in a very particular way. First, we operate in product-attribute space and build a model where utility is derived from consumption of a vector of product attributes as well as the variety associated with this vector. Second, our variety measure reflects the aggregate dissimilarity of purchased cereal brands as defined by the relative distance in product-attribute space.

For individual consumers, this variety measure can easily be constructed using micro-level food purchase scanner data if that data is matched to specific product attributes such as nutrient levels. Moreover, it would not be difficult to simply calculate variety measures associated with household purchase and examine how the measure vary by household characteristics. However, this analysis, perhaps using a reduced-form econometric model, could ignore full set of tradeoffs, including those between prices, attribute preferences, and variety, which play a strong role in consumer choices. It also might not account for the full set of dependencies between consumer choices and realized variety. Instead, a structural model seems necessary; however, previous research has not modeled variety explicitly using dissimilarities in product-attribute space.

We therefore rely on previous research to develop a new theoretical model that accounts for the total effects from two forces, the preference for variety and the direct preferences for product attributes, including nutrient levels. The strength of variety preference depends on the dissimilarity of selected products, household characteristics and an iid shock reflecting unobserved factors affecting consumers' variety preferences. The model leads to a system of equations that characterize consumers' optimal demand choices, including corner solutions, where these choices jointly determine an optimal level of variety.

The purchasing record of RTE breakfast cereals at the household level in the Nielson Homescan dataset provides a good data foundation to identify the roles played by preference for variety in shaping consumer demand. The RTE breakfast cereal product group contains among the most purchasing records in this dataset. These data contain detailed information on the participating households' purchase information and basic product attributes, as well as a complete set of socio-demographics at the household level. We supplement this dataset by matching more detailed product attributes, such as fiber, sugar, calorie content and a whole grain indicator to each household's purchase record. As a result, the matched dataset contains detailed information on consumer demographics, product attributes, and their purchasing records. Our study in fact is motivated by three observed facts in this matched dataset. First, consumers tend to choose multiple brands [1] when they purchase more than one unit of cereal. Second, the average number of units purchased per brand decreases as the consumer purchase more brands. Third, the probability of purchasing two particular products increases with their relative difference in characteristic space. All of the three facts suggest that consumer may have preference for variety.

We are not the first to investigate the effect of preference for variety on consumer demand. Jackson (1984) claims that consumers have hierarchy of purchase as income grows and this feature of behavior should be taken into account when estimating consumer demand. A number of subsequent studies about demand

[1] To be clear, we treat breakfast cereals from the same product line as different brands, and different product as well. For example, we treat General Mills Honey Nut Cheerios as a different product to regular General Mills Cheerios.

for variety, besides confirming Jackson (1984)'s finding on the positive correlation between income level and demand for variety, try to explore the impact of other socio-demographics on the variety of product consumed, such as household size, household composition, number and age of children, race, employment, age, and education of female (or male) household head, or even shopping attitudes (Pessemier and Handelsman, 1984; Jekanowski and Binkley, 2000; Stewart and Harris, 2005; Temple, 2006; Drescher, Thiele, Roosen, and Mensink, 2009; Thiele and Weiss, 2003; Liu, Shively, and Binkley, 2014). Other studies investigate how the frequency of the data used for research (Moon, Florkowski, Beuchat, Resurreccion, Paraskova, Jordanov, and Chinnan, 2002) and the number of quantities purchased for each product (Simonson and Winer, 1992; Allender, Richards, Park, and Hamilton, 2013) affect consumers' preference for variety. A more recent strand of research further examines how consumer demand is affected by both preference of variety, the cost of searching, as well as the availability of differentiated choices in the market(Adamowicz and Swait, 2012; Allender, Richards, Park, and Hamilton, 2013; Liu, Shively, and Binkley, 2014; Gronau and Hamermesh, 2008).

Our research relates and contributes to the existing literature in the following directions. This paper relates to and extends the literature on how product characteristics affect consumer demand. The traditional demand model based on attributes space typically treat products as a bundle of characteristics. Consumers maximize their utility by choosing the level of product attributes within their budget constraint (Lancaster, 1979; Berry, 1994; Berry, Levinsohn, and Pakes, 1995; Nevo, 2000). Our paper is in line with this literature on assuming that consumer derives utility from product characteristics, but we extend this line of literature in two ways. First, while the traditional attribute-based demand system usually assumes that the utility brought by each product depends on the attributes of that product, we extend this idea to assume that consumer utility is instead affected by the aggregate amount of attributes derived from all purchased products. This treatment implicitly assumes that some product attributes associated with consumers' basic needs, such as fiber and calorie, are homogeneous and perfect substitutes although they may be contained in different products. Second, following Drescher, Thiele, and Weiss (2008)[2], while admitting that the absolute level of characteristics largely determines consumer demand, this paper further recognizes that diversity of products—characterized by the diversity of product attributes—consumed by a consumer may also bring additional utility to this consumer due to consumer preference for variety, which originates from the uniqueness of each

[2]The most close work to us exploring the effect of preference for variety to our idea is Drescher, Thiele, and Weiss (2008). They use a representative consumers' utility function suggested by Anderson, Palma, and Thisse (1992, p.78) and model consumer's utility from purchasing a varied set of products as a function of total attributes across products, as well the measure of variety. However, they use a linear functional form and assume the level of variety only depends on the quantity share of each product.

product due to its particular composition of different characteristics. Combining these two extensions together, this paper predicts a more flexible substitution pattern across products where the demand for each product is not only determined by its is own product characteristics, but also by the total amount of characteristics from other products and how different its characteristics are compared with other products.

In addition, this paper also relates to the work on how to evaluate the effect of preference for variety on consumer demand. In essence, we model consumer preference for variety based on the curvature of the indifference curves implied by the utility function, which is in the spirit of the research by Kim, Allenby, and Rossi (2002) and Allender, Richards, Park, and Hamilton (2013). Different with their work, we explicitly model consumer preference for variety separately with consumers' direct preference for product attributes in a standard consumer demand framework, which also predicts a discrete-continuous demand structure in the presence of multiple product choices. Besides that, we further extend that consumers' preference for variety is affected by the dissimilarity of products in the characteristics space. A hypothetical scenario can highlight the main difference: two different bundles of n cereal brands would be considered equally varied in many prior measures of product variety. However, these two bundles will have different variety measure in our model if the nutrient levels and other attributes of the n brands are different across the bundles. In other words, our model expands the current treatment of variety, which usually relies on only the chosen number of products and/or the expenditure share on each product.

A simple way to construct variety measure is to use a count measure of the unique items purchased (Jackson, 1984; Shonkwiler, Lee, and Taylor, 1987; Middleton, 1991; Temple, 2006). However, this measure does not consider the distribution of quantity across all the items in the purchasing set. Several subsequent studies construct the product diversity measure using more information on expenditure share of each unique item, such as Berry Index (BI), Engropy Index (EI), Logit Transformation of BI and EI, Simpson Index, and Cumulative share (Drescher, Thiele, and Weiss, 2008; Theil and Finke, 1983; Moon, Florkowski, Beuchat, Resurreccion, Paraskova, Jordanov, and Chinnan, 2002; Stewart and Harris, 2005; Jekanowski and Binkley, 2000; Thiele and Weiss, 2003; Liu, Shively, and Binkley, 2014).

When considering the heterogeneity of products, especially for some products which are known to be highly differentiated like breakfast cereals, the level of diversity of a subset of products could be determined by their dissimilarity of characteristics among products (besides the quantity and expenditure shares of the purchased items). Although research by Gollop and Monahan (1991) and Pessemier and Handelsman (1984) attempt to account for this aspect, their demand estimation does not actually utilize the differences between products in attributes. Instead, they use the differences in input cost share, or a difference measure constructed using three ratings of attributes as an approximate to product dissimilarity. Our measure of product variety combines information on the number of cereal brands chosen, the quantities of each selected brand, and the dissimilarity among these brands captured by our constructed distance measure explicitly using several important product characteristics following the idea of distance metric method from Pinkse, Slade, and Brett (2002) and Pinkse and Slade (2004).[3] We will discuss these measures in more detail in Section 4.4.

We estimate the consumer demand predicted by our theoretical model using maximum likelihood techniques. Empirical results show clear evidence on the positive role of preference for variety on consumer demand, in terms of the sets of products purchased by each consumer, and the amount purchased for each product. In particular, a larger difference of product characteristics induces consumers to purchase more (or more likely) of that combination of products. We also find that the strength of preference for variety depends on household characteristics. In particular, consumer preference for variety is higher if a household has a higher income, is larger, and/or includes at least one child.

We then conduct a counterfactual analysis to quantify the effect of consumers having no explicit preference for variety. We find that setting the preference for variety in the consumer utility function to zero generates two substantial consequences: First, total sales from all products will be substantially reduced; Second, the market structure will be more concentrated, i.e., without a explicit consumer preference for variety, consumer choices will be more focused on several products with more healthy attributes.

The rest of the paper proceeds as follows. Section 4.2 introduce the data and several stylized facts observed from the data. We agree that preference for variety exits in the consumer demand. We then present a model of consumer demand by considering heterogeneous preference for variety in section 4.3. Section 4.4 describes the definition of variables used in the empirical estimation and introduces the construction of distance measure for product variety. We discuss estimation results and a counterfactural analysis in section 4.5 and 4.6. Finally, section 4.7 concludes.

[3] Pinkse, Slade, and Brett (2002) first proposed the distance metric method as a way to assess the price competition by assuming that the level of product differentiation and substitutability can be captured by the relative distance in attribute space between products. Then they further applied this method in evaluating consumers demand in the UK brewing industry (Pinkse and Slade, 2004). Following their idea, several other research apply similar methods into the demand estimation (Rojas and Peterson, 2008; Rojas, 2008; Pofahl and Richards, 2009; Bonanno, 2013; Brissette and Ruff, 2014). In this paper, we follow their method of calculating the distance in attribute space and apply it into the demand estimation of preference for variety.

4.2 Demand for Variety: Data and Stylized Facts

4.2.1 Data Sources

The empirical application in this paper uses a combined dataset from three sources, which together provide rich information on consumers' purchase record, their demographics, and product characteristics.

The first data source is the Nielsen Homescan dataset, which contains consumers' weekly purchase information on purchase date, store, prices, and quantity, as well as some product information such as brand, product size, organic claims. It also contains detailed information on household-level demographic characteristics, including household income, household size, existence of children for different age group, race, age and education of household head, and other information. This data encompasses households living in all 48 contiguous States and the District of Columbia; the households are grouped into 52 metropolitan market areas, plus an additional area that covers the rest of the United States.

The second source is the National Nutrient Database for Standard Reference (SR) from the U.S. Department of Agriculture, which provides the nutritional composition of various food products sold in the United States. It contains information on over 100 different nutrients for each food product, such as calorie, protein, fiber, sugar, fat, etc. All the nutrient values reported are based on a 100g edible portion. It also discloses detail descriptions for each food product, such as brand name and product type, as well as the product weight information. For our research, we use several nutrients that are key components for the RTE breakfast cereals, including fiber, sugar, fat, sodium, and calorie. An additional one, defined as the number of vitamins added to fortify the cereal product, is calculated by using the product description information of the five vitamin components in this dataset.[4]

To supplement the two datasets above, we collect additional product attributes by hand one by one from the producers' official webpage, for each of the cereal products used in our empirical analysis. The reason for this additional collection is to include a product attribute defined by whether or not whole grain is listed as the primary ingredient for the cereal product. To assist with this data collection, we use the "Wayback Machine" website that archives many prominent websites including the main page of RTE cereal producers. Finally, these three datasets are matched using each one of the product names.

We focus on the U.S. RTE cereal market in 2004 for the empirical analysis.[5] The Homescan data yields a sample of $723,849$ purchase records from $36,664$ households for this year. These records include purchase of both national brand

[4]The five vitamin components are vitamin A, vitamin D, vitamin E (total ascorbic acid), vitamin B-6, and vitamin B-12.

[5]At the end of 2004, one of the leading cereal producer announced an important reformulation to their cereal products. To keep stable of the product attributes in our estimation and avoid the impact of this strategic shock from that cereal producer, we decide to focus on only 2004.

products and private label products. Because the nutrition information for private label products is usually not available, we only focus on national brand cereals. To further reduce the scope of the analysis, we focus on 20 leading national brands that have the highest number of observed purchase records. These 20 brands includes the top ten family/adult cereals and top ten kids cereals, and account for about 40% of the whole market for the RTE breakfast cereals in 2004. In these data, we observe that households may rotate their purchased brands at the purchasing trip level. That is, although each household purchases a roughly stable number of brands in the long run, their purchasing behavior for each purchase trip is very noisy. We aggregate the purchase records of each household to the quarterly level in order to reduce the noise at the purchasing trip level. These aggregated purchasing records at the quarterly level capture the variety for consumers' long-run purchases.

Based on the criteria above, our constructed sample contains quarterly purchase records for 20 cereal brands and 31,175 households in the RTE breakfast cereal market. Because we can only observe purchase records for products actually bought, we construct a balanced panel by setting the household-specific purchase amount to be zero for the brands that are not purchased in that quarter. The final dataset for estimation contains $1,713,380$ observations in total.

4.2.2 Stylized Facts

As evidence for consumers' preference for product variety in the RTE breakfast cereal market, we present three stylized facts from our data.

Fact 1: Multiple brand purchases account for more than seventy percent of our quarterly data, and the average number of units for each brand decreases as the total number of units purchased increases.

Table 4.1 summarizes consumers' purchasing decisions on quantity and the number of brands selected. Here, we only consider national brand cereals and consumers' purchase of up to ten brands in a quarter are reported. It covers 86.49% of market sales and represents 96.07% of the total shopping trips for purchasing national brand cereals in 2004. We observe first that, most households purchase multiple brands in one quarter. Purchases of only one brand account for 26.59% of the total household-quarter observations. In contrast, purchases of 2-10 brands account for 69.47% of the household-quarter observations in the same period. These simple figures demonstrate a preference for variety, and converting quantities to expenditure share heightens the contrast: Single-brand purchases account for 9.18% of the market share, while the multiple-brand purchases accounts for 77.31% of the market. Second, and more interestingly, table 4.1 shows that as consumers purchase more brands, the average number of units purchased for each brand decreases. This decreasing trend is observed for different household sizes, although households with two family members have on average the largest number of units per brand. This decreasing trend suggests that consumers are balancing the total units and the total number of brands. In other words, consumers' cereal choices reflect a trade off between the marginal utility from consuming more units of their primary cereal choice and the marginal utility of consuming more varieties.

Fact 2: As the number of units purchased increases, the mumber of brands purchased also increases.

The second stylized fact observed in the data is that as consumers purchase more than one unit of cereal product, they would be more likely to choose multiple brands at a time. Table 4.2 reports the heterogeneous purchasing behavior of consumers for different units of products purchased in one quarter. The first column is the total number of units purchased per period. The remaining columns show the expenditure shares for different number of brands. We observe first that the expenditure share on single-brand purchases drops sharply as households purchase more units of RTE cereal products. For example, for the group of households that only purchase two units in a quarter, we observe that about 37% of the total expenditure is spent on only one cereal brand, while about 63% of the total expenditure is spent across two brands. As the number of units increases to twenty per quarter, only 2% of expenditure is spent on purchasing a single brand. This disproportional decrease of expenditure share spent on purchasing single brand product reflects consumers' preference for purchasing more varieties of brands.

For column two beyond, we see that the expenditures on single-brand purchases is reallocated to multiple-brands cases when more units are purchased. The bolded numbers in this table reflect which number of brands on average receives the highest expenditure share given the total number of units purchased (the row indicator of this table). It shows that consumers prefer to spend more money on a increasing number of brands as they purchase more units. Also, although consumers show preference for variety by choosing multiple brands when consuming more, they do not, on average, purchase the maximum number of brands possible. This additional fact indicates that although consumers do prefer a variety of products, there are other factors (e.g. presumably prices, heterogeneity in basic ingredients of each brands) which drive them towards a core set of cereal brands. In other words, consumers' internal preference for variety appears to be balanced against heterogeneous preference for price and other product attributes. These observations imply that a demand model that can capture this trade off is necessary to fully understand consumers' behavior.

Fact 3: The probability of purchasing two brands increases as the relative distance in attribute space increases.

Figure 4.1 explores the relationship between the probability of simultaneously purchasing two particular products and their difference in product-attribute space. For illustration purpose, we only disclose the twenty best selling cereal brands in terms of the total sales revenue in the original data, which is the same as the data we use in our empirical analysis. Following Rojas (2008)'s method, we define a multi-dimensional distance measure between any two brands as the inverse Euclidean distance based on the contents of fiber, sugar, fat, and sodium of these cereal products.[6] The larger value of the distance measure, the closer (or similar) between these two products in the attributes space. As a result, 390 pairwise distance measures are calculated for each pair of products among the top 20 cereal brands. The distance measure ranges from 0.0111 to 0.1620. We then evenly divide the range of distance measures into twenty groups and compute the purchase frequency for each group. The results are shown in figure 4.1, with the distance measure on the horizontal axis and purchasing frequency on the vertical axis. In general, this figure indicates that the larger the difference in attribute space between the two products (as captured by a smaller distance measure), the higher the probability that consumers would purchase both products simultaneously. In other words, consumers prefer to consume products that are dissimilar, again suggesting consumers' preference for variety.

4.3 A Model of Preference for Purchase Variety

In this section, we develop a model of consumer demand that reflects two considerations: direct preference for product attributes, including nutritional attributes, and preferences for variety across attributes.

Suppose there are $J+1$ products in the market. The first J products are our main focus indexed by $j \in \{1, 2, ..., J\}$. The last product is outside choice indexed by O. Each product contains K basic ingredients (e.g. calorie, fiber, and fat) about which consumers care. The same type of ingredient contained in each product is homogeneous in nature, but the amount contained by each product may differ. A consumer derives utility based on the total amount of each ingredient aggregated over products this consumer purchases. Denote $C^h = (C_1^h, C_2^h, \ldots, C_k^h, \ldots, C_K^h)$ as the total amount of ingredients consumer $h \in \{1, 2, \ldots, H\}$ derives from her consumption of multiple cereal products. Each element of C^h represents the total amount of a particular ingredient derived from all products consumed by this consumer, $C_k^h = \sum_{j=1}^{J} q_j^h C_{jk}$. Here C_{jk} is the amount of k-th ingredient contained in each unit of product j. It is an exogenous attribute specific to product j. Given the exogenous product ingredients, C_{jk}, the total amount of ingredients that consumer h consumes depends on her endogenous choice of demand for each product, $q_j^h \geq 0$.

While the total ingredients aggregated across products satisfy consumers' basic needs, the combination of different ingredients within each individual product

[6] More details of the distance measure will be explained in the section 4.4.

reflects variety.[7] Use V^h to denote the total variety of the products consumed by consumer h. It reflects the level of diversification among chosen products for household h. Here, the total effect of variety on consumers purchase can be reflected into ways: product quantity and characteristics. First, the variety of product set for each consumer h depends on which product(s) are chosen, and how much for each of them. On one hand, choosing a product j ($q_j^h > 0$) obviously could affect the composition of product characteristics among household h's choices and increases product variety. On the other hand, given a product j is chosen, the number of units purchased (q_j^h) further affects the impact of product variety on consumers demand. For example, a household h purchases twenty units of brand A and one unit of brand B in a shopping trip. The total utility derived from this choice set would be different with another combination of purchasing only one unit of brand A and twenty units of brand B. This could be because that household h is more in favor of brand A compared to brand B relatively. So brand A gets more weight in measuring the impact of variety in this composition accordingly.

Secondly, given the set of products selected by a consumer, the satisfaction of that consumer derived from consuming these selected products depends on how different these products are (which captures the objective dissimilarity of the products consumed), as well as consumer demographics (which captures the subjective attitude towards variety). To capture this idea, we utilize the relative distance between products in characteristics space to measure the differences in attributes across products and investigate how these differences could affect consumers' choices.

To simplify the analysis, we further assume that the utility derived from outside products is separable from other products and taken as a numéraire. As a result, the utility function for consumer h can be written in a general form as follows

$$U^h = U^h(C^h, V^h, \Theta) \cdot O^h,$$

where Θ is the set of parameters to be estimated. The budget constraint for the consumer h with income level Y^h facing product prices $\{p_j\}_{j=1}^J$ is

$$\sum_{j=1}^{J} p_j q_j^h + O^h = Y^h.$$

Consumer h chooses her consumption amount for each product j, $q_j^h \geq 0$, to maximize her utility. Note that facing a set of available products in the market, a consumer can choose not only which product(s) to consume, but also how

[7]For example, different combination of fat, sugar, and fiber may give the product a very special taste. We call this special taste formed by the particular combination of all attributes within a product a product variety in this paper. This product variety gives consumers one additional source of satisfaction—the more variety a consumer consumes, the higher satisfaction she may gain, as suggested in the stylized facts in Section 4.2.

much to consume for each of them. Different combinations of q_j^h, on one hand, gives the consumer different combination of total attributes, which delivers a basic utility to satisfy her direct preference of product attributes. On the other hand, different combination of selected products forms different product variety, which delivers additional satisfaction due to consumers' inborn preference for variety. Each consumer's choice of products reflects both of these two jointly determined considerations. The consumer's optimization problem can be written as

$$\max_{q^h=(q_1^h,q_2^h,\ldots,q_J^h)\geq 0} U^h(C^h,V^h,\Theta)\cdot O^h$$

$$s.t. \quad \sum_{j=1}^{J} p_j q_j^h + O^h = Y^h,$$

which is equivalent to the following unconstrained optimization problem given that consumer preference satisfies local non-satiation condition

$$\max_{q^h=(q_1^h,q_2^h,\ldots,q_J^h)\geq 0} U^h(C^h,V^h,\Theta)\cdot\left(Y^h-\sum_{j=1}^{J} p_j q_j^h\right). \tag{4.1}$$

The associated first order conditions are

$$\frac{\partial U^h}{\partial q_j^h} = \left[\sum_{k=1}^{K}\frac{\partial U^h}{\partial C_k^h}\frac{\partial C_k^h}{\partial q_j^h}+\frac{\partial U^h}{\partial V^h}\frac{\partial V^h}{\partial q_j^h}\right]\left(Y^h-\sum_{j=1}^{J} p_j q_j^h\right)-p_j U^h(C^h,V^h,\Theta)\leq 0,$$
$$for \quad j=1,\ldots,J. \tag{4.2}$$

At the optimal choice, the first order condition holds with equality if product j is purchased with positive quantity, i.e. $q_j^h > 0$. It holds with strict inequality if product j is not purchased i.e. $q_j^h = 0$. The first order condition shown in equation 4.2 has clear economic intuition: the consumer tries to equalize the opportunity cost of purchasing a product captured by the last term and the marginal utility derived from both the basic product attributes and her preference for product variety. The first term in the first order condition represents the marginal utility of consuming one more unit of product j. At the same time, in order to consume one more unit of product j, consumer h has to pay the cost of p_j, which can also be used to buy p_j units of the outside good given the unit price of outside good is assumed to be 1. So the second term in the first order condition, which equals the reduced number of outside goods (p_j) multiplying the marginal utility of the outside good ($U^h(C^h,V^h,\Theta)$), embodies the opportunity cost of consuming one more unit of product j. For a given product j, the optimal demand q_j^h is determined by equalizing the benefit and cost of consuming q_j^h. If the total marginal utility is always smaller than the opportunity cost for a product, the consumer chooses zero unit of that product. This truncation generates a consumer demand with multiple discrete-continuous choices, as what we observe in the data.

4.3.1 Parameterization

In the empirical analysis, we parameterize the utility function by initially assuming that utility from product characteristics and variety are separable.[8] In particular, we assume that the characteristics-based utility (U_{C^h}) and the variety-based utility (U_{V^h}) both take a Cobb-Douglas form[9]

$$U^h(C^h, V^h, \Theta) = U_{C^h} \cdot U_{V^h} \cdot O^h = \underbrace{\prod_{k=1}^{K} (\sum_{j=1}^{J} q_j^h c_j^k)^{\alpha_k}}_{U_{C^h}} \cdot \underbrace{\prod_{j=1}^{J} (1 + q_j^h)^{\beta_j}}_{U_{V^h}} \cdot \underbrace{\left(Y^h - \sum_{j=1}^{J} p_j q_j^h \right)}_{O^h} . \tag{4.3}$$

This setup has intuitive economic explanation. Within the first term, U_{C^h}, the characteristic specific parameter α_k measures the importance of characteristic k in its contribution to the total utility. The variety effect from consuming a set of products, U_{V^h}, depends on how much each product is consumed and the strength of preference for variety associated with each product.[10] The latter is captured by the parameter β_j, which we call preference-for-variety parameter (PFV parameter henceforth). It measures the utility elasticity of product q_j through the variety. A higher β_j means that the contribution of product j to the total variety, and thus the total utility, is higher. The PFV parameter depends on the relative distance of product j in product-attribute space compared with other products selected by consumer h, DS_j^h, as well as household demographics, $DEMO^h$. In addition, we allow for a random shock ϵ_j^h to β_j^h, which captures the unobserved heterogeneity

[8] Our model is set up following the spirit of Drescher, Thiele, and Weiss (2008). They model consumer's utility from purchasing a varied set of products as a function of total attributes across products and the measure of variety by using a representative consumers' utility function suggested by Anderson, Palma, and Thisse (1992, p.78). However, they use a linear functional form and assume the level of variety only depends on the quantity share of each product, which is different with our model.

[9] Kim, Allenby, and Rossi (2002) and Allender, Richards, Park, and Hamilton (2013) model consumers' preference for variety as the curvature of the indifference curve. Based upon their work, we model consumers' utility from product variety in a similar fashion. However, our model is different with their work on modeling consumers direct preference for product characteristics in a separate form besides modeling consumers' preference for variety.

[10] We assume the variety effect is in Cobb-Douglas form with respect to $(1 + q_j^h)$. This assumption is non-substantial and the key point is to ensure that the variety effect from consuming a product j increases in its consumption amount of j. While this assumption is not substantial, it does simplified the model. First, when product j is not purchased, $(1 + q_j^h)^{\beta_j}$ degenerates to be one, which can be think of as the baseline level of the variety effect derived from consuming outside products. Secondly, this simple form simplifies the estimation.

in consumers' tastes over different product varieties. In particular,

$$\beta_j = \beta_0 + \beta_{DS} DS_j^h + \beta_{DEMO} DEMO^h + \beta_{DEMO*DS} DEMO^h * DS_j^h + \epsilon_j^h. \quad (4.4)$$

We assume that the shocks to preference for variety, ϵ_j^h, is iid drawn across consumers and products.

Following these assumptions, we can write the consumer (logarithm) utility optimization problem as follows

$$\max_{q^h=(q_1^h,q_2^h,\ldots,q_J^h)\geq 0} \underbrace{\sum_{k=1}^{K} \alpha_k \ln(\sum_{j=1}^{J} q_j^h c_j^k)}_{\ln U_{C^h}} + \underbrace{\sum_{j=1}^{J} \beta_j \ln(1+q_j^h)}_{\ln U_{V^h}} + \underbrace{\ln\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)}_{O^h}.$$

The first order conditions associated with consumers' optimal choice are

$$\begin{aligned} \frac{\partial \ln U^h}{\partial q_j^h} &= \sum_{k=1}^{K} \alpha_k \frac{c_j^k}{\sum_{j=1}^{J} q_j^h c_j^k} + \beta_j \frac{1}{(1+q_j^h)} - \frac{p_j}{\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)} \leq 0 \\ & \quad for\ j = 1, \ldots, J. \end{aligned} \quad (4.5)$$

The first two terms in the first order condition summarize the benefits of consuming one more unit of product j. The (total) marginal utility of product j can come from the marginal utility derived from basic characteristics and that from product variety. The first term in particular represents the marginal utility derived from basic characteristics and is a function of the total amount of each of the K characteristics. Product j contributes to the utility by adding some amount to each of these characteristics, whose total effect defines product $j's$ characteristics-based marginal utility. Given the unit value of each characteristic for product j (c_j^k) and the quantity of all other products, the characteristic-based marginal utility of product j is diminishing in q_j^h if the total effect of aggregate characteristics on utility (α_k) is positive.

The second term of the first order condition corresponds to the variety-based marginal utility for product j. It depends on the strength of preference for variety (the PFV parameter) and the consumption amount of product j. By assumption, there is diminishing variety-based marginal utility in q_j^h if consumers have a preference for variety ($\beta_j > 0$). Both the basic characteristics effect and variety effect may contribute to the decreasing marginal utility. The third term in equation (4.5) is the monetary costs of consuming more product j.

This optimal condition clearly defines how different products are substituted by each other. On one hand, higher consumption of other non-j products reduces the marginal utility of consuming basic characteristics, which reduces the consumption of product j. The strength of this effect depends on how additional unit compares to attributes of all other products. On the other hand, the relative differences in characteristics of all products affects the PFV parameter for product j, that also has an impact on the marginal utility of product j, affecting its demand as a result. The third channel of substitution comes from the usual expenditure condition. If more of other products are purchased, there will be less resource used for purchasing product j, generating substitution across products through the budget constraint. So this model implies a very flexible substitution pattern across products, which comes from all the above three channels.

In equation (4.5), the first order condition with respect to product j holds with equality if $q_j^h > 0$, and with strict inequality otherwise. Multiplying both sides of equation (4.5) by $(1 + q_j^h) > 0$ yields

$$\sum_{k=1}^{K} \alpha_k \frac{c_j^k (1 + q_j^h)}{\sum_{j=1}^{J} q_j^h c_j^k} + \beta_j - \frac{p_j (1 + q_j^h)}{\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)} \leq 0, \quad for\ j = 1, \ldots, J. \tag{4.6}$$

Define $S_{cjk}^h = \frac{c_j^k (1+q_j^h)}{\sum_{j=1}^{J} q_j^h c_j^k}$ and note that it is product $j's$ contribution to characteristic k in her purchase set, adjusted by one more unit of j. Similarly, define $S_{Ej}^h = \frac{p_j (1+q_j^h)}{\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)}$ and it is simply consumer $h's$ (adjusted) expenditure on product j relative to the expenditure on outside choice. Using these terms and pluging equation (4.4) into equation (4.6) yields

$$\begin{aligned} S_{Ej}^h \quad \geq \quad & \sum_{k=1}^{K} \alpha_k S_{cjk}^h + \beta_0 + \beta_{DS} DS_j^h + \beta_{DEMO} DEMO^h \\ & + \beta_{DEMO*DS} DEMO^h * DS_j^h + \epsilon_j^h, \ \ for\ j = 1, \ldots, J. \end{aligned} \tag{4.7}$$

The equation with respect to product j holds with equality if $q_j^h > 0$, and with strict inequality if product j is not purchased. The model parameters can be estimated using maximum likelihood techniques, given the knowledge of the distribution of the error term up to unknown parameters.

To capture the possibility that the choice of whether or not to purchase a particular product may be affected by some additional unobserved factors, we further assume that the preference shock can be separated into two components: one affects the discrete choice, and the other affects the continuous choice of quantity

$$\epsilon_j^h = I(q_j^h > 0)\epsilon_{j1}^h + I(q_j^h = 0)\epsilon_{j2}^h.$$

Where ϵ_{j2}^h captures unobserved factors that affect a consumer's decision on whether to buy the product j, and ϵ_{j1}^h captures those unobserved factors that affect how much to buy.

As a result, the estimation equation can be rewritten as

$$\begin{aligned} S_{Ej}^h \geq & \sum_{k=1}^{K} \alpha_k S_{cjk}^h + \beta_0 + \beta_{DS} DS_j^h + \beta_{DEMO} DEMO^h + \beta_{DEMO*DS} DEMO^h * DS_j^h \\ & + I(q_j^h > 0)\epsilon_{j1}^h + I(q_j^h = 0)\epsilon_{j2}^h, \qquad for\ j = 1, \ldots, J. \end{aligned} \tag{4.8}$$

There are several advantages of this modeling framework. First, it accommodates the preference for variety and the direct preference for product characteristics, and can evaluate their relative importance in shaping consumer demand. Secondly, the framework generates a intuitive estimation equation, which can be estimated using a maximum likelihood estimator. Third, it allows consumers to choose product quantities including zeros. Finally, the demand equation system is directly based on a standard consumer optimization problem. As a result, it satisfies all the usual properties a demand function should possess. Moreover, the existence of outside option ensures that the adding up condition is always satisfied.

4.3.2 The Estimator

The model parameters can be estimated using maximum likelihood estimation method based on the demand equation system captured in equation (4.8). We further assume that the two preference errors follow two independent generalized extreme value (GEV) distributions.[11] The selection of distributions comes from the distribution of S_{Ej}^h in the data. We find that the distribution of S_{Ej}^h is close to GEV distribution. Define

$$\begin{aligned} \Delta(\Theta) & = S_{Ej}^h - \Big(\textstyle\sum_{k=1}^{K} \alpha_k S_{cjk}^h + \beta_0 + \beta_{DS} DS_j^h + \beta_{DEMO} DEMO^h \\ & \qquad + \beta_{DEMO*DS} DEMO^h * DS_j^h \Big) \end{aligned} \tag{4.9}$$

Where Θ is the set of model parameters to be estimated. The probability of choosing $q_j^h = 0$ is

$$Prob(q_j^h = 0) = Prob\left\{ \epsilon_{j2}^h < \Delta(\Theta) \right\}, \quad for\ j = 1, \ldots, J.$$

The logarithm likelihood to observe the sample is

$$\begin{aligned} LL(\Theta) = & \textstyle\prod_{n=1}^{N} \Big(Prob(q_j^h = 0) I(q_j^h = 0) \\ & + (1 - Prob(q_j^h = 0)) Prob(q_j^h | q_j^h > 0) I(q_j^h > 0) \Big), \end{aligned} \tag{4.10}$$

[11]The GEV distribution combines three simpler distribution, including the type I, type II and type III extreme value distribution. Using this distribution in our empirical analysis would allow the data choose the most "appropriate" distribution for itself.

Given the assumption that ϵ_{j1}^h and ϵ_{j2}^h are independent, the conditional density of observing q_j^h conditional on $q_j^h > 0$ is equal to the unconditional density,

$$Prob(q_j^h | q_j^h > 0) = Prob(q_j^h) = Prob\left\{\epsilon_{j1}^h = \Delta(\Theta)\right\}, \quad for\ j = 1, \ldots, J.$$

As a result, the model parameter Θ can be estimated by maximizing the following likelihood function[12]

$$\begin{aligned} \hat{\Theta} = \quad & \operatorname{argmax}_{\Theta} \tfrac{1}{N} \textstyle\prod_{n=1}^{N} \big(Prob(q_j^h = 0) I(q_j^h = 0) \\ & + (1 - Prob(q_j^h = 0)) Prob(q_j^h) I(q_j^h > 0)\big), \end{aligned} \tag{4.11}$$

where $I(\cdot)$ is the indicator function and $\hat{\Theta}$ is the estimate of model parameters.

4.4 Variable Definition and Distance Metric

4.4.1 Variables for Estimation

Prices are brand-level quarterly average for each household. Specifically, the price for each product is calculated by dividing the product-level total expenditure for each household in each quarter by the total quantity of this product purchased by this household in the same time period. The quantity units in the estimation are ounces. So the price is in US dollars per ounce. Since the prices of products not purchased by a consumer are not recorded in the Nielsen Homescan database, we impute these unobserved prices for the non-purchased products using the quarterly average price in the corresponding scantrack market following Arnade, Gopinath, and Pick (2008).

The total expenditure, Y^h, in equation (4.1), is approximated by the quarterly total expenditures for all dry groceries. We use this measure, instead of the quarterly household income, mainly for the following three reasons. First, we want to define the outside goods as closely related to the 20 cereal products we focus on, such that there is some substitution pattern between our focused products and outside goods. Following this idea, we think the total expenditure on dry groceries is a reasonable choice since cereals are contained in this category. Second, the quarterly total expenditure of the 20 leading national brands for each house-

[12]We made the iid assumption for ϵ_{j1}^h and ϵ_{j2}^h to simplify the estimation. If these two errors are correlated, then we just need to adjust Eq. (4.11) slightly by dealing with the conditional distribution of q_j^h conditional on $q_j^h > 0$. In the special case of $\epsilon_{j1}^h = \epsilon_{j2}^h$ (perfect correlation), Eq. (4.11) becomes the standard Tobit-type estimator,

$$\hat{\Theta} = \operatorname*{argmax}_{\Theta} \frac{1}{N} \prod_{n=1}^{N} \left(Prob(q_j^h = 0) I(q_j^h = 0) + Prob(q_j^h) I(q_j^h > 0)\right).$$

hold is quite small relative to the quarterly household income, and using quarterly household income for Y^h may provide insufficient variation. Moreover, since the household income in Homescan dataset is categorical (ranging from 3 to 30), use of this information will also impair the variation of the expenditure of the outside goods in the model.

All the household characteristics are constructed from the Nielsen Homescan data. We include the following demographic information: household income (HHINC), household size (HHSIZE), presence of at least one child with age below 18 (CHILD), educational attainment for female household head (FHIGHSC for high school, FSOMECOL for some college, and FCOLMORE for college and more), existence of household head with age equal or over 65 (AGE65), and a dummy variable if they have a female head (FHEAD) in a household. Table 4.3 presents summary statistics for these household characteristics.

We focus on the top 20 breakfast cereal brands.[13] Their nutrition profiles are collected from the USDA National Nutrient Database for Standard Reference for 2004 (Release 17). Consistent with previous research in breakfast cereal market, such as Nevo (2000) and Golub and Binkley (2005), we include the following nutrients which are commonly believed to be important cereal attributes: sugar (SUGAR), fat (FAT), dietary fiber (FIBER), sodium (SODIUM), calorie(CALORIE), and the number of vitamins added to fortify the product (NVF). The content of the first three nutrients is measured as grams per 100 grams of cereal products. The units for sodium and calories are $mg/100g$ and $kcal/100g$ respectively. By using the product description in this dataset, we construct the variable NVF by summing five binary vitamin-fortification indicators: vitamin A, vitamin D, vitamin E (total ascorbic acid), vitamin B-6, and vitamin B-12. For each vitamin considered, a binary variable is given the value one if the brand is enriched with an extra amount of this vitamin according to the reference value from the Recommended Dietary Allowances from the U.S. Food and Drug Administration.

Because cereal manufacturers disclose nutrition labels and product descriptions on their websites, we collected additional product attributes from archived web pages of these cereal producers in 2004 using the Wayback Machine, which is a service provided by the Internet Archive. Using this information, we are able to identify the primary ingredients of each cereal product and construct the binary variable whole-grain (WG) to indicate a cereal product that uses whole grain as first ingredient. Also, according to the cereal facts report by Yale University's Rudd Center for Food Policy and Obesity (Harris, Schwartz, and Brownell, 2009), we create another binary variable, KIDS, which identifies products that are targeted to children. Summary statistics for all the product characteristics are listed in table 4.4.

[13]Due to data use agreement with the Kilts Center for Marketing and Nielsen, we are not able to disclose the brand name of these 20 cereal product, as well as their manufacturer information.

Using prices and quantity information, as well as the product characteristics, we construct variables S^h_{Ej} (SE) and S^h_{cjk} (SH ATT)[14]using the definition in the modified first order condition in equation (4.6). For S^h_{cjk}, we consider the eight major product attributes we discussed above: WG, NVF, KIDS, FIBER, SUGAR, FAT, SODIUM and CALORIE. Summary statistics of S^h_{Ej}, and S^h_{cjk}s for eight product attributes, as well as price, p_j (P), quantity, q^h_j (Q) and total expenditure, Y^h (Y), which are used to calculate S^h_{Ej} and S^h_{cjk}, are reported in table 4.5.

4.4.2 Distance Metric Measure for Variety

Consumers' purchase decisions for cereal products are not only determined by the characteristics of the product itself, but also by the relative position to other brands. Especially when consumers purchase more than one unit, they would have to optimize over their variety preferences by evaluating one product's dissimilarity relative to other potential product choices. Therefore, we allow the variety of consumers' purchase to vary depending on the relative distance among the cereal products. Following Pinkse, Slade, and Brett (2002), Pinkse and Slade (2004) and Rojas (2008), we construct several distance measures in attributes space to quantify the dissimilarity of each unique product relative to the rest products in each consumer's chosen set.

Two types of distance measures are used to calculate the pairwise distance for the twenty products considered. The first one, namely multi-dimensional continuous distance measure ($\delta^{cont}_{j,j'}$), is calculated using continuous product attributes such as fiber and sugar by following Rojas (2008). It is defined as a function of the inverse Euclidean distance between any pair of products (j and j') in multi-dimensional continuous attribute space. In our context, these continuous attributes include fiber, sugar, fat, and sodium. The measure is defined as follows

$$\delta^{cont}_{j,j'} = \frac{1}{1 + 2\sqrt{\sum_{k^{cont}=1}^{K^{cont}} \left(c_j^{k^{cont}} - c_{j'}^{k^{cont}}\right)^2}}, \tag{4.12}$$

where $k^{cont} = \{1, \ldots, K^{cont}\}$ represents the index of the four continuous product attributes. $c_j^{k^{cont}}$ and $c_{j'}^{k^{cont}}$ represent the content of attribute k for product j and j' respectively. By construction, this continuous distance measure is positive between 0 and 1. It is smaller when the attribute-space difference between these two products is large.

The second distance measure is ($\delta^{disc}_{j,j'}$), is constructed based on discrete (binary) product attributes. If both products j and j' belong to the same product type (e.g., both are whole-grain or both are produced by the same manufacturer), the distance

[14]For saving space, we use "ATT" to represent the eight product attributes considered: whole-grain type (WG),number of vitamin fortification (NVF), kids cereal (KIDS), fiber (FIBER), sugar(SUGAR), fat(FAT), sodium(SODIUM) and calorie(CALORIE).

between these two products for that attribute will be one. It equals zero otherwise.

$$\delta_{j,j'}^{disc} = \begin{cases} 1 & if \ |c_j^{k^{disc}} - c_{j'}^{k^{disc}}| = 0, \\ 0 & if \ |c_j^{k^{disc}} - c_{j'}^{k^{disc}}| \neq 0. \end{cases} \tag{4.13}$$

Similar to the definition for continuous distance measure, $k^{disc} = \left\{1, \ldots, K^{disc}\right\}$ represents the discrete product attributes, and $c_j^{k^{disc}}$ and $c_{j'}^{k^{disc}}$ are the attribute type for product j and j' accordingly. Smaller value of $\delta_{j,j'}^{disc}$, which means $\delta_{j,j'}^{disc} = 0$, indicates the two products are located far away from each other in the characteristics space. Two discrete attributes are considered in the empirical estimation: the whole-grain type ($\delta_{j,j'}^{WG}$) and manufacturer ($\delta_{j,j'}^{MAKER}$).

Now suppose the consumer purchases a set of at least two products, and we want to measure the relative distance of one particular product to the rest. We define this one-to-many distance using the average distance between product j and all other chosen products. It is used to reflect the idea that consumers, who have preferences for variety, will make their purchasing decision by evaluating the relative differences between this product and other products. Consumers with a higher preference for variety would derive more utility from consuming a product that is located far away from the other products that have already been selected. Based on this idea, we construct three such average distance measures to describe how one product differs from a set of other products in attributes, based on the pairwise distance measured defined above.

The first measure, which we call DS MULTI, is defined as the distance of one product relative to a set of other chosen products in their continuous attributes,

$$DS\ MULTI = \frac{1}{\sum_{j'=1, j' \neq j}^{J} I\left(q_{j'}^h > 0\right)} \sum_{j' \neq j}^{J} I\left(q_{j'}^h > 0\right) \delta_{j,j'}^{cont}. \tag{4.14}$$

Indicator variable, $I(q_{j'}^h > 0)$, is used to show that product j' is selected by consumer h. DS MULTI measures the average of inverse distance of product j to other products in their continuous attributes, including fiber, sugar, fat and sodium. The lower is this measure, the more variety product j can contribute to the variety of continuous attributes of the chosen product set if product j is added.

In a similar fashion, we can define the other two measures of the average distance of product j to a set of other goods based on the two discrete distance measure defined in equation (4.13). In particular, DS WG measures the average inverse distance of product j to a set of other selected products in terms of the discrete attribute indicating whether or not a product's primary ingredient is whole grain.

$$DS\ WG = \frac{1}{\sum_{j'=1,j'\neq j}^{J} I\left(q_{j'}^{h} > 0\right)} \sum_{j'\neq j}^{J} I\left(q_{j'}^{h} > 0\right) \delta_{j,j'}^{WG} \tag{4.15}$$

and DS MAKER measures the average inverse distance of product j to a set of other selected products in terms of another discrete attribute indicating whether both product j and j' are made by the same manufacturer or not.

$$DS\ MAKER = \frac{1}{\sum_{j'=1,j'\neq j}^{J} I\left(q_{j'}^{h} > 0\right)} \sum_{j'\neq j}^{J} I\left(q_{j'}^{h} > 0\right) \delta_{j,j'}^{MAKER} \tag{4.16}$$

These three measures are constructed in a consistent way. By definition, the smaller the average distance for these three, the larger the difference of product j in these attributes spaces relative to other products and thus it has a higher effect on consumer variety through their preference for variety. The summary of all the distance measures are shown in table 4.4.

4.5 Empirical result

We estimate this model using the maximum likelihood estimation method and assume the two errors are distributed under the generalized extreme value distributions. The estimated results are shown in table 4.6.

4.5.1 Parameter Estimates

Direct Preference for Product Attributes

The first group of estimated parameters are associated with consumers' basic preference for product attributes. They are captured by the $\alpha_k's$ in equation (4.8), and the estimation results are reported in Panel A of table 4.6. By definition, α_k measures the direct contribution of total product attributes k to consumer utility. The estimation results show that whole grain (SH WG), number of vitamin fortification (SH NVF), and fiber (SH FIBER), which are all thought to be healthy ingredients, contribute positively to consumer utility. Calorie as a basic nutritional standard to satisfy consumers' basic energy needs contributes to the utility positively, which also makes sense. Additionally, consumers would be likely to spend more if that product is for kids, represented by the positive and significant coefficient for SH KIDS. In contrast, consumers show negative preference towards cereal products that has higher level of sugar content, possibly because too much sugar is known to be unhealthy. One interesting result shows up for consumers' preference of fat. Although dietary guideline suggests reducing fat intake, consumers in the cereal market show positive preference for this nutrient. A possible reason could be that fat also contributes to a better taste, especially for food products which are rich in fiber. The coefficient for sodium is positive but very small, showing that it may not be a major factor that affect consumers' choices.

Preference for Variety

The second group of parameter estimates are associated with consumers' preference for variety. They are reported in Panel B of table 4.6. The first interesting result lies in how the distance of product attributes affect the PFV parameter (β_j) and thus utility. The coefficient on DS MULTI and DS WG are both negative and significant, implying that larger difference in product characteristics (as captured by lower value of DS MULTI and DS WG) increases the value of β_j and contributes to higher utility due to preference for variety. In particular, the negative parameter of multi-dimensional distance measure (DS MULTI) is evidence that consumers would prefer to choose products that are located far away from each other in the multi-dimensional attribute space of the four nutrients: fiber, sugar, fat and sodium. When consumers purchase more than one cereal products, increased differences among these four attributes make it more likely these products will be chosen together. Combining this result with the parameter estimates associated with direct attribute preference, it shows that it is not only the absolute level of product characteristics that determines consumer demand, but that the diversity of product attributes also plays an important role in affecting consumers' demand choices. The estimated parameter of average distance measure for whole grain (DS WG) reflects similar attitude of consumers towards variety with the continuous product attributes. When they purchase multiple units of cereals, consumers would like to choose cereal products with whole grain as primary ingredient as well as those that do not. Again, both health and taste could play a role when consumers make purchase decisions on which set of cereals to choose, represented by a possible strategic choice of choosing both whole-grain and non-whole grain cereals.

In contrast, if we look at the result for the distance measure for manufacturer, consumers show no interest in purchasing products from different manufacturers at the same time. The positive and significant coefficient for DS MAKER indicates that consumers tend to buy products produced by the same producer when they decide to purchase multiple units, pointing to a fact that consumers are loyal to certain cereal producer.[15]

The second interesting finding associated with consumer preference for variety lies in how household characteristics affect the preference for variety. First of all, we find that household income has a positive impact on consumer preference for variety, which is consistent with earlier studies (Jackson, 1984; Pessemier and Handelsman, 1984; Jekanowski and Binkley, 2000; Stewart and Harris, 2005; Temple, 2006; Drescher, Thiele, Roosen, and Mensink, 2009; Thiele and Weiss, 2003; Liu, Shively, and Binkley, 2014). This finding is captured by the positive and significant coefficient on HHINC (0.0063). In addition, when one examines the three interaction terms between household income (HHINC) and the average distance for multi-continuous nutrients (DS MULTI), whole grain (DS WG), and manufacturer (DS MAKER). One finds that households with higher income would prefer a set of cereal products that are quite varied in the continuous nutrients, including fiber, sugar, fat, and sodium. On the other hand, the results show no impact on consumers' preference for variety represented by choosing both the whole-grain and non-whole grain cereals, or choosing cereals from different manufacturers simultaneously. Even though the estimates of these three interactions are negative, the total effect of income on preference for variety is till positive in general.

Household size also shows a positive impact on consumers' preference for variety represented by the diversity of the continuous attributes. Larger households are more likely to choose a set of cereals that are quite different in those continuous nutrients in order to satisfy various preference from all the family members. However, consumers are more likely to choose cereal products produced by the same manufacturer as household size increases, as suggested by the positive and significant estimate for the interaction term between HHSIZE and DS MAKER (0.0030). From the manufacturers' point of view, this result suggests a successful strategy of product proliferation that keeps household members loyal. Household size has no impact on consumers preference of variety for the whole grain type due to the insignificant estimates for the interaction between HHSIZE and DS WG. Again, the total effect of household size on preference for variety is also positive.

For households with at least one child, results show that consumers have a preference for variety on average. When they purchase multiple units of cereals, they would like to choose cereals with whole grain as primary ingredient, together with cereals that do not use whole grain as the first ingredient. However, this group of households would not like products to be varied in the continuous attributes of fiber, sugar, fat or sodium. Similarly, households with children prefer to choose

[15] Békési, Loyb, and Weissa (2013) find that only small share of consumers are variety-seekers for cereals from different producers. However, they do not explicitly model consumer demand for variety, while capture this behavior using a state dependence variable. Simonson and Winer (1992) find similar results in the yogurt market in the U.S. that when the number of purchase quantity increase, consumers would prefer to choose products from the manufacturers that they mostly buy, instead of going to try more variety with respect to different yogurt producers.

cereal products from the same manufacturer and show loyalty to it. Compare to the results about household income and household size, our results show that consumers do have preference for variety, but the variety can be reflected through different characteristics and which characteristic consumers care about would vary with their socio-demographics.

Education, has consistent effect on consumers preference for variety across different product characteristics. We consider three levels of educational attainment for female household head, including high school, some college, and college or more. Our estimated results show that high level of education of a female head has a positive affect on consumers' preference for variety on the continuous nutrients (fiber, sugar, fat and sodium), the whole-grain type of the first ingredient of cereal products, and the manufacturers. Especially, as a female head reaches higher educational attainment, their preference for variety over the whole-grain type increases gradually. Our finding is consistent with previous research that finds variety is positively related to education(Liu, Shively, and Binkley, 2014; Drescher, Thiele, Roosen, and Mensink, 2009; Moon, Florkowski, Beuchat, Resurreccion, Paraskova, Jordanov, and Chinnan, 2002; Stewart and Harris, 2005; Jekanowski and Binkley, 2000).

Finally, we find that households with female head would be more likely to choose cereals with higher level of variety.[16] Households where the head is aged 65 or more are also likely to choose a set of cereal products with higher level of variety. This finding is consistent with Topper (2014)'s finding that the oldest group of consumers would like to keep multiple types of cereals at a given time.

4.5.2 Preference for Variety: Household and Product Characteristics

4.5.2.1 Dispersion of Preference for Variety

Based on the estimated parameters, we calculated the fitted value of the preference for variety parameter (β_j) net of the random preference shock following equation (4.4). The fitted β_j is denoted as $\hat{\beta}_j$ in the following discussion. Our summary statistics show that, $\hat{\beta}_j$ is positive and has a mean value of 0.6311 within the range between 0.4795 and 0.7661. The standard deviation of estimated $\hat{\beta}_j$ is 0.0394. The kernel density of $\hat{\beta}_j$ is shown in figure 4.2. A positive $\hat{\beta}_j$ indicates that consumers do have a preference for variety. When these consumers choose one more unique cereal product, their utility will increase. Also, since $\hat{\beta}_j$ is positive and less than one, consumers' marginal utility for variety will decrease as they consume more of

[16]According to Topper (2014) from Mintel Academic, they find that "more than one third of cereal eaters (36%) indicate they always read the nutritional information on cereal, including nearly two in five women (39%). This increases the importance of featuring nutritional claims prominently, making it easier for consumers to find the nutritional claims they are looking for."

this product.

We also find considerable dispersion of consumer preference for variety across households and products. We calculate the interquartile range[17] for the $\hat{\beta}_j$ using the whole sample and find it to be 0.0565, which means the third quartile value is about 9.3% higher than the second quartile value (0.6033). If we further compare the $\hat{\beta}_j$ of the 10% percentile to that of the 90% percentile, the difference is even larger (0.1034). This gap indicates that consumers preference for variety varies substantially in our sample. Two possible reasons could contribute to this variation. One is that consumers have heterogeneous preference for variety due to different household characteristics. On the other hand, products with their unique attributes also contribute to the variation of consumers preference for variety. If a product is far away from most of the other products in the attributes space, consumers would have stronger preference of variety for it because these products are more unique in their "taste". In the next three subsections we discuss the variations of preference for variety in more detail.

4.5.2.2 Household Income and Preference for Variety

Figure 4.3 shows the heterogeneous strength of consumer preference for variety of households in different annual household income groups. We divide our sample into three income groups: (1) a low income group with household income less than $\$20,000$; (2) a middle income group with household income between $\$20,000$ and $\$59,999$; and (3) a high income group with income greater than or equal to $\$60,000$.[18] The kernel density of $\hat{\beta}_j$ is plotted in this figure for each of the three income groups. The figure shows that consumers with higher income have stronger preference for variety on average and thus are more likely to purchase more varied set of cereal products, which is consistent with previous findings (Pessemier and Handelsman, 1984; Jekanowski and Binkley, 2000; Stewart and Harris, 2005; Temple, 2006; Drescher, Thiele, Roosen, and Mensink, 2009; Jackson, 1984). In these existing studies, however, it is unclear whether this higher level of variety of purchased products is due to higher purchasing power of higher income household, or due to other reasons such as consumers' innate preference for variety or increased opportunity cost of time for higher income households. Our results suggest that, income increases lead to both higher purchasing power and stronger preferences for variety.

[17]The interquartile range (IQR) is a measure of variability, based on dividing a data set into quartiles. Specifically, the interquartile is calculated by using the third quartile value minus the second quartile value. In this paper, the second and third quartile avlues are 0.6033 and 0.6598 respectively. Then the IQR is 0.0565.

[18]According to Hisnanick and Giefer (2011), the bottom quintile of household income in the U.S. in 2004 is \$22,367, the middle quintile is \$40,016-\$60,895. By considering the income scales in the Homescan dataset, we choose the lowest annual income group to be less than \$20,000 and the highest income group to be \$60,000 or more.

4.5.2.3 Household Size and Preference for Variety

We also check how household size affects the revealed preference for variety at different levels. We divide our sample into five groups based on the number of persons in each household. The first four groups are for the households with number of people from 1 to 4 separately. The last group is for households with at least 5 members. We then plot the kernel density of $\hat{\beta}_j$ group by group, with the results reported in figure 4.4. In this figure, the distributions of $\hat{\beta}_j$ for larger households locate to the right-hand side of that for smaller households, showing that consumers' preference for variety increases consistently with the number of people in a household. This result is intuitive: larger households prefer a more varied set of cereal products because each member may have specific preference. Also, we find that the plotted density of $\hat{\beta}_j$ for small household is more concentrated relative to that for large households, indicating a relatively larger dispersion of preference for variety for larger households.[19]

Related to household size, we also compare the distribution of $\hat{\beta}_j$ for households with and without children. The results are shown in figure 4.5. The kernel density plot for households with children locates to the right-hand side of that for households without children, suggesting that other things being equal households with children would be more likely to purchase more varied set of cereals. Given that this result holds along with the household size result described above, the explanation for this result may be more about children's preference than increased household size.

4.5.2.4 Products and Preference for Variety

Besides the impacts from household characteristics, a product itself could also contribute to the variation of consumers preference. In this subsection we examine consumers' heterogeneous preference for variety over different products. As we see in equation (4.4), consumers tend to have a stronger preference for variety—as captured by a larger $\hat{\beta}_j$—to those goods that are more "unique" compared to other products. A cereal product that is much different from other options due to its inherent characteristics is more attractive to consumers if they prefer more variety for their purchasing set. Figure 4.6 displays the comparisons of consumers preference for variety according to each cereal brand. The horizontal axis of this figure is the brand ID[20] and vertical axis is $\hat{\beta}_j$ for each product. The lowest point of each bar represents the estimated value of $\hat{\beta}_j$ for the lowest 10% of our sample for

[19] To confirm our finding from figure 4.4, we calculate the standard deviation of β_j for each size group. It shows that the standard deviation for household with one or two members is about 0.0348, while it jumps to 0.0381 if a household has three members. It reaches 0.0389 when household have at least five members.

[20] Due to the data-use agreement, we are not able to disclose brand names and company names. As a result, each brand is given a brand ID from 1 to 20 in our research.

each brand, and the highest point is for the highest 90% accordingly. The number on top of each bar is the mean value of $\hat{\beta}_j$ for that cereal product. Our results show that the average value of consumers' preference for variety is significantly higher for some cereal product, for example the third, sixth, and thirteenth brand (0.6394, 0.6369, 0.6398). In other words, consumers who purchase brand three, six, and thirteen are able to derive higher utility due to stronger preference for variety for these products. On the other hand, consumers' preference for variety show little differences among the rest.

4.6 Counterfactual Analysis: Removing the Preference for Variety

We conduct a counterfactual experiment by explicitly removing consumer preference for variety in their utility function, i.e. by setting $\beta_j = 0$ in equation (4.3). As a result, the modified utility function only reflects consumer demand for basic preference of product characteristics. The difference between the demand predicted in the counterfactual and that predicted in the full model (in the data) reflects the total effect of preference for variety on consumer demand.[21]

After setting β_j to zero, the optimal choice of a consumer with income Y_h is defined by the (logarithm) utility optimization problem below

$$\max_{q^h=(q_1^h,q_2^h,\ldots,q_J^h)\geq 0} \underbrace{\sum_{k=1}^{K} \alpha_k \ln(\sum_{j=1}^{J} q_j^h c_j^k)}_{\ln U_{C^h}} + \underbrace{\ln\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)}_{O^h}. \tag{4.17}$$

Each consumer's optimal choice is then characterized by the following system of first order conditions

$$\frac{\partial \ln U^h}{\partial q_j^h} = \sum_{k=1}^{K} \alpha_k \frac{c_j^k}{\sum_{j=1}^{J} q_j^h c_j^k} - \frac{p_j}{\left(Y^h - \sum_{j=1}^{J} p_j q_j^h\right)} \leq 0, \quad for\ j = 1, \ldots, J. \tag{4.18}$$

Given income, product characteristics and price, this system determines consumer's optimal demand for all the 20 products. Similar in equation (4.5), this equation holds with equality if the consumer chooses a positive amount of product j, and it holds with inequality if she chooses zero amount for product j. The only

[21] In reality, if there were no preference for variety in consumer utility, the equilibrium price would have been changed (usually lower) in the counterfactual analysis. Here without modeling firms' pricing strategy, for simplicity we assume that the price in the counterfactual remains unchanged. So we should think about our counterfactual results as the upper bound of the effect of preference for variety on the market size. Although there is such a limitation, we believe this counterfactual size does show the importance of preference for variety on consumer demand.

difference between Eq. (4.18) and (4.5) is that there is no preference for variety in (4.18).

4.6.1 Effect on Market Size

We solve for the optimal demand $q_j^h \geq 0$ for each consumer exactly from the system defined in equation (4.17), using constrained optimization in Matlab. Then we compute the total sales of all the 20 products for all households for the counterfactual. The results are reported in table 4.7, which show that setting β_j to zero causes total sales to drop from 9.3859×10^5 to 6.9474×10^5 US dollars. If retailing prices are unchanged, removing the inborn preference for variety in consumer utility function would therefore reduce the total market size of the twenty cereal products by about 26%.

4.6.2 Heterogeneous Effect on Different Products

Table 4.8 further investigates the product-by-product heterogeneous effect of preference by setting $\beta_j = 0$ for all products. The effects on each cereal product are quite different: sales for some products decrease but increase for others. If we compare the change of product-level sales in the counterfactual with the previous results, we find that the market size of product with higher $\hat{\beta}_j$ tends to decrease more. For example, the three products with the highest $\hat{\beta}_j$s, namely product 3, 6 and 13, have the largest drop in sales after removing preference for variety. The reason is that they lose more variety-based advantage compared with other products after removing consumers' preference for variety, thus they lose more market. In contrast, those products with low values of $\hat{\beta}_j$ tend to win more market when there is no preference for variety in the consumers' utility function. The change of market share for each cereal product as presented in the last two columns in general shows a similar pattern. However the pattern is not quite so clear cut because the heterogeneous reaction from removing consumers' preference for variety represents a combined effect of adjustment of demand due to direct preference of product characteristics and preference for variety.

4.7 Conclusions

In this paper, we investigate the role of preference for variety in shaping consumer demand in the ready-to-eat breakfast cereal market. We develop a model to characterize consumer purchasing behavior, which is determined by both their direct preference for product attributes and their satisfaction from enjoying varied cereal products. We explicitly measure the product dissimilarity using the relative distance in characteristic space between products and use it to examine how this product dissimilarity induces consumers to purchase a variety of cereal products when facing multiple choices. Moreover, we also investigate the link between household socio-demographics and their heterogeneous preference on evaluating the product variety in the model.

The empirical results from Nielsen purchase record show that consumers do have preference for variety. On average, consumers prefer to choose cereals that are different in nutrient content on fiber, sugar, fat and sodium. They also prefer to put in their purchase basket cereals that are both made and not made from whole grain simultaneously. We also find that consumers of diverse socio-demographics show heterogeneous preference for variety. On average, households who have higher income, is larger, or have at least a child at home, prefer (or be likely) to choose a set of cereals of more variety. Having a female household head also contributes to a positive evaluation on product diversity and this impact is even stronger if the female head has higher education attainment.

Finally, we conduct a counterfactual analysis to quantify the money-valued impact of consumers' preference for variety. We find that, the market size reflected by the total sale revenue will be reduced substantially by about 26% if we assume that consumers have no preference for variety. The effect is heterogeneous across different products. In general, those products whose attributes are very different from others lose more market share, and those products whose attributes are close to other products in the market gains some market share after removing consumer preference for variety.

Tables and Figures

Table 4.1. Average number of units per brand by household size and brands group

No. of brands per quarter	Ave units per brand by household size[1] 1	2	3	4	Market share [2]	Shop. trips [3]
1	2.12	2.23	1.99	1.92	9.18%	30614
2	1.86	2.04	1.90	1.87	12.81%	23853
3	1.79	1.93	1.83	1.79	13.23%	17517
4	1.71	1.89	1.83	1.80	12.11%	12403
5	1.75	1.84	1.78	1.79	10.28%	8659
6	1.69	1.77	1.78	1.71	8.35%	6113
7	1.69	1.79	1.71	1.73	6.88%	4408
8	1.68	1.76	1.74	1.73	5.60%	3133
9	1.58	1.68	1.72	1.73	4.45%	2274
10	1.61	1.67	1.75	1.76	3.59%	1623

[1] Households with size between 1 and 4 represent 91.82% of the whole households who purchase national brands. Statistics for larger households are provided as request.

[2] Market share is calculated by using total expenditure in each brand group divided by the total expenditure of all national brands.

[3] Shopping trips in this table are defined by household-quarter observations.

Table 4.2. Distribution of expenditure share by number of units and brands purchased

Total units purchased [1]	Distribution of expenditure share by number of brands purchased[2]										
	1	2	3	4	5	6	7	8	9	10	11+[3]
1	1.000										
2	0.370	**0.630**									
3	0.175	**0.413**	**0.413**								
4	0.133	0.268	**0.352**	0.247							
5	0.082	0.193	**0.287**	0.285	0.153						
6	0.081	0.148	0.235	**0.249**	0.198	0.088					
7	0.056	0.121	0.176	**0.222**	0.202	0.155	0.067				
8	0.063	0.113	0.152	0.176	**0.197**	0.158	0.102	0.039			
9	0.048	0.080	0.129	0.160	**0.177**	0.173	0.130	0.074	0.029		
10	0.043	0.069	0.117	0.142	0.159	**0.163**	0.142	0.101	0.050	0.015	
11	0.033	0.070	0.100	0.134	**0.153**	0.149	0.130	0.108	0.083	0.032	0.009
12	0.036	0.065	0.099	0.115	0.127	0.137	**0.140**	0.110	0.084	0.054	0.033
13	0.025	0.064	0.069	0.109	0.127	**0.138**	0.128	0.121	0.090	0.069	0.053
14	0.032	0.048	0.083	0.101	0.108	0.118	0.121	**0.125**	0.094	0.077	0.092
15	0.024	0.051	0.057	0.087	0.101	0.113	**0.120**	0.111	0.107	0.082	0.146
16	0.022	0.044	0.065	0.084	0.101	0.098	0.120	**0.124**	0.109	0.081	0.153
17	0.021	0.029	0.052	0.075	0.093	0.103	0.118	**0.120**	0.100	0.102	0.188
18	0.023	0.047	0.055	0.066	0.095	0.090	0.088	0.097	0.106	**0.107**	0.225
19	0.012	0.052	0.049	0.081	0.077	0.068	0.099	**0.107**	0.084	0.092	0.278
20	0.020	0.047	0.068	0.057	0.054	0.078	0.080	0.082	0.088	**0.115**	0.312
21+[3]	0.012	0.024	0.030	0.041	0.049	0.047	0.053	0.062	0.066	0.069	0.547

[1] The total units is the total number of quantity purchased by each household in each quarter.

[2] Expenditure share is calculated by using the total expenditure for each group.

[3] For purchase of equal to or over 11 brands or 21 units in a quarter are not reported in detail.

Table 4.3. Summary statistics of demographics

Variable	Description	Mean	Std.
Continuous			
HHSIZE	Number of individuals in the household	2.66	1.37
HHINC	Household annual income	19.23	5.73
Discrete		Frequency of one	
CHILD	Household has children with age below		0.32
FHIGHSC	Highest edu. attainment for female head: high school		0.28
FSOMCOL	Highest edu. attainment for female head: some college		0.30
FCOLMOR	Highest edu. attainment for female head: college or more		0.32
AGE65	Age of household head is equal to or larger than 65		0.27
HEADF	Household head is female		0.93

[1] All means are simple average. Std. refers to standard deviation.

Table 4.4. Summary statistics of product characteristics and average distance measure

Variable	Description	Mean	Std.
Product Attributes			
Continuous			
FIBER	Total dietary fiber (g/100 g)	5.46	3.81
SUGAR	Total sugars (g/100 g)	27.35	13.30
FAT	Total lipid (fat)(g/100 g)	2.92	2.39
SODIUM	Sodium/100 (mg/100g)	6.08	1.97
CALORIE	Food energy/100 (kcal/100 g)	3.71	0.25
NVF	Number of vitamin fortified	2.85	1.88
MAKER	Manufacturer for the RTE breakfast cereal	2.05	0.80
Discrete		Frequency of one	
WG	Product has whole grain as first ingredient		0.35
KIDS	Target to children		0.50
Average Distance			
DS WG	Distance measure for whole-grain first ingredient	0.49	0.42
DS MAKER	Distance measure for cereal manufacturer	0.31	0.39
DS MULTI [2]	Multi-dimensional distance measure	0.04	0.02

[1] All means are simple average. Std. refers to standard deviation.

[2] Multi-dimensional distance measure is constructed by using four product attributes: fiber, sugar, fat, sodium.

Table 4.5. Summary statistics of purchase information and attribute share

Variable	Description	Mean	Std.
Purchase			
P	Quarterly average purchase price/household ($)	0.160	0.04
Q	Quarterly total quantity/household (oz)	2.826	11.32
Y	Quarterly total expenditure of all dry goods/household	363.3	198.79
SE	Adjusted total expenditure per product/household ($)	0.002	0.0047
Share of Product Attributes			
SH WG	Contribution of whole-grain type	0.394	0.90
SH KIDS	Contribution of kids cereal	0.468	0.90
SH NVF	Contribution of total vitamin fortification	0.374	1.01
SH FIBER	Contribution of fiber content	0.101	0.28
SH SUGAR	Contribution of sugar content	0.096	0.21
SH FAT	Contribution of fat content	0.092	0.23
SH SODIUM	Contribution of sodium content	0.172	0.93
SH CALORIE	Contribution of calorie content	0.074	0.17

[1] All means are simple average. Std. refers to standard deviation.

Figure 4.1. Paired product distance and simultaneous-purchasing frequency

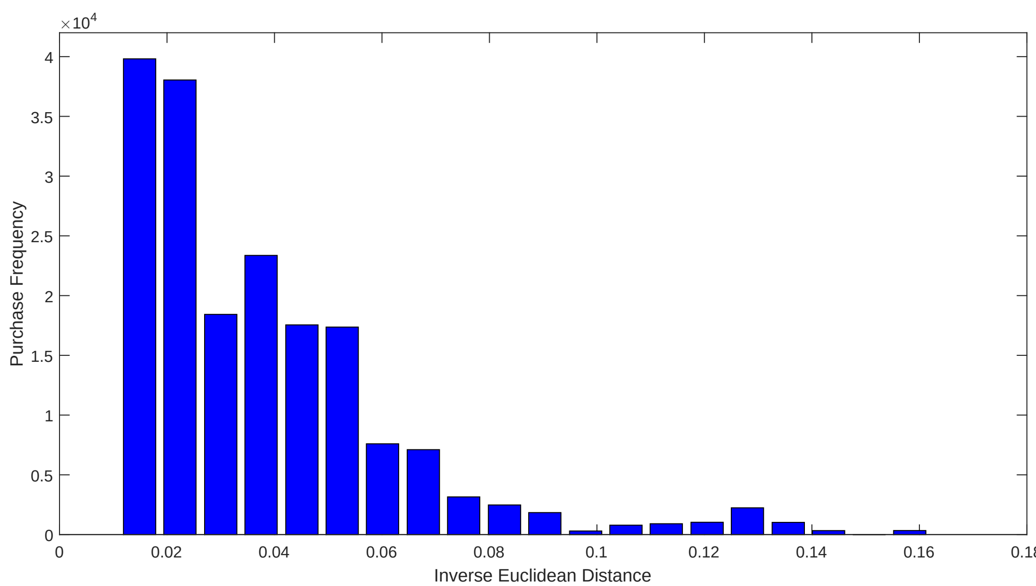


Table 4.6. Parameter estimates of consumer preference

Variables		Coeff.	Z stat.	Coeff,	Z stat.	Coeff.	Z stat.
Panel A: Direct Preference of Product Attributes (α_k)							
SH WG		0.0179	26.21				
SH NVF		0.0093	10.95				
SH KIDS		0.0074	14.84				
SH FIBER		0.0104	23.70				
SH SUGAR		-0.0301	-22.27				
SH FAT		0.0281	21.22				
SH SODIUM		0.0032	11.65				
SH COLORIE		0.0167	3.33				
Panel B: Preference for Variety (β_j)							
β_0	CONSTANT	0.5007	1143.19				
β_{DS}	DS MULTI	-0.0650	-135.45				
	DS WG	-0.0122	-24.35				
	DS MAKER	0.0103	20.42				
β_{DEMO}	HHINC	0.0063	14.56				
	HHSIZE	0.0030	6.83				
	CHILD	0.0031	5.67				
	FHIGHSC	0.0051	11.21				
	FSOMCOL	0.0065	15.32				
	FCOLMOR	0.0091	18.76				
	AGE65	0.0101	21.11				
	FHEAD	0.0120	27.41				
$\beta_{DEMO*DS}$ (*Interactions*)		DS MULTI		DS WG		DS MAKER	
	HHINC	-0.0018	-3.82	-0.0008	-1.66	-0.0002	-0.40
	HHSIZE	-0.0009	-2.00	-0.0005	-1.11	0.0030	6.02
	CHILD	0.0153	27.57	-0.0258	-45.89	0.0144	22.73
	FHIGHSC	-0.0005	-1.05	-0.0012	-2.34	-0.0005	-0.99
	FSOMCOL	-0.0010	-2.13	-0.0016	-3.01	-0.0009	-1.66
	FCOLMOR	-0.0016	-3.21	-0.0027	-4.53	-0.0012	-2.34
	AGE65	-0.0019	-3.27	-0.0044	-6.92	-0.0011	-1.89
	HEADF	-0.0030	-6.32	-0.0031	-6.25	-0.0020	-3.98

[1] Reported parameters are the estimates using the normalized value of each variables in our demand model.

Table 4.7. Counterfactual: effect of preference for variety on market size

Total sales: no PFV	Total sales: data	Effect of PFV
6.9474e+05 (USD)	9.3859e+05 (USD)	25.98%

[1] The effect of PFV is calculated as the percentage change of total sales when PFV is removed.

Table 4.8. Counterfactual: effect of preference for variety by products

Products	Total sales (10^5 USD)		Effect of PFV (10^5 USD)	Market share	
	counterfactual	data		counterfactual	data
1	0.1150	0.1753	-0.0603	0.0166	0.0187
2	0.5399	0.8658	-0.3259	0.0777	0.0920
3	0.5967	1.2577	-0.6609	0.0859	0.1340
4	0.2674	0.5417	-0.2743	0.0385	0.0577
5	0.3504	0.2099	0.1405	0.0504	0.0224
6	0.4950	0.9316	-0.4366	0.0712	0.0993
7	0.4064	0.2845	0.1219	0.0585	0.0303
8	0.3132	0.1961	0.1171	0.0451	0.0209
9	0.3602	0.2791	0.0811	0.0518	0.0297
10	0.3080	0.2372	0.0708	0.0443	0.0253
11	0.4058	0.3401	0.0657	0.0584	0.0362
12	0.4414	0.7273	-0.2859	0.0635	0.0775
13	0.3567	0.8085	-0.4518	0.0513	0.0861
14	0.2239	0.4429	-0.2190	0.0322	0.0472
15	0.4377	0.4317	0.0059	0.0630	0.0460
16	0.4458	0.3793	0.0665	0.0642	0.0404
17	0.4410	0.4402	0.0008	0.0635	0.0469
18	0.1363	0.2896	-0.1533	0.0196	0.0309
19	0.1792	0.3169	-0.1377	0.0258	0.0338
20	0.1275	0.2306	-0.1031	0.0184	0.0246

[1] The effect of PFV is calculated as the percentage change of total sales when PFV is removed.

Figure 4.2. Probability density of estimated $\hat{\beta}_j$

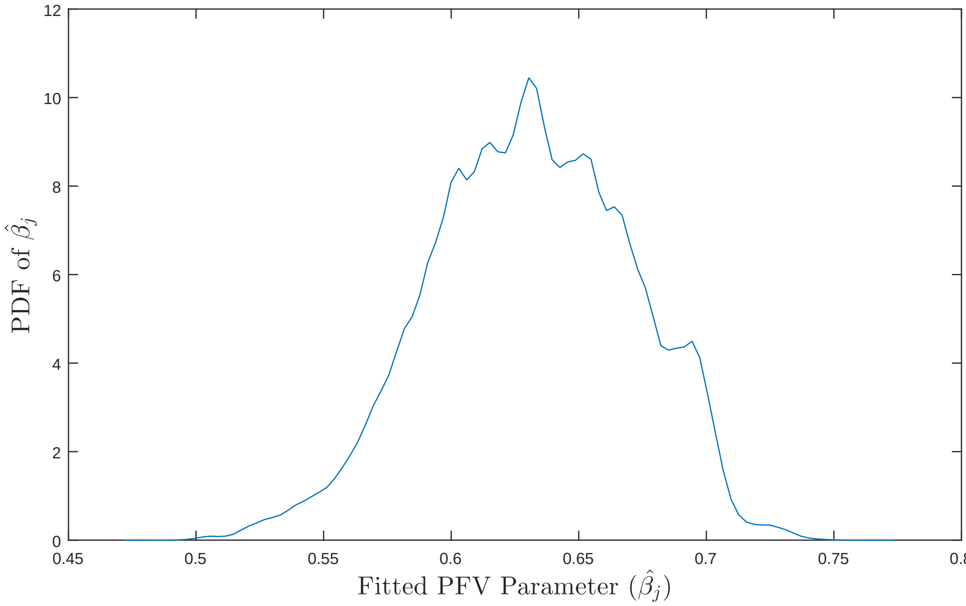
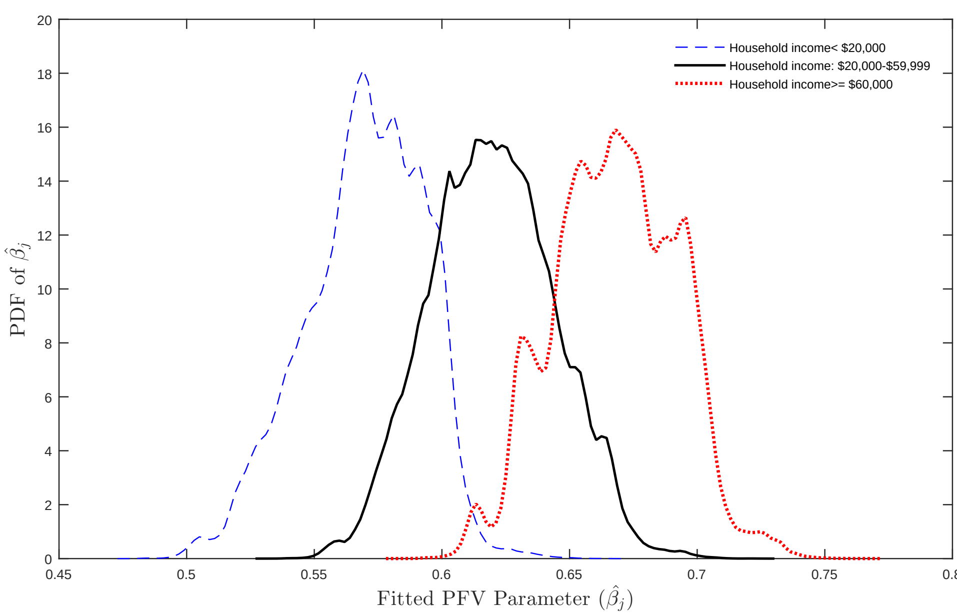
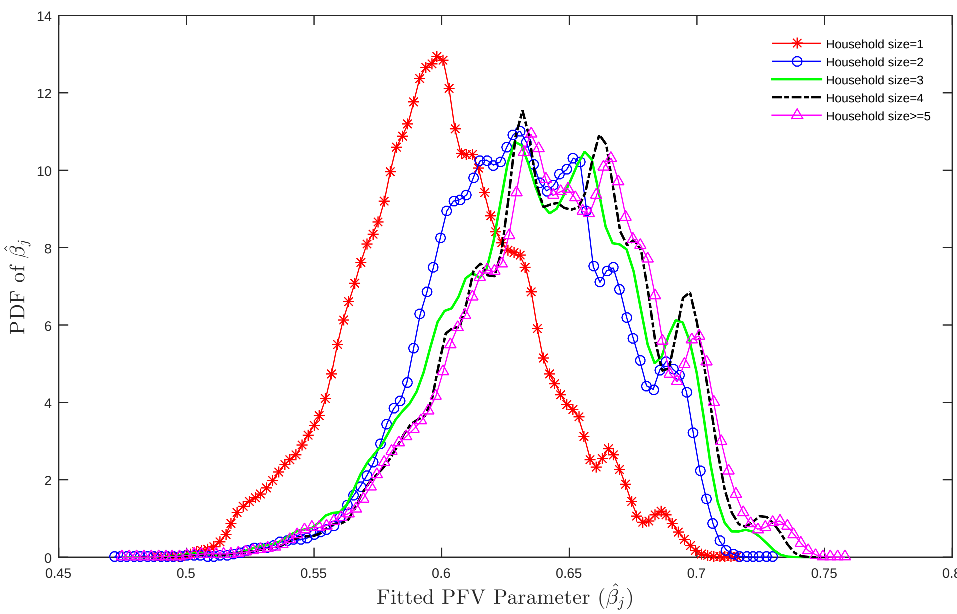


Figure 4.3. Estimated $\hat{\beta}_j$ by household income level



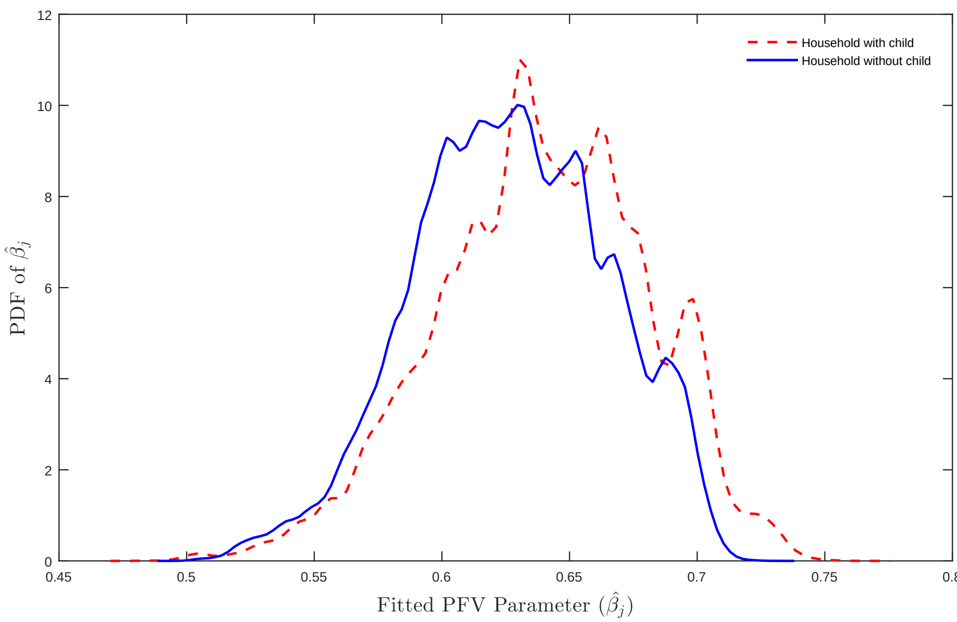
[1] The average value of $\hat{\beta}_j$ for each group from the lowest to the highest income level is: 0.5700, 0.6198, 0.6679.

Figure 4.4. Estimated $\hat{\beta}_j$ by household size



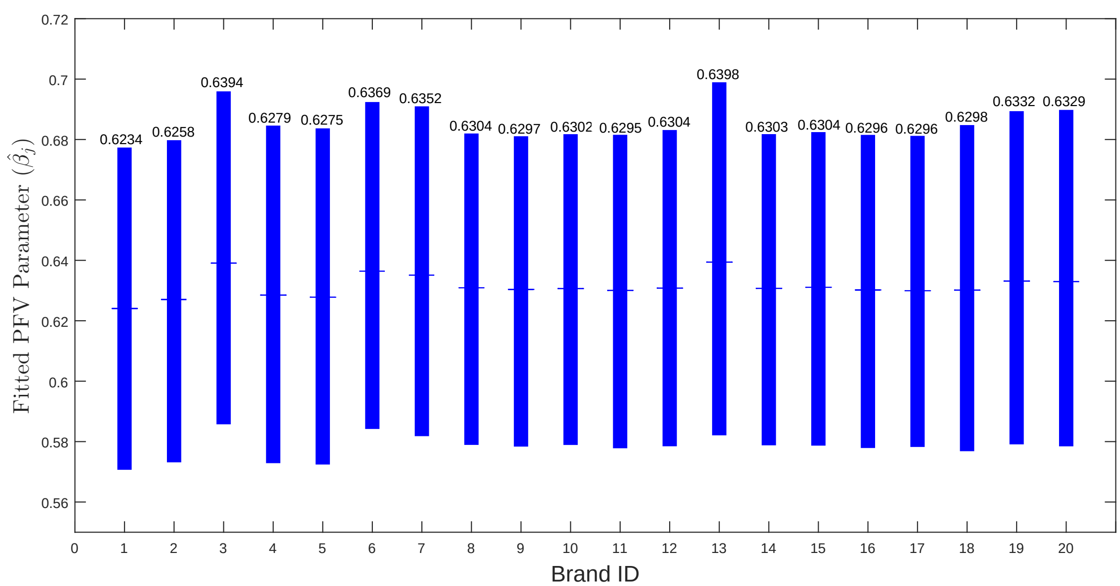
[1] The average value of $\hat{\beta}_j$ for each group from the smallest to the largest size group is: 0.6007, 0.6328, 0.6389, 0.6445, 0.6453.

Figure 4.5. Estimated $\hat{\beta}_j$ by household with/without child



[1] The average value of $\hat{\beta}_j$ for household with child is 0.6271, while it is 0.5700 for household without child.

Figure 4.6. Percentile of $\hat{\beta}_j$ for consumers' preference for variety over brands



Chapter 5

Conclusions and Implications

This dissertation investigate the relationship between health-related product characteristics and consumers purchasing behaviors in the ready-to-eat breakfast cereal market. Three specific topics are studied to understand this relationship. In chapter two, we examine how the health-related product characteristics, such as sugar, fiber, and whole grain, affect consumers' purchasing decision. We use an alternative demand estimation approach that relies on Pinkse, Slade, and Brett (2002)'s distance metric method, which is significantly simplified and practical in estimating censored demand model. In chapter three, we use demand results from chapter two and further evaluate the welfare change for both consumer and producer due to the reformulation of cereal products. Finally, in chapter four, we propose a different model that explicitly measures the impact of the preference for variety using a measurement that includes health-related product characteristics. Although each chapter explores independent topics, the findings in each part are closely related and complement to each other which contribute to a better understanding of the whole process of purchasing breakfast cereals.

Health and Demand

Consumers' preferences for health-related attributes in breakfast cereal products are consistently found in all three essays. In essay one, we find that consumers become less price sensitive to price changes if a cereal product is made using whole grain as primary ingredient. In essay two, this result confirmed by consumers' welfare gains from a hypothetical experiment that either one of the top two cereal manufacturers converts all their products into whole grain. Again, the third essay finds a similar result that cereal products made of whole grain will contribute to a higher utility for consumers. Fiber, another important healthy attribute, is also found to positively affect consumers' purchase decisions. In essay three, we find that consumers would gain a positive utility if a cereal product contains more fiber. This result complements of results in essay one, where we find that consumers who favor cereals rich in fiber would be very likely to switch to another cereal product that is high in fiber content, given a price changes. Although we find that consumers would experience welfare loss given all cereal manufacturers increase fiber content in the experimental analysis, this loss is found to be mostly caused by the increase of price. Finally, both essay one and essay three find a similar result that consumers are in favor of cereal products with more vitamins fortified.

Although consumers show strong preferences for healthy attributes like fiber and whole grain, their purchase choices are also affected by another important factor, taste, which sometimes appears to distract consumers from choosing the most healthy products. We find that consumers still show strong preference to the sweet cereals. They would even switch away if that product is reformulated with less sugar. Similar results are found for the fat content, which is another important nutrient that affects the taste of cereals. These findings show important implications to both manufacturers and health policy makers that consumers require a good balance between healthy diet and better taste even though they acknowledge that eating in a healthy way is very important to their life. Besides that, our results show that there still some consumers show stronger concern of healthy eating when they choose the cereal products. Our essay two result shows that those consumers who continue to buy the cereal products reformulated with less sugar and fat, actually experience significant welfare gains.

In addition, from this research, government agencies and health policy makers could get more information about the relationship between the health-related product attributes and consumers purchasing behaviors in the cereal market. For the purpose of improving healthy diet for people in the United States, policy makers should continue to support the nutrition claim for whole grain in the label regulation in cereal market. In addition, they should provide more education programs and food guide to consumers to emphasize the potential health risk of consuming more sugar and fat. On the other hand, polices affecting manufacturers production cost would also be considered as another effort to improve consumers diet quality. Mandatory or instructive regulations, price support program or other supporting programs could be used to encourage manufacturers to reformulate cereal products with more fiber, less sugar and fat would lead to more healthy cereals supplied to the consumers in this market.

Health and Variety

Essay three shows that, in addition to price and taste for specific product attributes, variety seeking is an equally important consumer force. Consumers who purchasing a more diversified combination of cereal products would gain extra benefit.

Specifically, our essay three result shows that consumers in general would like to choose a set of cereals that are far apart in the product attribute space represented by fiber, sugar, fat, and sodium. Although we have already shown that consumers have direct preference on the health-related product attribute, their choices are not just limited to the healthiest cereals in the market. Instead, most of the consumers' purchase set is composed by a set of cereals that vary in these four key nutrients. Although we could understand this multiple-choice decision is caused by the different preferences from each family member, our result continues to hold for single-member households, which confirms that consumers in the cereal market do have a preference for variety. From another point of view, these results could imply a fact that consumers show a preference for diversified taste in addition to caring about healthy eating. In general, sugar, fat, and sodium are mostly the three basic elements that affect the flavor of a cereal product, and fiber, on the other hand, also contributes to the taste based on its content level.

Again, the joint force from healthy eating and better taste also determines consumers' decisions of purchasing cereals with/without whole grain. Although we find that consumers prefer cereals that are made using whole grain as the primary ingredient, they also show their preference of variety by purchasing both whole-grain cereal and non whole-grain cereal all together. Consumers' choice of variety in whole grain demonstrates a balancing of healthy diet and good taste.

As a result, understanding these purchase behaviors would help cereal manufacturers successfully differentiate their products to compete for more consumers in this market. Cereal manufacturers could also learn from this part of research to strategically reduce probability of substitution among their own products. For example, to successfully introduce a new product, cereal manufacturer should consider to introduce a product with one or more healthy nutrients improved that are significantly different with their existing products. Besides that, our finding could also better serve food retailers in product placement or promotions. Retailers should consider to place their cereal products that are are more different to each other either in nutrients or flavor could lead to a increase the total sale of this product. Similarly, retailers should avoid promoting similar cereal products at the same time.

Targeting Consumers

Due to the availability of detailed demographic information from the comprehensive dataset used in this research, we are able to explore consumers' heterogeneous preferences by including a list of social-demographic factors in our estimation. Understanding the purchasing behaviors for each group of consumers classified by their social-demographic factors could provide better insight about the whole market and help firms improve their targeting of customers.

Our results from the three essays show that larger families would purchase more cereals in general and their choices are more diversified compared to small-size households. Although household income is not found to have impact of choosing more cereals since the unit price of cereals is so small relative to the total income of each household, it has positive and significant impact on choosing more variety.

Education is another important factor that affects consumers' cereal purchase decisions. Our results show that although education attainment in general has no impact on the quantity for each cereal, the education level of female household head shows a positive and significant impact on the level of variety for each purchase set. Specifically, the higher education attainment the female household head get, the more variety the household would prefer. As a result, cereal manufacturers and retailer might consider providing more bundles of diversified cereals in the market that have larger and wealthier families, or more families have better educated female household heads.

In addition, our results show that age is also an important demographic factor that affects consumers' choices of breakfast cereals. Manufacturers and retailers should pay more attention to markets with a higher percentage of households with high-age household heads since these type of households might prefer more options for breakfast given their household heads might have more time to cook at home. However, firms should target households which have household head with age more than 65. The possible reason is this type of households might have fewer shopping frequency due to convenience of transportation and they would be more likely to stock different cereal products whenever they decide to eat it as breakfast. Finally, households with kids also show strong interest of diversified cereal set which is another marketing information that manufacturers/ retailers should create bundles with different cereals, for example a package containing both kids cereal and adult cereal, might help to boost their total market sales or benefit.

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Working Papers

"How Important is Preference for Variety in Consumer Demand: Evidence from Ready-to-Eat Cereal Market", with Edward C. Jaenicke, 2016.
"Demand for Ready-to-Eat Cereals with Household-level Censored Purchase Data and Nutrition Label Information: A Distance Metric Approach", with Edward C. Jaenicke, Tobenna D. Anekwe, and Alessandro Bonanno, 2016.
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