Zwick Center for Food and Resource Policy

Working Papers Series

No. 11

The Use of Voluntary Marketing Initiatives to Improve the Nutritional Profile of Kids Cereals*

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May, 2012

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This project was supported by Agriculture and Food Research Initiative Competitive Grant no. 2010-65400-20440 from the USDA National Institute of Food and Agriculture. Thanks to Bryan Bollinger, Masakazu Ishihara, Gary Lillien, Christian Rojas, and Vishal Singh for discussions which lead to improvements in this paper. The paper has also benefit from questions and comments by Seminar Participants at New York University, University of Connecticut, University of Massachusetts, Fordham University, and the 10th International Industrial Organization Conference. We are also thankful for the Zwick Resource and Food Policy Center (formerly the Food and Marketing Policy Center) at the University of Connecticut for providing the data and computing resources. Authors appear in alphabetical order and accept responsibility for any mistakes in the paper.

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ABSTRACT

This article develops a framework to analyze voluntary marketing initiatives aimed at reducing children's exposure to high-calorie packaged foods. Our empirical investigation focuses on children's ready-to-eat cereal; we begin by estimating a limited awareness differentiated product demand model using a panel of consumer purchase and television advertising data. We use the demand estimates in a dynamic model of pricing and advertising competition in which firms have the option of participating in an initiative that defines nutritional standards for products targeted toward children. Participation requires that firms either comply with nutritional standards by reformulating their product or stop advertising. Results from our analysis indicate that leading firms should choose participation and reformulation as the strictly dominant strategy as long as prospective product reformulation costs do not exceed the marginal profitability of reformulation.

1 Introduction

Caloric imbalance caused by a sedentary lifestyle and the excessive intake of food high in calories, sugar, and saturated fat is a direct cause of widespread childhood obesity, which has significant immediate[1] and long-term[2] health effects (Centers for Disease Control and Prevention [CDC], 2012). Cutler, Glaeser, and Shapiro (2003) find that increased caloric intake rather than reduced caloric expenditure explains the rise in American obesity since the 1970s. According to CDC, the prevalence of obesity in children has increased three fold in as many decades, from 5% to 18% for kids age 6-11 and from 7% to 20% for kids age 12-19.

In 2006, the Council of Better Business Bureaus (BBB) launched the Children's Food and Beverage Advertising Initiative (CFBAI), a self-regulatory program designed to shift the mix of food and beverage products advertised to children to encourage healthy dietary choices. CFBAI's participants include many of the largest food and beverage companies, such as McDonald's, Burger King, Coca-cola, PepsiCo, Kraft, and ConAgra. Until recently, CFBAI firms set their own nutrition criteria. In July 2011, CFBAI released uniform nutrition criteria for foods advertised to children. The new agreement requires partner firms to meet these criteria by the end of 2013. A second initiative, intended to limit child exposure to unhealthy foods, was developed by an interagency working group (IWG) under the 2009 Omnibus Appropriations Act. The IWG recommends the voluntary adoption of nutrition principles for foods advertised to children by 2016. The IWG guidelines impose nutrition criteria viewed as overly strict by the food and beverage industry, and the guidelines have sparked heated debate.

Complying with either initiative means firms must decide on participation in the voluntary marketing initiative, which implies reformulating their products to well-defined nutritional standards and suspending advertising directed toward children for products deemed unhealthful. We develop a market-based framework to guide the decision making of marketers and inform policy making. Our approach is to formulate and estimate a model of strategic participation in voluntary programs, product reformulation, pricing,

[1] Immediate health effects of obesity: 1) Obese youth are more likely to have risk factors for cardiovascular disease, such as high cholesterol or high blood pressure. In a population-based sample of 5- to 17-year-olds, 70% of obese youth had at least one risk factor for cardiovascular disease; 2) Obese adolescents are more likely to have prediabetes, a condition in which blood glucose levels indicate a high risk for development of diabetes; 3) Children and adolescents who are obese are at greater risk for bone and joint problems, sleep apnea, and social and psychological problems, such as stigmatization and poor self-esteem.

[2] Long-term health effects of obesity: 1) Children and adolescents who are obese are likely to be obese as adults and are therefore more at risk for adult health problems, such as heart disease, type 2 diabetes, stroke, several types of cancer, and osteoarthritis; 2) One study showed that children who became obese as early as age 2 were more likely to be obese as adults; 3) Obesity is associated with increased risk for many types of cancer, including cancer of the breast, colon, endometrium, esophagus, kidney, pancreas, gall bladder, thyroid, ovary, cervix, and prostate, as well as multiple myeloma and Hodgkin's lymphoma

and advertising for a portfolio of products that comply with a set of well-defined nutrition and promotion standards.

We offer an empirical market model to determine profitable pricing, advertising, product reformulation, and participation in a marketing initiative that establishes uniform nutrition and promotion standards. Our model will be used to forecast consumer choices and firm profits in the long term. The core contribution of this research is that it provides a framework for marketing mix planning and informs policy makers about the impact of the CFBAI and IWG proposals on both consumers and industry.

Our starting point is an aggregate logit demand model with a heterogeneous consumer preference specification (Berry, Levinsohn, & Pakes, 1995 (henceforth BLP); Nevo, 2001). We build on this model by incorporating a theory of consumer product awareness in which advertising increases product salience and consequently increases the probability of product purchase. Instead of assuming all consumers are equally aware of and hence choose from the same set consisting of all products available in the marketplace, we explicitly allow for advertising stock to influence this set (Cohen & Rabinowitz, 2011). Goeree (2008) relaxes the full-awareness assumption and allows for awareness set heterogeneity by modeling consumer awareness of a product as a function of exposure to product advertising. We calibrate the model on children's ready to eat (RTE) breakfast cereal scanner and advertising exposure data from eight major U.S. cities between February 2006 and December 2008. The children's cereals are a category of direct concern to policy makers in the debate that surrounds the marketing of food to children (Schwartz, Vartanian, Wharton, & Brownell, 2008).

We use the demand estimates to specify a model of firm profits. Applying a dynamic equilibrium concept, we solve for the equilibrium strategy profits, pricing, advertising, reformulation, and participation. Once a firm decides to participate in a voluntary advertising restriction agreement, it needs to reformulate its "unhealthy" products or stop advertising those products. Regardless of the firm's participation and reformulation decision, it needs to decide on its pricing and advertising strategies for any given participation and reformulation decisions made by its competitors. We solve for Markov perfect equilibria (MPE) backwards, as follows; First, we solve for optimal markups and advertising levels, given the participation and reformulation decisions of each strategic player, then we calculate each firms' expected payoff under each scenario. The participation and reformulation game is played simultaneously among the leading firms. In equilibrium, the firms choose the participation and reformulation strategies affording the highest payoff, given the participation and reformulation decisions of its competitors.

Our principle empirical finding from the children's RTE breakfast cereal category is the existence of a dominant compliance strategy. Specifically, the two largest firms in the industry choose to voluntarily participate by reformulating their products, as long as the prospective fixed costs of product reformulation do not exceed the marginal profitability of reformulation. This result is driven by two key empirical results: First, kid cereal buyers prefer less sugar, saturated fat, and sodium; second, kid cereal advertising is very effective at capturing buyer attention. The first result is supported by a line of empirical research on breakfast cereal demand that finds that some buyers in the United States have historically preferred less sugar in their cereals (Nevo, 2001; Hitsch, 2006), and research based on more recent market data that indicates the majority of U.S. cereal buyers have evolved to prefer less sugar in their cereal (Chidmi & Lopez, 2007; Chen & Jin, 2012; Cohen & Rabinowitz, 2012).[3] This result is also consistent with the observed general consumer trends pointing to healthier cereals (e.g, Toth, 2011). We provide statistical robustness checks to further support the result. It is also worth noting that Kellogg's and General Mills made substantial investments to improve the nutrition profiles of their kids products without altering the product experience.[4] Demonstrating that sugar is not equivalent to taste is an important fact to consider when asserting that product reformulation in observed attributes does not interact with unobserved product attributes. The disutility of sugar in kids cereal is also structurally consistent with this observed R&D strategy, one that aims to improve the product in a way that satisfies consumer needs and wants.

Why, then, is a marketing initiative necessary? The marketing initiative establishes a set of transparent uniform standards and serves as a clearing house through which policy makers passively monitor the quality of food marketed to children; consumers ensure the health quality of processed foods; and firms disseminate product nutrition information. The marketing initiative membership provides an informative signal to policy makers, consumers, and competitors that products marketed by member firms are healthy. For example, the CFBAI charter establishes core principles and uniform standards that participating firms comply with to present themselves as marketers of better-for-you products for kids.

Additional results indicate that advertising levels and strategies based on optimizing the mix of price and advertising are not observed. This finding suggests that firms poorly allocate their advertising budget in the kids cereal category. Hence, the initiative and the principal findings potentially serve as catalysts for firms to improve their advertising strategies.

[3] Nevo (2001) and Hitsch (2006) analyze data from 1988-1992, Chidmi and Lopez (2007) analyze data from 1996-2000, Chen and Jin (2012) analyze data from 1997-2003, and Cohen and Rabinowitz (2012) analyze data from 2006-2008.

[4] From overall taste to fine details such as the length of time the marshmallows float in milk (Jargon, 2011).

We continue the introduction with a discussion of some related literature. The rest of the article is organized as follows: We present the children's RTE cereal industry, the history of voluntary marketing initiatives, and the data used for the study. Then, we explain our econometric model and discuss identification issues and estimation methods. Finally, we exhibit the estimation and compliance results, and discuss the implications for marketing and policy practitioners.

1.1 Discussion of Related Literature

Our empirical approach distinguishes the current study from a strand of existing research that assesses the effects of advertising restrictions on competition or consumption. Most of this research deals deals with advertising restrictions in the cigarette and alcoholic beverage industry (e.g., Sass & Saurman, 1995; Gallet, 2003). Clark (2007) examines the effect of Quebec's mandatory ban on child-directed advertising on the market structure in the children's cereal market, whereas Dhar and Baylis (2011) investigate the effect of this same ban on fast-food purchases. This research generally uses quasi-experimental designs to evaluate the short- or medium-term effects of implemented advertising restrictions on pricing, concentration, or consumption. Except for Huang and Yang (2011), all these studies examine mandatory advertising restrictions, which are exogenous to firm strategy. Huang and Yang (2011) investigate the effect of a voluntary advertising restriction on consumer's choices under the assumption that the restriction is exogenous to the consumers. In contrast, we endogenize the firms' participation decisions and then study firm strategies and market structure as a result of these decisions.

This article aligns with the demand modeling literature assessing the impact of advertising. Shum (2004) specifies advertising expenditure as a complement to product choice and documents that it encourages households to switch to cereals they haven't purchased recently. Chen and Jin (2012) apply Ackerberg's (2001) argument that consumers in experience-good markets are fully aware of products they've purchased previously to identify informative versus prestige effects of advertising within a demand model. Draganska and Klapper (2011) supplement market-level scanner data with consumer-level survey data to aid identification of informative versus prestige effects of advertising. Dubé, Hitsch, & Manchanda (2005) and Cohen and Rabinowitz (2012) use measures of advertising exposure reach and frequency called Gross Rating Points (GRPs) and specify advertising's cumulative impact. Dubé et al. (2005) investigate equilibrium advertising dynamics in isolation. Cohen and Rabinowitz (2012) demonstrate the importance and ramifications of modeling price competition as well as advertising competition simultaneously in a differentiated product market. The current research advances this strand of literature by incorporating equilibrium participation and product reformulation decisions, which has practical implications for the voluntary marketing initiative participation question.

Our model is built on the premise that consumers have smooth and continuous heterogeneous attention levels, relating it to the literature on choice set formation. There is considerable heterogeneity in choice sets across consumers (e.g., Chiang, Chib, & Narasimhan 1999; Mehta, Rajiv, & Srinivasan 2003) and ignoring this heterogeneity could result in biased demand estimates (Bajari & Benkard, 2005; and Goeree, 2008). The heterogeneity could arise due to physical availability, i.e., different assortments across stores (Bruno & Vilcassim, 2008) or stock-outs (Musalem, Olivares, Bradlow, Terwiesch, & Costen, 2010), or varying levels of product awareness owed to advertising expenditure (Goeree, 2008; Draganska & Klapper, 2011) and exposure (Cohen & Rabinowitz, 2012), or other promotions (Pancras, 2010). Adding to the latter line of research, the primary source of heterogeneity in brand awareness across consumers in our model is product-level advertising exposure.

To the best of our knowledge, this research is the first to empirically investigate firms' decisions on participating in a voluntary agreement. There has been an increasing reliance on voluntary agreements for achieving environmental objectives since the 1990s (Dawson & Segerson, 2008) and recently for mitigating childhood obesity, yet only few studies have examined the enforceability of voluntary agreements and none empirical. For instance, Brau and Carraro (2011) and Dawson and Segerson (2008) both consider a policy environment in which a group of firms must decide whether to sign a voluntary agreement on abating pollution with an industry-wide target. Their research showed that there are different conditions under which voluntary agreements could be an equilibrium despite the free-riding problem. Our empirical framework could be adapted to analyze participation of self-regulation in other industries.

2 Food Marketing to Children

This section explains the institutional backdrop against which our study is motivated and conducted. It starts with a summary of the policy environment. Next, it discusses the actions of the major firms marketing children's RTE cereal. Then, it overlays the brands and market data we analyze, as well as the simulations we conduct, on the institutional backdrop.

2.1 Policy Environment

Figure 1 chronicles the "Marketing Healthier Foods to Kids" story timeline. Against the backdrop of increasing public concern over childhood obesity issues congress enlisted The Institute of Medicine (IOM) to compile a report entitled, "Preventing Childhood Obesity: Health in the Balance" in 2004. The same year Congress directed the CDC to undertake a study of the role of food and beverage marketing on nutrition status of children and teens, and topically, how marketing approaches might be used to remedy the emerging epidemic. The CDC turned to the IOM in 2005 for a report on the "Food Marketing to Children and Youth: Threat or Opportunities," an influential report that serves as a comprehensive review of scientific studies assessing the influence of marketing on nutritional beliefs, choices, practices, and outcomes for children and youth. The IOM study notes that the majority of food and beverage products marketed to kids is high in total calories, sugar, salt, and fat, and low in nutrients. The study's major conclusion is that "TV advertising influences the food preferences, purchase requests, and diets, at least of children under the age of 12 years, and is associated with the increased rates of obesity among children and youth." The IOM subsequently called for "substantially more industry and government attention, action, and cooperation on an agenda to turn food and beverage marketing forces toward better diets for American children and youth."

In April 2006, the Federal Trade Commission (FTC) recommended that the Better Business Bureaus (BBB) consider possible actions to address the concerns over childhood obesity and food marketing to children. In response the BBB launched the Children's Food and Beverage Advertising Initiative (CFBAI) in November 2006 to change the nutritional profile of food and beverage products marketed to children. Shortly thereafter, Congress's 2009 Omnibus Appropriations Act formed an interagency working group (IWG) composed of the FTC, CDC, Food and Drug Administration (FDA), and the U.S. Department of Agriculture (USDA) to work on a proposal for voluntary principles and nutritional standards to guide industry self-regulation. When the IWG released its proposed guidelines in April 2011 calling for all food marketers to expand voluntary regulation, it was met with resistance from the food and beverage industry lobby. In response, in July 2011, the CFBAI released category-specific uniform nutrition criteria for foods advertised to children. The agreement requires partner firms to meet these new "tough but realistic" criteria by the close of 2013 (BBB,2011). The IWG recommends the voluntary adoption of nutrition principles for foods advertised to children by 2016. After hearing rebuttal from the food and beverage industry lobby, the IWG included a provision stipulating that the focus be on marketing directed to children 12 or younger (as opposed to 2-17), will not limit marketing that is family-oriented or to a general audience, and will not limit the use of established brand characters such as Toucan Sam (the Froot Loops cereal spokes-cartoon), or other elements of packaging that is "inextricably tied to the food's brand identity." (Vladeck, 2011) In addition, the Consolidated Appropriations Act of 2012 has a provision requiring the IWG to conduct a benefit-cost analysis before the proposed guidelines be adopted.

2.2 Children's Ready-To-Eat Cereal

RTE breakfast cereals are marketed directly to children and adolescents (children brands), to family (family brands) for family's consumption, and to adults (adult brands) to satisfy adults' dietary needs and taste preferences. We focus on the children's RTE breakfast cereal segment in our empirical investigation. The kid cereal segment consists of brands that possess strong interactions with each other. Including other category segments into the evaluation might dilute the switching patterns observed in the data. For example, a household may always purchase a kid cereal and an adult cereal for different members of their household. However, the data does not reflect the intended user of each product, and in effect may falsely indicate a switch form a kid cereal to an adult cereal (Cohen & Rabinowitz, 2012). Children's RTE breakfast cereals are the largest category of packaged foods directly marketed to children. Harris et al. (2009) summarizes some industry facts: The industry spends \$229 million on advertising for these kids brands; children's exposure to cereal advertising represents a quarter of all food and beverage product Television commercials viewed by children; children's cereal brands are usually the least healthy cereals, in fact, on the average, child RTE cereals contain 85% more sugar, 65% less fiber, and 60% more sodium compared to adult cereals; and cereal companies also advertise more intensively to children relative to any other age group, and on average, children see twice as much cereal advertisements on television compared to adults. We focus on the top four manufacturers, Kellogg's, General Mills, Post, and PepsiCo, who together accounted for more than 80% of children cereal sales in the U.S. market between 2006 and 2008, with the two largest firms, Kellogg's and General Mills, accounting for 60% of market sales.

Kellogg's and General Mills joined CFBAI in 2006 and pledged to devote 100% of their children-directed advertising to healthier, "better-for-you" products. Post became a signatory in 2009 and began to implement its own pledge by 2010. In July 2011, CFBAI released its category-specific uniform nutrition criteria (CFBAI, 2011a), which all participates need to comply with by the close of 2013. CFBAI has spurred product improvement research, and development teams have worked since 2005 to improve the health profile of products; General Mills and Kellogg's rolled out improved products in 2009 after the end of our data sample. According to CFBAI's latest news release, before the start of CFBAI, some children's cereal contains as much as 16 grams of sugar per serving. As of 2011, 86% of children's cereal contain fewer than 10 grams of sugar per serving (CFBAI, 2011b).

2.3 Market Data

The data we study comes from three sources: The MINTEL Global New Products Database, the A.C. Nielsen HomeScan panel, and the Nielsen Media Research advertising database. All the data we analyze are from eight designated marketing areas (DMAs) (Atlanta, Boston, Chicago, Houston, Los Angeles, New York, Philadelphia, and Seattle-Tacoma) from February 2006 through December 2008. This period corresponds to the years prior to release of either the CFBAI's or the IWG's nutritional guidelines. The period is several months prior to the passing of the Omnibus Appropriations Act. It is also important to note that brand manufacturer Web Sites as well as the MINTEL nutrition facts database, documents that none of the cereal products we analyze were reformulated during the study period. We will now describe each database in turn.

We focus on eight children's cereal brands with the largest market shares in the eight DMAs we study. Children's RTE cereals in general, and these eight brands in particular, represent an important dietary component for U.S. children. Households with any child under 12 accounted for 41% sales in volume for all RTE breakfast cereals in our data, and these eight brands accounted for 18% sales in volume purchased by these households. Moreover, 80% of households with any child under 12 purchased at least one of the eight brands in our sample period. The left side of Table 1 lists the eight brands and the four firms that manufacture them, and Figure 2 displays the package fronts of the eight products, all featuring bright colors and some cartoon characters designed to appeal to children. The third, forth, and fifth columns of the table list saturated fat, sodium, and sugar levels per serving for the eight products. There is a considerable range in the saturated fat levels, ranging from 0.09 gram per ounce at the low end for Kellogg's Frosted Flakes and Apple Jacks, and 0.56 gram per ounce at the high end for Kellogg's Froot Loops. There is also considerable range in sodium. PepsiCo's Quaker Cap'n Crunch has the highest sodium, 209 milligrams per ounce, and Kellogg's Froot Loops has the lowest sodium level, 132 milligrams per ounce. The range of sugar levels is relatively tighter, ranging from 9.5 grams per ounce (General Mills's Cinnamon Crunch) to

13.7 grams per ounce (Kellogg's Apple Jacks).

CFBAI standards are based on serving size. Both Kellogg's and General Mills pledged to advertise only products containing 12 grams of sugar or fewer per serving by 2009 when they joined CFBAI (the CFBAI uniform standards released in 2011 further pushed sugar content to 10 grams or fewer per serving). Only two out of the eight brands contain fewer than 12 grams of sugar per ounce of cereal. Across the brands we study, the typical serving size is 30 grams, since 1 ounce is equal to 28.35 grams, this standard is roughly 12 grams of sugar per ounce. Sugar level is measured as total sugar, the sum of added sugar and naturally occurring sugar. On the other hand, IWG standards are based on Reference Amount Customarily Consumed (RACC) and there are small and large RACC. The small RACC is 30 grams and the IWG standard is to reduce *added* sugar content to fewer than 7.8 grams per small RACC. Strictly speaking, this comes out to 7.37 grams per ounce and combined with naturally occurring sugar levels in kids cereal puts total acceptable sugar under the IWG standard of fewer than 8 grams per ounce for the cereals we consider.

The Nielsen HomeScan data we study tracks the purchases of children's RTE breakfast cereal for a panel of 13,985 households across the eight DMAs. These data include purchases made at big box retailers, grocery stores, convenience stores, and on-line retailers for at-home consumption. For each purchase, we know time and location of the purchase, price, and quantity, and other product characteristics such as brand and package size. Columns 6 and 7 record average price and observed price variance for the eight brands in our study. The prices across brands are generally comparable, with Frosted Flake and Cap'n Crunch having lower price per ounce or equivalently per serving lower than others.

The Nielsen Media Research data provide brand level television advertising exposure on a weekly basis for the same DMAs during the same weeks. Advertising exposure is measured in gross rating points (GRPs). GRP measures the reach and frequency of commercials for a particular product during a specified week. For example, if a commercial is aired on TV in a market twice in a same week, with the proportion of audience in the market reached each time being 5% and 8%, then GRP is 13%. We also use advertising expenditure data at the same level of aggregation to compute the average price of advertising per GRP. Using firm-specific measures of advertising controls for the observed heterogeneity in advertising spot selection, because the price of advertising spots vary across television listings according to the market for television advertising spots. During our sample period, each of the eight brands on the average delivered 16,997 GRPs for children under 12, whereas the average brand-level GRP for children under 12 for the remaining 116 adult and family cereal brands is only 2,604. These eight brands also were marketed primarily to children, with GRPs for children under 12 accounting for about 73% of total GRP on the average, whereas for the other 116 adult and family brands, children under 12 only received about half of the overall advertising exposure. Table 1 summarizes biweekly GRPs and expenditure levels of the eight brands in our study. Except for Quaker Cap'n Crunch, all brands have high levels of GRPs and expenditures.

3 Models

3.1 Demand Model

We start with specifying a random coefficient consumer utility as in BLP. Suppose we observe $m = 1, ..., M$ markets, the conditional indirect utility of consumer i from purchasing a product $j, j = 1, ..., J$ in market m is given by

$$u_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}, \tag{1}$$

where $\delta_{jm} = X_j'\beta + \xi_{jm}$ is the mean utility the consumer derives from product j in the market m, and $\mu_{ijm} + \epsilon_{ijm}$ captures the heterogeneity in consumers' tastes. ϵ_{ijm} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution. μ_{ijm} represents the deviation of consumer i idiosyncratic utility from the mean utility and is given by.

$$\begin{aligned} \mu_{ijm} &= aln(y_{im} - p_{jm}) + X_j'(\Omega D_{im} + \Sigma\nu_i)) && (2) \\ &= aln(y_{im} - p_{jm}) + \sum_{k=1}^{K} X_{jm}^{k'}(\sigma_k \nu_i^k + \pi_{k1} D_{i1} + \cdots + \pi_{kd} D_{id}), \qquad \nu_i \sim N(0, I_k). && (3) \end{aligned}$$

where the a parameter is the marginal utility of income, D_{im} is a vector of household-specific variables, Ω is a matrix of coefficients that measure how the taste characteristics varies across households, and Σ is a scaling matrix. The unobserved household characteristics ν_i is assumed to have a standard multivariate normal distribution. y_{im} is income. The consumer can choose an outside option. Normalizing p_{0m} to zero, the indirect utility from the outside option is:

$$u_{i0m} = aln(y_{im}) + \xi_{0m} + \epsilon_{i0m}. \tag{4}$$

If a consumer is aware of all J products available in the market, then because ϵ_{ijm} has a type I extreme value distribution, the conditional probability that consumer i purchases product j in market m is then given by

$$s_{ijm} = \frac{exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{r=1}^{J} exp(\delta_{rm} + \mu_{irm})}$$

We depart from this standard model by allowing for the possibility that a consumer might not be equally aware of all products available in the market. In this limited-awareness framework, the consumer will choose from the subset of the products that she is aware of. Following Goeree (2008), S represents a particular awareness set for consumer i, C_j is the set of all awareness sets that include product j, and consumers are aware of the outside option with probability 1. the conditional probability that consumer i purchases j becomes:

$$s_{ijm} = \sum_{S \in C_j} \prod_{l \in S} \phi_{ilm} \cdot \prod_{k \notin S} (1 - \phi_{ikm}) \cdot \frac{exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{r \in S} exp(\delta_{rm} + \mu_{irm})}, \tag{5}$$

which can be decomposed into three parts: (i) $\prod_{l \in S} \phi_{ilm}$, the probability consumer i is aware of j; (ii) $\prod_{k \notin S}(1 - \phi_{ikm})$, the probability consumer i is aware of the other products competing with j; and (iii) $\frac{exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{r \in S} exp(\delta_{rm} + \mu_{irm})}$, the probability consumer i would buy j given his/her choice set.

The awareness utility ϕ_{ijm} describes the effectiveness of advertising at raising the awareness of consumer i about product j at market m, and it is given by:

$$\phi_{ijm} = \frac{exp(\gamma_{jm} + \tau_{ijm})}{1 + exp(\gamma_{jm} + \tau_{ijm})}, \tag{6}$$

Analogous to δ_{jm} and μ_{ijm}, γ_{jm} captures mean market awareness utility, and τ_{ijm} captures the consumer awareness heterogeneity. The specific functional form of γ_{jm} is:

$$\gamma_{jm} = \Gamma(g^a_{jm}), \tag{7}$$

where,

$$\Gamma(g^a_{jm}) = \begin{cases} \alpha^a log(1 + g^a_{jm}) & \text{if } g^a_{jm} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The consumer-specific deviation from the mean market awareness utility is captured by τ_{ijm}, which is defined as:

$$\tau_{ijm} = \frac{\Gamma(g^a_{jm})}{\alpha^a}(\rho D_{im} + \nu_i \sigma_a), \quad \nu_i \sim N(0,1), \tag{9}$$

where D_{im} and ν_i are observed and unobserved household characteristics as defined before; D_{im} is translated into preferences by ρ; and σ_a captures the scale of the distribution characterizing awareness heterogeneity.

Advertising goodwill stock captures the dynamic carry-over effects of advertising's impact on awareness and hence demand, which is modeled as a distributed lag of advertising:

$$g_{jm} = \sum_{k=1}^{\infty} \lambda^k \Psi(A_{jm,t-k}), \tag{10}$$

where $\Psi(\cdot)$ is a nonlinear goodwill production function, t and k are time periods. We assume $\Psi(0) = 0$ and is a nondecreasing function of advertising proliferation, A_{jm}. Firms produce goodwill by adding to the existing stock to generate an augmented goodwill stock,

$$g^a_{jm,t} = g_{jm,t} + \Psi(A_{jm,t}). \tag{11}$$

The augmented goodwill stochastically depreciates overtime according to the following law of motion:

$$\begin{aligned} g_{jm,t+1} &= \lambda g^a_{jm,t} + \nu_{jm,t+1} \\ &= \lambda(g_{jm,t} + \Psi(A_{jm,t})) + \nu_{jm,t+1}. \end{aligned} \tag{12}$$

$\lambda \in (0,1)$ is a geometric decay factor. $A_{jm,t}$ measures the reach and frequency of an advertising for a particular product in a market as captured by GRPs in period t. An expansion of equation (12) yields:

$$g_{jm,t} = \sum_{k=1}^{\infty} \lambda^k \Psi(A_{jm,t-k}) + \omega_{jm,t}, \tag{13}$$

where $\omega_{jm,t} = \sum_{k=0}^{\infty} \lambda^k \nu_{jm,t-k}$. We apply the goodwill production function suggested by Dubé, Hitsch, and Manchanda (2005):

$$\Psi(A) = \begin{cases} log(1+A) & \text{if } A > 0 \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Combining all the components described above and integrating over the market of consumers, the market demand share is:

$$s_{jm} = \int_{B_{jm}} s_{ijm} F(\nu; \Theta_h) dF(\alpha^a), \tag{15}$$

where Θ_h is the set of heterogeneity parameters and B_{jm} is the consumer set that leads to the purchase of product j in market m.

3.2 Description of the Pricing and Advertising Game

The firms play the following game. At the beginning of the game (period zero), firms simultaneously decide whether to participate in a voluntary agreement on a set of nutrition and marketing standards. If the firm decides to participate, then it also needs to decide whether to reformulate its "unhealthy" products according to defined nutrition standards. If the firm reformulates, then it is free to choose the advertising levels for its products. Otherwise, the firm must suspend advertising for unhealthy products in subsequent periods. If the firm decides not to participate in the voluntary agreement, then the firm does not need to reformulate its products while it can still choose any level of advertising for its products. Each firm, regardless of its participation and reformulation decisions, must decide prices and advertising in each period for all its products, conditional on its costs and other firms' participation and reformulation decisions. Because it is advertising stock that enters the demand in our setting, the game is dynamic.

In each period, a firm F maximizes profits jointly over all the products in its portfolio G_F, given its participation and reformulation decisions, the market subscript m is not pertinent to the current discussion and is eliminated to simplify the exposition:

$$\Pi(g_t, A_t, P_t) = \sum_{j \in G_F} \pi_j(g_t, A_t, P_t) \tag{16}$$

where ,

$$\pi_j = \pi_j(g_t, A_t, P_t) = \int (p_{jt} - c_j) Q_j(g_t, A_t, P_t, \xi_t, \nu_{j,t}) f(\xi_t) d\xi_t - k_F A_{jt}. \tag{17}$$

The demand for product j, Q_{jt}, is the market demand share, given by equation (15), scaled by market size M. Q_{jt} is a function of product characteristics, prices, P_t, advertising, A_t, goodwill stock, g_t, as well as the vectors of demand shocks, ξ_t, and goodwill shocks, ν_{jt}. The product-specific demand shock ξ_{jt} that enters the mean choice utility is observed before firms set price and advertising, and the shock to goodwill ν_{jt} which captures consumers' response to a product's advertising occurs after the firm determines advertising levels. Because firms set price and advertising before the goodwill shock, ν_{jt}, is realized, they maximize the expected per-period profit. c_j is a constant marginal cost of production, and k_F is the advertising price faced by firm F.

At the start of a period, firms observe the state of the market, g_t, where $g_t = (g_{1t}, .., g_{Jt})$ is a vector that contains all existing advertising stock and product attributes observed by the firm. Firms then make pricing and advertising decisions for each product $\sigma_j(g_t) = (P_{jt}, A_{jt})$ in their portfolio, conditional on the strategies of other firms in the market. In other words, once firms observe the state vector, they choose prices and advertising, then the goodwill shock, ν_{jt}, is realized and the profits are determined. If a firm decides to participate in the voluntary agreement but chooses not to reformulate its "unhealthful" products, then it can only have zero advertising in each period. In all other cases, advertising is not constrained.

The strategy profile vector $\sigma = (\sigma_1, ..., \sigma_N)$ contains the price and advertising decisions of all N firms and their products. The expected discounted profits for firm F in state g_t under strategy σ are:

$$V^F(g_t|\sigma) = \mathbb{E}\Big(\sum_{s=t}^{\infty} \beta^{s-t}\Pi_F(g_s, \sigma_F(g_s))|g_t\Big) \tag{18}$$

Firms will maximize the stream of expected profits by choosing a strategy profile σ_F, for any given participation and reformulation decisions. The MPE of the dynamic advertising game, given the participation and reformulation decisions of all the firms, is characterized by a list of strategies $\sigma^* = (\sigma_1^*, ..., \sigma_N^*)$ such that no firm can profit by deviating from its strategy in any subgame starting at state g. We establish the existence of the MPE by numerically solving for equilibria given our demand estimates.

After identifying equilibrium solutions for all possible combinations of the participation and reformulation decisions of the firms, we are able to attach a payoff to any of these possible scenarios. Then, it is straightforward to identify the MPE of the participation/reformulation decisions for any of the firms.

3.3 Identification

We use two sets of moments to identify two sets of the demand parameters. First, we use macro-moments as described by BLP to identify mean preference parameters which capture the mean preference of the consumers. Second, we further exploit our homescan data and derive micro-level moments from the gradient of consumer-level choice model (as in Cohen & Rabinowitz, 2012) to identify the heterogeneity parameters that characterize the distributions of consumer level awareness and taste.

3.3.1 Mean Preference Parameters

The source of identification for the mean preference coefficients of price, advertising stock, and product attributes is variations in market shares attributable to changes in these variables that are orthogonal to demand unobservable. Potentially, all these variables could be endogenous, if firms observe all or part of the demand shocks ξ_j that are unobservable to the econometrician, and take these shocks into account when executing their marketing mix decisions.

To deal with the potential price endogeneity, we follow BLP and use market level macro-moments as instruments in a GMM framework. Specifically, we use input cost shifters and advertising cost shifters as excluded instruments for price. These shift profits correlating them with cereal price, yet they are orthogonal to cereal demand shocks to the extent that they are exogenously determined in competitive input markets.

Goeree (2008) uses advertising expenditure to proxy for advertising exposure consumer receive. Instead, we use advertising exposure directly as measured by GRPs in our demand estimation, which is the basis of the contracts between advertisers and television stations. Advertising expenditure levels are chosen by the firms, but the firms do not have full control over advertising exposure consumers receive in a given period. It is standard practice that advertising contracts have "make good" clauses that stipulates that if the contracted amount of GRPs are not completely delivered in a given period, then the television stations will "make good" and deliver the remainder GRPs in subsequent periods (Dubé et al., 2005; Cohen & Rabinowitz, 2011). This "make good" clause provides an institutional fact that generates variations in advertising exposure out of the firm's control. When media outlets "make good," we would observe low-levels of advertising exposure, particularly at the end of advertising campaigns. We present graphical evidence consistent with "make goods" observed in our advertising data. Figure 3 shows a histogram of advertising exposure in our data with large numbers of low-level advertising exposure. These low-level advertising exposure levels are consistent with the "make good" clause.

Goeree (2008) relies upon the same set of instruments used for addressing price endogeneity to control for potential advertising expenditure endogeneity, justifying these instruments on the grounds that these cost shifters enter the firms' first-order conditions of their profit-maximizing problem but are unlikely to be correlated with the unobservable demand shocks. We also conduct a Hausman test on exogeneity of the advertising exposure in our model with similar instruments. The result of the Hausman specification test indicates that there is no systematic difference in the coefficient estimates for the specification that treats advertisign as exogenous versus the specification that treats it as endogenous.

With product attributes, we argue that firms infrequently reformulate their products in reality, and in our model the firms only choose whether to reformulate at the start of the game to an agreed nutrition standards. In fact, none of the brands changed their formulae during our data period. Therefore, we argue that it is reasonable to treat product attributes as predetermined at the demand estimation stage.

3.3.2 Heterogeneity Parameters

Our demand model allows for consumer heterogeneity in their tastes for product attributes and in their awareness set formation. Traditionally, the heterogeneity parameters are also identified through macro-level moments from market-level data (e.g., BLP; Nevo, 2001; Goeree, 2008). We further exploit our data and the density implied by the household-level logit choice model to aid estimation of the distribution of consumers preferences. Specifically, we use the method proposed in Cohen and Rabinowitz (2011) and use score function moments implied by the density of consumer level choices. The score function with respect to the vector of choice utility heterogeneity parameters (θ_1) is given by:

$$\mathbb{S}(\theta_1^m) = \sum_{S \in C_j} K_s \text{Prob}_{ijt}^S \left(\frac{\partial \mu_{ijt}}{\partial \theta_1^m} - \sum_{k \in S} \text{Prob}_{ikt}^S \frac{\partial \mu_{ijt}}{\partial \theta_1^m} \right), \tag{19}$$

where $K_s = \prod_{l \in S} \phi_{ilt} \prod_{r \notin S} (1 - \phi_{irt})$ and $\text{Prob}_{ijt}^S = \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k \in S} exp(\delta_{kt} + \mu_{ikt})}$, the probability of choosing j conditional on being aware by consumer i.

Likewise, the score with respect to the vector of awareness utility heterogeneity parameters (θ_2) is:

$$\mathbb{S}(\theta_2^m) = \sum_{S \in C_j} K_s \text{Prob}_{ijt}^S \left[\sum_{l \in S} (1 - \phi_{ilt}) \frac{\partial \tau_{ijt}}{\partial \theta_2^m} - \sum_{r \notin S} \phi_{irt} \frac{\partial \tau_{ijt}}{\partial \theta_2^m} \right], \tag{20}$$

And the consumer choice micro-moments are defined as:

$$E[\mathbb{S}(\theta_1 | \delta, \gamma)] = 0; \tag{21}$$

$$E[\mathbb{S}(\theta_2 | \delta, \gamma)] = 0. \tag{22}$$

These micro-moments differ from those of Petrin (2002), which rely on the assumption that deviation of observed consumer choices from predicted probability and consumer characteristics are mean independent. In contrast, our micro-moments are the score function of the likelihood of consumer purchases conditional on mean preferences. The econometric specification is equivalent to Chintagunta and Dubé(2005). However, we place their econometric specification into the MPEC estimation framework to improve the numerical performance of the estimation estimation (a more detailed discussion is provided in Cohen & Rabinowitz, 2001). Therefore, our micro-moments are derived from a full maximum likelihood estimation approach, yet we place them in the GMM framework, and consequently, we gain efficiency without making additional functional form restrictions.

4 Demand Estimation Approach

Like most of the previous literature that estimates random coefficient multinomial logit demand models, we also use the GMM estimation method. An advantage of using the GMM is that it can easily accommodate our micro-moments in addition to the macro-moments. This literature typically implements GMM estimation of the model with a Nested Fixed Point Algorithm (NFP), which involves inverting the non-linear market-share functions and searching for the parameters in two nested loops. Dubé, Fox and Su (2012) illustrate how NFP is vulnerable to numerical inaccuracies due to the nested loops. They propose recasting the GMM estimation of the BLP model as a Mathematical Programs with Equilibrium Constraints (MPEC), which is faster and produces more robust results because MPEC eliminates the calls to the nested loops. Specifically, MPEC recasts the GMM estimation problem as one nonlinear minimization with equality constraints. The objective function is the GMM objective function, and constraints include the BLP-type moments conditions and the condition that the observed market shares are equal to predicted market shares. As in Cohen and Rabinowitz (2011), we extend the MPEC approach to estimate the limited-awareness random coefficient discrete choice demand model.

Specifically, we recast the GMM estimation as follows: Let W be the GMM weighting matrix, the constrained optimization formulation is:

$$min_x \quad g'Wg$$

$$
\begin{aligned}
s.t. \quad & c_1 : \frac{1}{n}\sum_i s_{ijt}(\delta, \gamma|\mu, \tau) = S_{jt}^{obs} \\
& c_2 : g = \sum_{\forall j,t} IV'(\delta_{jt} - x'_{jt}\beta) \\
& c_3 : \sum_{\forall i,j,t} \mathbb{S}(\mu, \tau|\delta, \gamma) = 0. \qquad (23)
\end{aligned}
$$

where W be the GMM weighting matrix. Constraint c_1 requires that the observed and predicted market shares are equal to each other. c_2 is the set of macro-moments conditions used to identify mean preference parameters. Constraint c_3 is the consumer choice micro-moment condition used to identify the heterogeneity parameters described in the identification section. We code the MPEC problem in MATLAB platform and apply KNITRO via the TOMLAB optimization environment, a state-of-the-art optimization tool that exploits gradient information from the objective function and the constraints to conduct optimization.

One additional challenge in the demand estimation is that we do not observe consumers' awareness sets. Georee (2008) simulates the unobserved awareness sets. A drawback with the simulation approach is that the simulation errors may be propagated to the demand estimates. Rather than simulating the awareness sets, we directly integrate over all possible awareness sets and hence avoid any errors related with simulated awareness sets that potentially taint the competitive simulation analysis.

5 Simulating Firm Strategy

Having obtained the demand estimates, we turn to solving the MPE advertising and pricing strategies for each given combination of the participation and reformulation choices of the firms. As with the demand estimation, we again formulate the dynamic programming problem conditional on a given combination of the participation and reformulation decisions as a MPEC problem:

$$
max_{p_t, A_t, g_{t+1}} \quad \sum_f V^F
$$

$$
\begin{aligned}
s.t. \quad & c_1 : g_{t+1} = \lambda[g_t + \Psi(A)] + \nu_i \\
& c_2 : p - c = [O^F \times_{elt} \Omega(p, A)]s(p, A) \\
& c_3 : \Pi_A(p_{t+1}, g_t) = E[\beta \Pi_A(p_{t+1}, g_{t+1})]
\end{aligned} \tag{24}
$$

where V^F is the expected discounted profit given in equation (18). The first constraint, c_1, is the equation of motion for advertising goodwill; c_2 is the static optimal price markup condition from the first order condition of the firm's profit maximizing problem; and c_3 is the Euler equation defining the intertemporal optimal advertising condition. We compute the integral in $c3$ with Monte Carlo simulations. To initiate advertising stock, we use the first 12 periods. In the simulation we assume a discount factor $\beta = 0.9916$, or equivalently an annual interest rate of 11%. Our data supplies both advertising expenditure and advertising exposure. Therefore we operationalize the advertising costs with average expenditure per GRP for a given DMA. We also need an estimate of marginal cost of production. We do not have information on the marginal costs of the products. We solve for the implied price-cost margins from the first order conditions of a static price optimization problem and obtain an estimate of marginal costs assuming that the observed prices are optimal. Then, we further assume the marginal costs stay constant for each product in our simulation. The assumption could be unrealistic as the marginal costs of production could change when products are reformulated. Because the product reformulation in our simulation exercise involves reducing sugar content without changing the amount of other ingredients, the marginal costs implied by the pre-reformulation prices can be viewed as an upper bound. It is worth pointing out that the framework outlined in this article is intended for use by the firms, who will have a more accurate estimate of their marginal costs than outside researchers.

6 Results

In this section, we first present the results from the demand model and some evidence testifying to the robustness of the strength an direction of the parameter estimates. Next, this section conducts the simulation that uses the market model to examine Kellogg's and General Mills's decision to participate in a voluntary agreement, and also on whether to reformulate some of the products or cease advertising for the products if they participate.

6.1 Demand Estimation Results

Table 2 records demand estimates for homogeneous consumer demand specifications. We instrument for prices in all specifications because our model asserts that firms observe demand factors when setting price that are unobserved by us. The price instruments include variables related to costs of production and advertising, as these shift profit margins but are not directly correlated with consumer demand. Specifically, we use prices and lag prices of milk, wheat, and lag prices of advertising as our excluded price instruments. In addition, following Hausman (1996), we also use as excluded instruments product prices in other DMAs. The Hausman instruments rely on the assumption that the prices in different markets are correlated via common cost shocks, but not through common demand shocks. National advertising, if not controlled for, could influence demand in different markets simultaneously, thus invalidating this assumption. As long as we control for advertising exposure in different markets, the Hausman instruments are appropriate.

To investigate the robustness of our parameter estimates we estimate several specifications. In Table 2 Columns (1) and (2) report the results from a homogeneous full-awareness logit demand model with a static advertising effect. The first model is estimated with the eight popular kids cereal products, introduced in section 2. The second model is estimated by holding the healthier and market leading cereal, Kellogg's Frosted Flakes, out of the analysis. Column (3) and (4) display the same full and jackknifed sample results for a homogeneous-consumer limited-awareness logit demand model with advertising carryover. For all four specifications, the first stage F exceeds 11.9, indicating that the price instruments are relevant. In addition, the p-values for the Hansen's J tests are 0.6 or higher, offering no evidence that the price instruments are correlated with unobserved demand shocks. In the last two columns, α captures the marginal awareness utility of advertising stock, whereas λ and γ are the depreciation factor and the random disturbance in the dynamic goodwill process. The α is positive and significant, indicating that advertising enhances consumers' awareness. In all four specifications, we find negative and significant price coefficients, and positive and significant advertising effect estimates. We also find a negative and significant sugar coefficient in all specifications, indicating a general disutility of sugar in the children's cereal segment among consumers. The jackknife statistical procedure provides evidence that the popular healthier cereal is not driving the negative statistical significance of the sugar characteristic.

To investigate the overall taste for sugar in the RTE cereal market, we estimate the full awareness models with a larger set of the top 30 cereal products and a nonlinear specification on sugar utility. The

30 cereals we include are a broad cross section RTE cereals from all major RTE cereal categories. In estimating this larger set, we specify a polynomial in sugar to recover the rate at which the cereal buyers marginal utility of sugar diminishes. The results appear in appendix Table A1. The first two columns show the estimates from linear and nonlinear sugar specifications with homogenous consumers. Column (3) and (4) are the heterogeneous consumer counterparts. In column (5), we include brand fixed effects in place of the time-invariant product attributes, including sugar, fat, sodium, and firm dummies in a heterogeneous consumer model. The mean taste coefficients for these time-invariant product attributes are recovered from the brand dummy estimates in a generalized least square regression (see Nevo, 2000, p. 536). As pointed out by Nevo (2000), including brand dummies can minimize omitted variable bias. To obtain the heterogeneity parameters we specify consumer heterogeneity as a function of price, advertising, and the time-invariant product attributes and estimate those with micro-moments. First, one will notice that the estimated price sensitivity for this larger set of brands is larger than for the model calibrated on the kids brand, which suggests buyers are less price sensitive when purchasing kids cereal. Next, it is also apparent that advertising is more effective in the larger market than the kids market. One possible explanation is that this result is driven by the fact there there is a degree of separation between kid cereal ad viewers and kid cereal buyers, whereas adult cereal ad viewers are likely to be the buyers. The price coefficients shrinks in size by about one-third when we account for heterogeneity, and they are similar in all three heterogeneous specifications. The sugar coefficient is negative and significant across all linear specifications. In the nonlinear specifications the coefficients of linear and cubic terms of sugar are both negative and significant, whereas that of the quadratic term is positive and significant. The sodium coefficient is positive in the two homogeneous specifications, and in the heterogeneous specification with linear sugar. But, it switches sign in the last two heterogeneous specifications with nonlinear sugar. Comparing the last two specifications, we notice that accounting for brand fixed effects increases the magnitudes of sugar and sodium coefficients, indicating more accentuated disutility in sugar and sodium.

The estimates for the sugar response function based on the brand fixed effect specification indicates that the marginal utility of sugar is approximately $-5.581+2*(9.591)*Sugar-3*6.737*Sugar^2$. Because kids cereal sugar levels, normalized to 1, are contained in the interval $(.693, 1)$ the marginal utility for sugar in kids cereal is negative, which is consistent with the estimates computed for the models estimated with the kids cereal product set. Similar to the linear utility specifications, the marginal utility of sugar for the polynomial specification decreases over the interval (.693; 1) at a decreasing rate $(2*9.591-2*3*$

$(6.737) * Sugar$), and the logit demand response function is convex for purchase share under 0.5. Together these facts imply decreasing sales returns to sugar reduction below 7.8 grams per ounce, or in other words extremely low sugar cereals are just too bland. Neither of the CFBAI or IWG nutritional standards penetrates this lower bound, therefore, complying with either does not slow sales.

The rate of decrease in the marginal utility decreases over this interval as well ($2 * 9.591 - 2 * 3 * (6.737) * Sugar$). Because logit demand response function is convex for shares under 0.5, the result implies decreasing sales returns to reducing sugar levels over 7.8 grams per ounce, which is below the threshold set by the nutritional standards we test. Decreasing sales returns to reducing sugar is also the result for the linear specification.

Intra-household purchase decision making can explain, at least partially, the general disutility for high sugar levels. Our household purchase data provides information for a subset of households on the primary shoppers for each transaction. We find that for households with any child under 12, the focal consumer group of the voluntary marketing initiative, female household members between 18 and 45 or likely the mother of the household, are the primary shoppers purchasing the eight brands. Although children may influence the purchase and may themselves prefer sugary cereals, cereal buyers appear to choose relatively healthy products for their household. In fact, Harris, Schwartz, Ustjanauskas, Ohri-Vachaspati, and Brownell (2011) find that children will eat and like low-sugar cereals when they are served, and even when the children are free to add table sugar to cereal, they still eat less total refined sugar than if they are offered high-sugar cereals.

Table 3 records parameter estimates for the heterogeneous consumer renditions of the demand models we estimate. Column (1) and (2) exhibit estimates from random coefficient full awareness demand models without and with advertising carryover, respectively. Column (3) contains estimates from our random coefficient limited awareness demand model with advertising carryover. Each of these three specifications incorporate micro-moments in estimation to aid identification of the parameters that capture awareness and preference heterogeneity within our model.

The key parameter estimates on price are negative and highly significant in all specifications in Table 3. It decreases from -5.85 in column (1) to -5.33 in column (2), indicating that failure to account for advertising effect in a full-awareness framework results in overestimated price sensitivities. It further decreases to -4.90 in column (3), the random coefficient limited-awareness model in which advertising carryover increases product salience. Our findings are consistent with Goeree (2008) and Cohen and Rabinowitz (2012), who find that the price coefficient estimates from full-information models are biased towards being too elastic. In contrast, Draganska and Klapper (2011) find an opposite bias of traditional models ignoring heterogeneity in consumers' awareness. Both Goeree (2008) and Draganska and Klapper (2011) provide arguments on why the direction of the bias in their findings. Therefore, this is an empirical question, and the answers depend on the specific market studied.

In the limited-awareness specification in column (3), α is the parameter capturing marginal awareness utility of advertising goodwill, and λ and σ define the dynamic process of advertising goodwill. In the heterogeneous full-awareness model with advertising carryover (column (2)), α instead captures marginal choice utility of advertising goodwill, and likewise λ and σ define the dynamic process of advertising goodwill. Both α and λ are positive and significant in all three specifications, with α more than twice as large in the limited-awareness specifications as in the full-awareness specification. This indicates that ignoring heterogeneity in consumers' awareness discounts the marginal value of advertising carryover. λ measures the duration of advertising effects. Ranging between 0.70 to 0.77, our results indicate that advertising effect can last over 10 biweekly periods, or roughly five months for our products, consistent with other studies on the cumulative effects of advertising (e.g., Clarke, 1976).

In all specifications in Table 3, product attributes, including sugar, sodium, saturated fat, and fixed effects of the two largest firms (i.e., Kellogg's and General Mills) enter a consumer's choice utility besides price. The coefficients on all product attributes except for sodium are statistically significant in all specifications. Consistent with the homogenous specifications, the signs of the mean coefficients for sugar and saturated fat are both negative, indicating that on average consumers dislike children cereal products that are high in sugar or saturated fat.

We report the price and advertising elasticities averaged across all markets based on our heterogeneous limited-awareness demand model estimates in Table 4. The own-price elasticities are around -1 for all products, with Kellogg's Frosted Flakes being the least elastic. First, recall the comparison of results for models estimated on a larger set of cereal products: these indicate cereal buyers in general are more price sensitive than kid cereal buyers. This result is partially accounted for by the fact that households buy in multiple cereal categories, so models calibrated on large product sets overestimate switching. The market share of Kellogg's Frosted Flakes, the market leader, would gain most when other products increase their prices. Our price elasticities are considerably smaller (in absolute value) than cereal price elasticities documented in earlier literature. For instance, Nevo (2001) investigates the entire cereal market and uses market level data and reports own-price elasticities ranging from -4.25 to -2.47. Chidmi and Lopez (2007) use chain-level data and obtain own-price elasticities between -7.52 and -2.44. Besides differences in sample and brands included, a number of factors might explain the differences. First, almost all the extant research uses the full awareness model which imposes more restrictive substitution patterns because it does not allow for heterogeneity in consumer awareness. As a result, relaxing the bias from the full awareness assumption could potentially further reduce price sensitivity, as reported by Goeree (2008) and Cohen and Rabinowitz (2012). Table A2 (a) in the appendix reports the elasticities based on the heterogeneous full awareness model with advertising stock, and there the own-price elasticities are between -1.2 and -1.7, closer to those reported in extant research than elasticities based on the limited awareness specification. Second, most of the previous literature does not incorporate advertising stock in their demand models. Hitsch (2006) estimates a cereal demand model incorporating dynamic advertising, and he obtains price elasticities smaller in size compared to the previous research. His own-elasticities average around -3.30, but market-leading brands have own-price elasticities around -1.8. Cohen and Rabinowitz (2012) also document that including advertising stock reduces price sensitivity and increases the impact of advertising. Table A2 (b) reports elasticities based on the heterogeneous full awareness model with static advertising exposure. Here the own-price elasticities further increase to between -1.85 and -1.25. Third, most of the previous research use advertising expenditure data whereas we use advertising exposure data in the estimation. As explained before, advertising exposure is more likely to be exogenous due to the "make-good" clauses. We estimate a heterogeneous full awareness model with static advertising expenditure in lieu of advertising exposure, which benchmark our results against previous estimates. Own-elasticities based on this specification, reported in Table A2 (c) range between -2.96 and -1.93, comparable to previous estimates. Finally, we use a numerically superior estimation algorithm, rather than the nested fixed point (NFP) algorithm previous researchers use (Dubé et al., 2012). Knittel and Metaxoglou (2008) illustrate the numerical challenge of finding (unique) local optimum using NFP algorithm. Using the same dataset in Nevo (2001), after excluding results implied by starting values that fail to converge under tighter NFP tolerance, they record own-price elasticities between -2.47 to -1.34, similar to the elasticities based on the full awareness specification reported in Table A2 (a) and Table A2 (b), and lower than those in Table A2 (c).

The advertising elasticities represent a 1% change in quantity demanded due to a 1000% change in GRPs. Own-advertising elasticities range from 8.48 (Quaker's Cap'n Crunch) to over 15 (Kellogg's Froot

Loops, Apple Jacks, and General Mills's Cocoa Puff), suggesting strong advertising effects. An increase in advertising exposure of Kellogg's and General Mills's products generally have larger effects on the market shares of other products, with the cross elasticities in the range of -0.40 to -1.10. Among these, an increase in the advertising exposure of General Mills's Cinnamon Toast Crunch has the largest effects on the market shares of the other products' shares. In contrast, an increase in the advertising exposure of Quaker's Cap'n Crunch will lead to smaller decreases in the market shares of other products, with the cross elasticities in the range of -0.34 to -0.39.

6.2 Market Simulation Results

Specifying the demand estimates in equation (15), we proceed to simulate firms' marketing strategies. Specifically, we consider the following exercise. Kellogg's and General Mills, the two top manufacturers and advertisers in the children's cereal segment, have the option of joining a voluntary agreement in which the signatories either reformulate their products so all products in their portfolio contain fewer than 12 grams of sugar per ounce, or suspend advertising of these products. Reducing sugar to fewer than 12 grams per ounce is a conservative goal: it was specified in Kellogg's and General Mills's CFBAI pledges when they first joined CFBAI, and both companies have achieved this goal as of writing this article. We also consider an alternative stricter standard of eight grams of sugar per ounce and the results are qualitatively similar. We do not consider reformulating other nutrients such as sodium or saturated fat because, for children's cereal, sugar is the nutrient of focus and is mirrored in caloric levels. In fact, all the eight brands we consider meet the nutrition criteria in either CFBAI or IWG for sodium and saturated fat. Both the participation and reformulation decisions are made by the firms simultaneously at the beginning of the first period. If a firm decides to participate in the voluntary agreement, then it will decide whether or not to reformulate the products that exceed the sugar content criteria. If the firm decides to participate but not to reformulate, then it has to stop advertising those products not complying with the standards. If it participates and reformulates to comply to the criteria, then it can choose any advertising level. If the firms do not participate, they do not need to reformulate and they can keep advertising all their products. The nonparticipation could damage the public image of the companies, but this is not easy to quantify. We assume that the demand for children's cereal will not be affected by the participation and reformulation decision per se. One might expect participation to improve consumer perception of the brand, implying that our profit estimates under compliance are a conservative figure, hence, it would not perturb the equilibrium. The participation and reformulation decisions affect demand via their effects on product attributes, pricing, and advertising levels.

Among the eight brands we focus on, there are three Kellogg's brands, i.e., Frosted Flakes, Froot Loops and Apple Jacks, with the latter two brands containing sugar higher than 12 grams per ounce serving. There are three General Mills brands, i.e., Cinnamon Toast Crunch, Lucky Charms, and Cocoa Puffs, with the latter two also failing the 12 grams of sugar per ounce criterion. Therefore, both firms would need to reformulate two products or eliminate their advertising of those products if they join the voluntary agreement. There are two brands with the least market shares, i.e., PepsiCo's Quaker Cap'n Crunch and Post's Fruity Pebbles. We assume in this simulation that the manufacturers of these two "fringe" brands do not consider whether to join the voluntary agreement at the time.

With two firms and three binary options, i.e., not to participate, participate and reformulate, and participate but not reformulate the unhealthy products (therefore restricting advertising of these products), there is a total of nine scenarios we need to consider in this simulation exercise. For each of the scenarios, we solve for the MPE pricing and advertising strategies for 30 biweekly periods. As noted in Dubé et al. (2005), simulated advertising and pricing are not in-sample predictions, because we simulate for optimal strategies based on demand estimates, which require no assumptions on optimizing.

Table 5 reports the average simulated per-period prices, advertising GRPs, and market shares for each of the brands in all nine scenarios. Prices generally do not vary much across different strategies. Interestingly, when firms participate in the voluntary agreement and reformulate their products, they also raise the prices of their reformulated products slightly, relative to those when they do not reformulate or when they do not participate in the voluntary agreement.

Compared to the status quo, Kellogg's heightens its advertising exposure for most of its products, especially Froot Loops, when it stays out of the agreement, whereas General Mills participates but does not reformulate its products, and General Mills increases advertising intensity for Cinnamon Toast Crunch, the only product it is allowed to advertise. Kellogg's products enjoy higher market shares, so does General Mills's Cinnamon Toast Crunch, at the expense of the other General Mills's products. Meanwhile, the two "fringe" products advertise at a very low level. When both firms participate but do not reformulate, four of the products that are too high in sugar by Kellogg's and General Mills have zero advertising exposure. Consequently, these four products lose considerable market shares. In this scenario, the two "fringe" products take advantage of the advertising vacuum and aggressively advertise their products. As a result, Post Fruity Pebbles increases its market share, whereas Quaker's Cap'n Crunch maintain its market share.

When Kellogg's participates and reformulates its products, and General Mills participates but does not reformulate, Kellogg's increases its advertising of Froot Loops excessively (specifically 48%), but lowers advertising exposure of Apple Jacks a bit. Conversely, in the case that General Mills participates and reformulates, whereas Kellogg's participates but does not reformulate, General Mills slightly raises advertising of Lucky Charms and Cocoa Puffs (increases of 3% and 19%, respectively). In both cases, the market shares of reformulated products are higher than if the firm does not participate in the voluntary agreement.

6.3 Advertising Strategy

Figure 4 illustrates density estimates of observed GRPs, and strategically optimal GRPs under both the full-awareness and limited-awareness models. The density of the observed GRPs is bimodal, with the lower mode at zero, indicating pulsing behavior. The density for optimal GRPs under the limited-awareness model is also bimodal, with a lower mode at zero and an upper mode located left of the observed distribution's upper mode. The density of the full-awareness predicted GRPs, in contrast, is a unimodal, right-skewed distribution. This implies the optimal strategies under the full- awareness assumption involve increasingly high frequencies of incrementally low-level advertising. Relative to the full-awareness strategies, the optimal strategies based on a limited-awareness model involve higher frequencies of no advertising, and larger pulses of advertising. The limited-awareness density shows greater affinity toward the observed data than does the full-awareness density. Although it appears that firms have already adopted advertising strategies that are closer to the optimal strategies predicted by the limited-awareness model than to those predicted by the full-awareness demand model, Kolomogorov-Smirnov tests reject the notion that the observed data are generated by either model. This indicates that existing firm strategies are suboptimal. Taking the Kolomogorov-Smirnov test results together with the observation that the optimal pulse levels are lower than the observed pulse levels, one can conclude that current advertising is generally excessive.

Excessive advertising not only hurts rivals' profitability, it also hurts one's own profitability. Villas-Boas (1993) shows theoretically that when advertising increases the probability a consumer considers a product, then Markov Perfect Advertising strategy for oligopolistic firms is to pulse out of phase, i.e., schedule advertising in alternative periods. The intuition is simply that it is more profitable to increase consideration when the consideration for competitors' products is lower. Villas-Boas (1993) also provides a model-free test for the prediction of such "avoidance" behavior. Specifically, he investigates the presence of negative correlation in the advertising expenditures for products in nine categories and finds that six out of these nine categories have statistically significant correlations that are negative. When there is an advertising "war," then positive correlations could be observed. Our analysis, which conducts a brand level investigation affords the opportunity to give a sharper look at interbrand (between firms) and intrabrand (within firm) advertising competition.

Table 6 presents advertising competition patterns summarized by correlations of GRP series among the eight brands we study. In the top panel of the table, we show the correlations across different products based on observed GRPs. A negative sign indicates avoidance, whereas a positive sign indicates competition. Though there are both negative and positive correlations, only positive correlations, or advertising competition, are statistically significant. In the lower triangle of the top panel we show the relative Euclidean distance of estimated consumer utility for products. The bottom panel presents the same for the simulated Markov Perfect Equilibrium advertising GRPs under the status-quo scenario based on the limited-awareness demand model estimates. The correlations indicate a mix of statistically significant competition and avoidance behavior. We notice that avoidance occurs when the products are dissimilar in the utility space as measured by the relative Euclidean distances, whereas competition tends to occur when the products appear to be more similar. The contrast between the in-sample and predicted optimal GRPs suggests that the actual advertising might be excessive in a dynamic sense because the firms are not strategically schedule their advertising to avoid advertising wars. The correspondence of avoidance and competition with the relative Euclidean distances is consistent with the finding of Grossman and Shapiro (1984) that advertising can be excessive in an oligopoly relative to socially optimal level of advertising when products are relatively similar. Despite that informative advertising improves the matching between consumers and products, particularly when products are substantially differentiated. The appearance of both results in our empirical analysis is a poignant finding with clear managerial implications.

We further investigate firm-level advertising competitions. Table 7 reports the correlations among GRP series at firm level. Again we show in the top panel in-sample correlations and in the bottom panel simulated Markov Perfect Equilibrium GRPs under the status-quo scenario based on the limited-awareness demand model estimates. The correlations among observed GRP paths are generally smaller in size and statistically insignificant, relative to the simulations. On the other hand, the correlations based on the simulations indicate that the optimal strategies depend on firm sizes of the strategic players. Specifically, Kellogg's and General Mills, the two leading firms, appear to avoid each other in their advertising. Kellogg's also appears to schedule advertising out of phase with Post. Post competes with both General Mills and Pepsi Co. Villas-Boas (1993) notes that the effect of advertising on consideration varied across brands, and he speculates that this effect will be smaller for large firms than for smaller firm. Our simulation lends support to his hypothesis. The larger firms tend to avoid more often than the smaller firms, because the effect of advertising on consideration is smaller for them.

Previous research by Dubé et al. (2005) found no evidence of either competition or avoidance in their empirical application in the frozen entrée category. Rather, Markov Perfect Equilibrium advertising strategies predicted by their dynamic model with advertising carryover have zero correlation, indicating that a firm mostly schedules its advertising to control its own goodwill and demand. We attribute our contrasting result to the fact that our model endogenizes the profit instrument, i.e., price, as well as the fact that our empirical analysis applies more generally to multi-product firms concerned with intra-brand sales cannibalization.

Table 8 summarizes discounted expected profits for each of the two companies over the 30 biweekly periods for all three options in a matrix. For both firms, the strictly dominant strategy is to join the voluntary agreement and reformulate their high-sugar products. On the other hand, the strictly dominated strategy for either firm is to participate but not reformulate these products. This is not surprising given that the majority of consumers dislike sugar based on our demand estimates, and advertising greatly increases product awareness. Firms capitalize on this fact by decreasing the sugar content and also intensify advertising for the reformulated products. If they decide to participate but not reformulate, they have to stop advertising which decreases the probability that a consumer is aware of these products in the first place. The high sugar content further lowers the probability that a consumer chooses these products even if she is aware of them. Joining the voluntary agreement is profitable. Kellogg's would increase its expected discounted profits by 31.0%, and General Mills would increase its by 5.5%, over the 30 periods, when both of them participate and reformulate, relative to the status quo scenario when neither of them participate in the voluntary agreement.

We benchmark our simulation against simulations based on estimates from a full-awareness random coefficient model (in column (2) of Table 3) to gauge whether incorporating heterogeneity in consumer awareness produces different results. Table A2 in the appendix presents simulated average GRPs, prices and market shares resulting from the full-awareness model. Optimal GRPs and prices based on the full-information model estimates are generally lower than those from the limited-information model. This is expected given that the limited-information removes a downward bias in advertising impact and an upward bias in price sensitivity from the full-awareness model. The estimated payoffs based on these simulation results are reported in Table A3. In the full awareness setting, to join the voluntary agreement and reformulate cereal products is still the dominant strategy for both Kellogg's and General Mills. Although when comparing with findings from limited awareness model, estimated profits are generally lower under full awareness. For example, in the strictly dominant strategy, it will lead to a 10.3% lower estimated profits than in the case of limited awareness (from 29 million to 26 million) when Kellogg's is setting equilibrium prices and advertising levels under the full awareness assumption. Under the same conditions, General Mills's estimated profits would decline by 4.5% (from 23 million to 22 million). The asymmetry can be explained by the different styles in advertising strategies by the two firms. By taking into account heterogeneity across consumers in their awareness sets, the limited-awareness model rewards advertising more than the conventional model, and hence Kellogg's, the more aggressive firm sees more profit when advised by this model than when its advertising strategies are advised by the full-awareness model.

7 Conclusion

Combating childhood obesity is a priority for policy makers. Voluntary agreements that aim to reduce marketing to children unhealthful foods have been viewed as a viable solution. This research introduces a framework to analyze a series of interlinked managerial decisions related to: joining a voluntary agreement; reformulating products that are deemed unhealthful; pricing and adverting the brand portfolio. Positioned at the intersection of public policy and marketing, the research promises to appeal to a wide audience. It is the first empirical study to our knowledge that analyzes the managerial decisions and implications of participating in a voluntary agreement that sets marketing and nutrition standards. It is also one of the first studies that analyze the implications of such voluntary advertising bans on consumer choices and firm responses.

Our demand model recognizes the heterogeneity in consumer product awareness and therefore the set of products they choose from. We allow advertising to influence consumers' awareness in a dynamic framework. Using recently developed empirical methods, we obtain demand estimates for children RTE cereals by combining market level and consumer level data to more efficiently estimate heterogeneous consumer preferences. We then obtain Markov perfect pricing and advertising decisions, and back out the Markov perfect participation and reformulation decisions for a hypothetical scenario where two largest cereal firms contemplate whether to join a voluntary agreement that would restrict their advertising of some products unless they reduce the sugar content of these products.

There are a few limitations to our approach. For tractability, we model the firms' product reformulation as a binary choice. That is, if a firm decides to reformulate, we assume that it will change the recipe of a product so the nutritional content meets the threshold stipulated in the voluntary agreement. This assumption is in line with stylized facts. For example, Kellogg's reformulated its products so they contain exactly 12 ounces of sugar per serving as pledged. We do not model the reformulation decision as a continuous decision where a firm need to choose the optimal nutrient content as long as it is below a certain standard. We do not model the possible trade-offs across different nutrients in a recipe, that is, we assume that it is technically feasible for a firm to reduce its sugar content without increasing fat content of a product, and view the required research and development as a sunk cost. Finally, we remain agnostic about the public relationship aspect of a firm's participation and reformulation decision. A factor that arguably makes our prediction stronger because our result relies on a conservative demand response that omits the intrinsic utility enhancement of buying from a "socially responsible" firm. A firm might be viewed as more socially responsible when it signs on to a voluntary agreement and adorns its packaging with a "seal of approval," but we do not take this potential payoff into account. Future work may attempt to measure the impact of the public relations and labeling effect.

Our demand estimates highlight the importance of advertising in building and maintaining product awareness. The demand estimates also indicate that kid cereal buyers attach negative marginal utility to sugar and saturated fat. Our simulation results testify that it is a strictly dominant strategy for both firms to join the voluntary agreement and reformulate their products in the children's RTE cereal category. These actions will bring in higher profit than the status quo when they do not participate in such advertising restrictions. The results are particularly interesting given the strong resistance from the food and beverage industry met by recently proposed IWG nutritional guidelines. These results arise because the demand estimates indicate that consumers largely prefer healthy products that contain less sugar or saturated fat. Therefore, joining a voluntary agreement and make healthier products could be a win-win strategy for both the industry and the public.

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Table 1. Summary Statistics of Children Brands

Firm	Brand	Sat. Fat (g/oz)	Sodium (mg/oz)	Sugar (g/oz)	Shares (%)		Price ($/oz)		GRP		GRP Expenditure ($ 1,000)	
					Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Kellogg's	Frosted Flakes	0.09	134	10.7	2.84	1.34	0.143	0.028	362	285	291	345
GM	Cinnamon Toast Crunch	0.47	192	9.5	1.93	1.07	0.164	0.036	580	237	365	226
GM	Lucky Charms	0.19	189	12.1	1.55	0.83	0.183	0.041	544	295	310	176
Kellogg's	Froot Loops	0.56	132	13.2	1.22	0.66	0.170	0.042	208	304	156	234
Kellogg's	Apple Jacks	0.09	133	13.7	0.96	0.54	0.170	0.047	218	279	196	257
GM	Cocoa Puffs	0.19	160	13.2	0.70	0.73	0.179	0.046	325	272	190	170
Pepsi Co.	Quaker Cap'n Crunch	0.41	209	12.2	0.69	0.46	0.146	0.046	57	123	65	104
Post	Fruity Pebbles	0.21	164	12.3	0.65	0.44	0.166	0.048	236	260	129	188

Table 2. Demand Estimation Results for Homogeneous Models

Specifications	Full Awareness MNL w/ Static Advertising		Limited Awareness MNL w/ Advertising Stock		
Samples	Full	Jacknifed	Full	Jacknifed	Full
	(1)	(2)	(3)	(4)	(5)
Price	-4.416***	-4.304***	-3.857***	-4.472**	-3.218***
	(0.963)	(1.057)	(0.949)	(1.814)	(0.926)
Sugar	-3.600***	-3.329***	-3.878***	-3.443***	
	(0.253)	(0.304)	(0.445)	(0.572)	
Sodium	-0.505*	-0.426	0.063	-0.473	
	(0.266)	(0.305)	(0.427)	(0.966)	
Saturated Fat	-0.223***	-0.187**	-0.503***	-0.074	
	(0.065)	(0.079)	(0.089)	(0.157)	
General Mills	0.626***	0.632***	0.560***	0.692***	
	(0.067)	(0.070)	(0.131)	(0.126)	
Kellogg's	0.902***	0.876***	0.917***	0.912***	
	(0.074)	(0.085)	(0.079)	(0.257)	
Advertising	0.228***	0.261***			
	(0.084)	(0.101)			
Brand Dummies					Y
α			0.869**	0.739***	0.688**
			(0.434)	(0.272)	(0.305)
λ			0.769*	0.690***	0.796***
			(0.404)	(0.088)	(0.226)
σ			-0.496	-0.248	-0.551
			(1.475)	(2.788)	(0.978)
Constant	0.018	-0.350	0.291	-2.005	-3.458***
	(0.406)	(0.620)	(0.863)	(1.810)	(0.371)
Observations	3,520	3,080	3,520	3,080	3520
First Stage F-Statistic	14.158	11.893	14.158	11.893	12.465
p-value	0.000	0.000	0.000	0.000	0.000
Hansen J Statistic	2.585	3.079	1.773	2.874	4.380
p-value	0.629	0.799	0.777	0.579	0.223

Note. Full samples contain all eight brands and jacknifed samples remove Kellogg's Frosted Flake, the least sugary cereal brand that has the largest market share. *** significant at 0.01 level, ** significant at 0.05 level, * significant at 0.1 level.

Table 3. Demand Estimation Results for Heterogeneous Models

Specifications	Full Awareness MNL w/o Advertising (1)		Full Awareness MNL w/ Advertising Stock (2)		Limited Awareness MNL w/ Advertising Stock (3)	
Variables	Mean	Deviations	Mean	Deviations	Mean	Deviations
Price	-5.846***	-2.072***	-5.333***	-1.353***	-4.894***	-1.616***
	(1.231)	(0.429)	(0.876)	(0.304)	(0.968)	(0.056)
Sugar	-4.062***	0.450	-4.419***	-0.278***	-3.884***	-0.303***
	(0.390)	(0.342)	(0.379)	(0.034)	(0.442)	(0.027)
Sodium	-0.531	-0.290***	-0.517	-0.652***	-0.121	-0.506***
	(0.577)	(0.110)	(0.761)	(0.230)	(0.421)	(0.027)
Saturated Fat	-0.609***	-0.662***	-0.642***	-0.591***	-0.643***	-0.478***
	(0.205)	(0.085)	(0.170)	(0.075)	(0.088)	(0.043)
General Mills	0.628***	-0.319***	0.578***	-0.207***	0.491***	-0.354***
	(0.049)	(0.066)	(0.063)	(0.049)	(0.131)	(0.035)
Kellogg's	0.905***	0.177***	0.929***	0.302***	0.884***	0.233***
	(0.126)	(0.015)	(0.065)	(0.037)	(0.079)	(0.029)
α			0.376**	0.106***	0.874**	0.203***
			(0.171)	(0.036)	(0.427)	(0.023)
λ			0.693*		0.759*	
			(0.360)		(0.407)	
σ			-0.412		-0.487	
			(0.864)		(1.463)	
Constant	-1.252**	-0.165**	-1.111***	0.102***	0.552	0.094***
	(0.592)	(0.082)	(0.315)	(0.035)	(0.850)	(0.024)
Observations	3,520		3,520		3,520	
First Stage F-Statistic	14.158		14.158		14.158	
p-value	0.000		0.000		0.000	
Hansen J Statistic	2.301		2.131		1.601	
p-value	0.681		0.712		0.809	

Note. *** significant at 0.01 level, ** significant at 0.05 level, * significant at 0.1 level.

Table 4. Predicted Price and Advertising GRP Elasticities

		Kellogg's Frosted Flakes	GM Cinnamon Toast Crunch	GM Lucky Charms	Kellogg's Froot Loops	Kellogg's Apple Jacks	GM Cocoa Puffs	Pepsi Co. Quaker Cap'n Crunch!	Post Fruity Pebbles
Price Elasticities									
Kellogg's	Frosted Flakes	-0.839	0.094	0.095	0.093	0.094	0.096	0.095	0.095
GM	Cinnamon Toast Crunch	0.049	-1.050	0.056	0.055	0.056	0.057	0.057	0.057
GM	Lucky Charms	0.044	0.049	-1.187	0.049	0.050	0.051	0.051	0.051
Kellogg's	Froot Loops	0.042	0.047	0.048	-1.095	0.047	0.048	0.048	0.048
Kellogg's	Apple Jacks	0.031	0.035	0.036	0.035	-1.111	0.037	0.036	0.036
GM	Cocoa Puffs	0.022	0.025	0.025	0.025	0.025	-1.194	0.026	0.026
Pepsi Co.	Quaker Cap'n Crunch	0.015	0.018	0.018	0.017	0.018	0.018	-0.975	0.018
Post	Fruity Pebbles	0.022	0.025	0.025	0.024	0.025	0.026	0.026	-1.100
Advertising GRP Elasticities									
Kellogg's	Frosted Flakes	13.909	-0.739	-0.703	-0.810	-0.722	-0.659	-0.357	-0.484
GM	Cinnamon Toast Crunch	-0.821	13.209	-0.758	-0.763	-0.583	-0.397	-0.339	-0.423
GM	Lucky Charms	-0.805	-0.958	13.656	-0.776	-0.593	-0.404	-0.345	-0.431
Kellogg's	Froot Loops	-1.102	-1.082	-0.871	15.519	-0.669	-0.455	-0.388	-0.485
Kellogg's	Apple Jacks	-0.930	-1.072	-0.863	-0.868	15.577	-0.451	-0.385	-0.481
GM	Cocoa Puffs	-0.919	-1.063	-0.856	-0.861	-0.658	15.644	-0.383	-0.478
Pepsi Co.	Quaker Cap'n Crunch	-0.621	-0.572	-0.461	-0.463	-0.354	-0.241	8.488	-0.257
Post	Fruity Pebbles	-0.903	-1.070	-0.862	-0.866	-0.662	-0.451	-0.385	15.728

Note. Elasticities are based on random coefficient limited awareness model with advertising stock reported in column (3) of Table 3. Each entry represents the mean elasticities averaged across all of 55 biweek periods and 8 DMAs. Each cross elasticity give the percentage change in demand of the row cereal product with respect to changes in price or advertising GRP exposure of the column product. Advertising elasticities represent a 1% change in quantity demanded due to a 1000% change in advertising GRP.

Table 5. Predicted Average GRP, Prices and Market Shares of Different Participation Scenarios

General Mills' Strategy	Firm	Brand	Kellogg's does Not Participate			Kellogg's Participates but does Not Reformulate			Kellogg's Participates & Reformulates		
			GRP	Price ($/oz)	Shares (%)	GRP	Price ($/oz)	Shares (%)	GRP	Price ($/oz)	Shares (%)
General Mills does Not Participate	Kellogg's	Frosted Flakes	550	0.332	2.39	578	0.331	2.11	564	0.334	2.22
	GM	Cinnamon Toast Crunch	707	0.311	2.18	700	0.311	2.77	696	0.311	2.47
	GM	Lucky Charms	265	0.321	1.68	288	0.321	1.69	102	0.320	1.40
	Kellogg's	Froot Loops	591	0.286	1.47	0	0.282	1.09	854	0.289	2.23
	Kellogg's	Apple Jacks	203	0.346	1.11	0	0.343	0.81	707	0.350	1.68
	GM	Cocoa Puffs	157	0.351	0.98	33	0.351	0.94	30	0.350	0.86
	Pepsi Co.	Quaker Cap'n Crunch	3	0.314	0.61	0	0.314	0.47	0	0.314	0.45
	Post	Fruity Pebbles	79	0.253	0.80	1	0.253	0.71	0	0.252	0.63
General Mills Participates but does not Reformulate	Kellogg's	Frosted Flakes	588	0.332	2.56	578	0.331	3.04	623	0.334	2.43
	GM	Cinnamon Toast Crunch	740	0.310	2.38	680	0.311	2.42	683	0.310	2.09
	GM	Lucky Charms	0	0.318	1.18	0	0.318	0.91	0	0.318	0.78
	Kellogg's	Froot Loops	640	0.286	1.74	0	0.282	1.16	875	0.289	2.02
	Kellogg's	Apple Jacks	185	0.346	1.49	0	0.343	0.78	119	0.349	1.59
	GM	Cocoa Puffs	0	0.350	0.60	0	0.350	0.67	0	0.349	0.58
	Pepsi Co.	Quaker Cap'n Crunch	0	0.314	0.41	278	0.314	0.67	0	0.314	0.40
	Post	Fruity Pebbles	0	0.252	0.50	114	0.254	0.87	0	0.252	0.55
General Mills Participates & Reformulates	Kellogg's	Frosted Flakes	532	0.332	2.13	568	0.331	2.56	631	0.334	2.68
	GM	Cinnamon Toast Crunch	704	0.311	2.33	691	0.311	2.42	736	0.311	2.60
	GM	Lucky Charms	239	0.322	1.70	272	0.322	1.76	136	0.321	1.47
	Kellogg's	Froot Loops	581	0.286	1.53	0	0.282	1.08	958	0.289	2.15
	Kellogg's	Apple Jacks	214	0.346	1.14	0	0.343	0.73	668	0.350	1.61
	GM	Cocoa Puffs	187	0.353	1.09	187	0.353	1.23	125	0.352	1.04
	Pepsi Co.	Quaker Cap'n Crunch	2	0.314	0.54	1	0.314	0.43	0	0.314	0.42
	Post	Fruity Pebbles	80	0.253	0.83	20	0.253	0.74	0	0.252	0.74

Table 6. Measuring Advertising Competition

		Kellogg's Frosted Flakes	GM Cinnamon Toast Crunch	GM Lucky Charms	Kellogg's Froot Loops	Kellogg's Apple Jacks	GM Cocoa Puffs	Pepsi Co. Quaker Cap'n Crunch!	Post Fruity Pebbles
Observed									
Kellogg's	Frosted Flakes		0.100	0.398*	0.243	-0.081	0.312*	0.218	0.008
GM	Cinnamon Toast Crunch	0.916		0.422*	-0.034	-0.073	0.533*	-0.279	0.006
GM	Lucky Charms	1.151	0.234		0.086	0.271	0.494*	-0.068	0.103
Kellogg's	Froot Loops	0.966	0.049	0.185		0.169	0.003	-0.230	-0.230
Kellogg's	Apple Jacks	1.285	0.368	0.134	0.319		-0.009	-0.073	0.106
GM	Cocoa Puffs	1.772	0.856	0.621	0.806	0.487		0.191	0.067
Pepsi Co.	Quaker Cap'n Crunch	1.759	0.842	0.608	0.793	0.474	0.013		0.195
Post	Fruity Pebbles	1.656	0.740	0.506	0.690	0.372	0.116	0.103	
Simulated									
Kellogg's	Frosted Flakes		-0.096	-0.192	0.039	-0.086	-0.096	-0.218	-0.474*
GM	Cinnamon Toast Crunch	0.916		-0.191	-0.097	-0.267	0.582*	0.271	0.501*
GM	Lucky Charms	1.151	0.234		-0.229	0.386*	-0.096	-0.007	0.036
Kellogg's	Froot Loops	0.966	0.049	0.185		0.021	-0.338*	-0.047	-0.206
Kellogg's	Apple Jacks	1.285	0.368	0.134	0.319		-0.248	0.106	0.106
GM	Cocoa Puffs	1.772	0.856	0.621	0.806	0.487		0.199	0.508*
Pepsi Co.	Quaker Cap'n Crunch	1.759	0.842	0.608	0.793	0.474	0.013		0.670*
Post	Fruity Pebbles	1.656	0.740	0.506	0.690	0.372	0.116	0.103	

Note. The upper-triangle shows the correlation between observed and simulated GRPs (* significant at .1 level). The lower-triangle shows the relative distance of utilities. Red and green colors refer to negative and positive correlation, respectively. Negative and positive correlation in GRP waves are consistent with avoidance and competition respectively.

Table 7. Firm Level Advertising Competition

	Kellogg's	General Mills	Pepsi Co.	Post
Observed				
Kellogg's		+	-	-
General Mills	0.244		-	+
Pepsi Co.	-0.070	-0.062		+
Post	-0.072	0.081	0.195	
Simulated				
Kellogg's		-	-	-
General Mills	-0.313*		+	+
Pepsi Co.	-0.130	0.206		+
Post	-0.394*	0.483*	0.670*	

Note. * Significant at .1 level.

Table 8. Payoffs of Kellogg's and General Mills in Strategic Form ($ Million)

	K (1)	K (2)	K (3)
GM (1)	(22, 21)	(18, 24)	(28, 21)
GM (2)	(26, 18)	(22, 17)	(27, 15)
GM (3)	(21, 22)	(19, 24)	(29, 23)

Note. Two players: Kellogg's (K) and General Mills (GM).
Each player has the following three strategies:
(1): Not participate;
(2): Participate, but not reformulate and with restricted advertising;
(3): Participate and reformulate;
In each parentheses, the first number is Kellogg's payoff and the second one is General Mills'.

Table A1. Full Awareness Demand Estimation Results with 30 Major Cereal Brands as Inside Goods

Specifications	**Homogenous MNL**		**Heterogeneous MNL**					
	Linear Sugar	Nonlinear	Linear Sugar		Nonlinear Sugar		Brand Fixed Effect	
	(1)	(2)	(3)		(4)		(5)	
Variables			Mean	Deviations	Mean	Deviations	Mean	Deviations
Price	-15.898***	-16.276***	-7.801***	0.756***	-10.612***	4.587***	-10.080***	-0.047***
	(1.384)	(1.259)	(0.527)	(0.266)	(0.540)	(1.833)	(1.711)	(0.011)
Sugar	-0.198***	-2.622**	-0.241***	-0.176	-1.643***	-0.891**	-5.581**	-0.895***
	(0.065)	(1.297)	(0.062)	(0.130)	(0.551)	(0.423)	(2.836)	(0.308)
Sugar^2		11.648**			6.509***	-1.287*	9.591**	-2.032
		(5.170)			(1.227)	(0.665)	(4.854)	(3.725)
Sugar^3		-17.502**			-5.948***	1.977***	-6.737***	1.193***
		(7.420)			(0.785)	(0.285)	(2.524)	(0.423)
Sodium	0.336***	0.470***	0.330***	0.040***	-0.220*	-0.351***	-1.557***	1.523***
	(0.098)	(0.109)	(0.103)	(0.008)	(0.125)	(0.167)	(0.505)	(0.174)
Saturated Fat	-0.059	-0.059	-0.232***	-0.573***	-0.402***	-0.691***	-0.175	-0.380**
	(0.055)	(0.062)	(0.055)	-(0.087)	(0.062)	(0.129)	(0.389)	(0.162)
General Mills	0.554***	0.681***	0.461***	-0.325***	0.536***	-0.263***	0.067	-0.195***
	(0.079)	(0.046)	(0.066)	(0.031)	(0.066)	(0.059)	(0.270)	(0.046)
Kellogg's	1.082***	0.563	1.082***	0.015***	0.951***	0.094*	0.795***	0.365
	(0.057)	(0.074)	(0.052)	(0.001)	(0.052)	(0.054)	(0.248)	(1.539)
α	0.662***	1.091***	0.658***	0.103	0.797***	-0.153*	3.434**	-0.093
	(0.043)	(0.055)	(0.048)	(0.080)	(0.147)	(0.080)	(1.540)	(0.059)
λ			0.598**		0.687*		0.645*	
			(0.227)		(0.394)		(0.351)	
σ			-0.319		-0.323		-0.406	
			(0.369)		(0.539)		(0.714)	
Constant	-2.419***	-2.407***	-2.543***	-0.444***	-1.979***	-0.495***	--	--
	(0.207)	(0.210)	(0.168)	(0.129)	(0.183)	(0.052)	--	--
Observations	4,770	4,770	4,770		4,770		4,770	
First Stage F-Statistic	82.386	78.395	82.386		78.395		14.299	
p-value	0.000	0.000	0.000		0.000		0.000	
Hansen J Statistic	2.352	2.158	1.937		1.906		4.149	
p-value	0.799	0.827	0.858		0.862		0.528	

Note. *** significant at 0.01 level, ** significant at 0.05 level, * significant at 0.1 level.

Table A2(a). Predicted Price and Advertising GRP Elasticities of Full Awareness Model with Advertising Stock

		Kellogg's Frosted Flakes	GM Cinnamon Toast Crunch	GM Lucky Charms	Kellogg's Froot Loops	Kellogg's Apple Jacks	GM Cocoa Puffs	Pepsi Co. Quaker Cap'n Crunch!	Post Fruity Pebbles
Price Elasticities									
Kellogg's	Frosted Flakes	-1.220	0.121	0.135	0.188	0.196	0.134	0.181	0.191
GM	Cinnamon Toast Crunch	0.084	-1.474	0.191	0.086	0.081	0.178	0.110	0.095
GM	Lucky Charms	0.081	0.165	-1.708	0.079	0.078	0.156	0.088	0.083
Kellogg's	Froot Loops	0.092	0.061	0.065	-1.553	0.100	0.066	0.093	0.097
Kellogg's	Apple Jacks	0.073	0.044	0.049	0.076	-1.553	0.050	0.072	0.077
GM	Cocoa Puffs	0.046	0.087	0.089	0.046	0.045	-1.762	0.049	0.047
Pepsi Co.	Quaker Cap'n Crunch	0.039	0.035	0.032	0.041	0.042	0.031	-1.414	0.045
Post	Fruity Pebbles	0.052	0.037	0.038	0.054	0.056	0.037	0.056	-1.551
Advertising GRP Elasticities									
Kellogg's	Frosted Flakes	4.718	-0.458	-0.537	-0.671	-0.367	-0.538	-0.206	-0.253
GM	Cinnamon Toast Crunch	-0.423	5.026	-0.413	-0.456	-0.434	-0.278	-0.190	-0.287
GM	Lucky Charms	-0.354	-0.671	5.065	-0.366	-0.364	-0.219	-0.238	-0.372
Kellogg's	Froot Loops	-0.207	-0.377	-0.132	3.142	-0.246	-0.136	-0.207	-0.231
Kellogg's	Apple Jacks	-0.159	-0.080	-0.094	-0.175	3.004	-0.097	-0.156	-0.179
GM	Cocoa Puffs	-0.120	-0.216	-0.228	-0.127	-0.127	4.417	-0.125	-0.126
Pepsi Co.	Quaker Cap'n Crunch	-0.251	-0.178	-0.181	-0.275	-0.129	-0.179	2.796	-0.103
Post	Fruity Pebbles	-0.132	-0.378	-0.208	-0.145	-0.158	-0.085	-0.139	3.487

Note. Elasticities are based on demand estimates from random coefficient full awareness model with advertising stock reported in column (3) of Table 2. Each entry represents the mean elasticities averaged across all of 55 biweek periods and 8 DMAs. Each cross elasticity give the percentage change in demand of the row cereal product with respect to changes in price or advertising GRP exposure of the column product. Advertising elasticities represent a 1% change in quantity demanded due to a 1000% change in advertising GRP.

Table A2(b). Predicted Price and Advertising GRP Elasticities of Full Awareness Model with Static Advertising GRP

		Kellogg's Frosted Flakes	GM Cinnamon Toast Crunch	GM Lucky Charms	Kellogg's Froot Loops	Kellogg's Apple Jacks	GM Cocoa Puffs	Pepsi Co. Quaker Cap'n Crunch!	Post Fruity Pebbles
Price Elasticities									
Kellogg's	Frosted Flakes	-1.245	0.239	0.218	0.189	0.214	0.146	0.194	0.247
GM	Cinnamon Toast Crunch	0.098	-1.580	0.226	0.098	0.128	0.254	0.111	0.127
GM	Lucky Charms	0.145	0.176	-1.849	0.099	0.137	0.157	0.117	0.147
Kellogg's	Froot Loops	0.185	0.074	0.092	-1.634	0.151	0.069	0.200	0.142
Kellogg's	Apple Jacks	0.100	0.104	0.116	0.159	-1.606	0.066	0.085	0.084
GM	Cocoa Puffs	0.051	0.101	0.142	0.097	0.054	-1.784	0.119	0.054
Pepsi Co.	Quaker Cap'n Crunch	0.080	0.041	0.068	0.053	0.048	0.095	-1.506	0.103
Post	Fruity Pebbles	0.086	0.101	0.038	0.117	0.109	0.065	0.072	-1.768
Advertising GRP Elasticities									
Kellogg's	Frosted Flakes	3.527	-0.350	-0.444	-0.503	-0.279	-0.396	-0.151	-0.178
GM	Cinnamon Toast Crunch	-0.309	4.144	-0.292	-0.339	-0.338	-0.226	-0.145	-0.223
GM	Lucky Charms	-0.270	-0.556	4.066	-0.278	-0.279	-0.187	-0.196	-0.261
Kellogg's	Froot Loops	-0.156	-0.337	-0.094	2.424	-0.183	-0.097	-0.169	-0.179
Kellogg's	Apple Jacks	-0.140	-0.057	-0.081	-0.125	3.278	-0.076	-0.123	-0.140
GM	Cocoa Puffs	-0.097	-0.184	-0.169	-0.104	-0.091	3.381	-0.097	-0.107
Pepsi Co.	Quaker Cap'n Crunch	-0.179	-0.146	-0.132	-0.218	-0.111	-0.146	2.005	-0.073
Post	Fruity Pebbles	-0.100	-0.287	-0.154	-0.123	-0.132	-0.067	-0.098	3.007

Note. Each entry represents the mean elasticities averaged across all of 55 biweek periods and 8 DMAs. Each cross elasticity give the percentage change in demand of the row cereal product with respect to changes in price or advertising GRP exposure of the column product. Advertising elasticities represent a 1% change in quantity demanded due to a 1000% change in advertising GRP.

Table A2(c). Predicted Price and Advertising GRP Elasticities of Full Awareness Model with Static Advertising Expenditure

		Kellogg's Frosted Flakes	GM Cinnamon Toast Crunch	GM Lucky Charms	Kellogg's Froot Loops	Kellogg's Apple Jacks	GM Cocoa Puffs	Pepsi Co. Quaker Cap'n Crunch!	Post Fruity Pebbles
Price Elasticities									
Kellogg's	Frosted Flakes	-1.934	0.279	0.316	0.223	0.365	0.186	0.328	0.357
GM	Cinnamon Toast Crunch	0.160	-2.521	0.365	0.225	0.213	0.365	0.217	0.257
GM	Lucky Charms	0.326	0.293	-2.958	0.111	0.207	0.286	0.169	0.202
Kellogg's	Froot Loops	0.284	0.125	0.271	-2.606	0.228	0.106	0.258	0.215
Kellogg's	Apple Jacks	0.198	0.117	0.177	0.362	-2.414	0.187	0.142	0.190
GM	Cocoa Puffs	0.078	0.149	0.174	0.115	0.072	-2.684	0.175	0.071
Pepsi Co.	Quaker Cap'n Crunch	0.117	0.070	0.110	0.220	0.163	0.317	-2.362	0.120
Post	Fruity Pebbles	0.146	0.228	0.067	0.166	0.396	0.137	0.190	-2.819
Advertising GRP Elasticities									
Kellogg's	Frosted Flakes	9.595	-0.833	-1.013	-1.310	-0.820	-0.955	-0.362	-0.408
GM	Cinnamon Toast Crunch	-0.744	11.065	-0.688	-0.972	-0.769	-0.521	-0.340	-0.575
GM	Lucky Charms	-0.729	-1.418	11.201	-0.630	-0.678	-0.437	-0.627	-0.623
Kellogg's	Froot Loops	-0.479	-0.826	-0.234	6.183	-0.423	-0.220	-0.414	-0.476
Kellogg's	Apple Jacks	-0.368	-0.171	-0.182	-0.361	9.449	-0.269	-0.336	-0.376
GM	Cocoa Puffs	-0.228	-0.426	-0.401	-0.267	-0.215	8.149	-0.230	-0.311
Pepsi Co.	Quaker Cap'n Crunch	-0.433	-0.414	-0.385	-0.501	-0.245	-0.365	4.889	-0.193
Post	Fruity Pebbles	-0.222	-0.684	-0.448	-0.319	-0.298	-0.171	-0.245	7.506

Note. Each entry represents the mean elasticities averaged across all of 55 biweek periods and 8 DMAs. Each cross elasticity give the percentage change in demand of the row cereal product with respect to changes in price or advertising GRP exposure of the column product. Advertising elasticities represent a 1% change in quantity demanded due to a 1000% change in advertising GRP.

Table A3. Full Awareness Predicted GRP, Prices and Market Shares of Different Scenarios

General Mills' Strategy	Firm	Brand	Kellogg's does Not Participate			Kellogg's Participates but does Not Reformulate			Kellogg's Participates & Reformulates		
			GRP	Price ($/oz)	Shares (%)	GRP	Price ($/oz)	Shares (%)	GRP	Price ($/oz)	Shares (%)
General Mills (GM) does Not Participate	Kellogg's	Frosted Flakes	527	0.329	2.33	576	0.330	2.06	558	0.331	2.18
	GM	Cinnamon Toast Crunch	701	0.309	2.17	681	0.311	2.69	686	0.309	2.49
	GM	Lucky Charms	269	0.319	1.66	286	0.321	1.67	95	0.318	1.40
	Kellogg's	Froot Loops	556	0.284	1.52	0	0.278	1.27	837	0.287	2.29
	Kellogg's	Apple Jacks	184	0.347	1.08	0	0.339	0.85	687	0.347	1.51
	GM	Cocoa Puffs	122	0.349	0.93	28	0.348	0.89	24	0.347	0.78
	Pepsi Co.	Quaker Cap'n Crunch	2	0.311	0.57	0	0.312	0.48	0	0.312	0.30
	Post	Fruity Pebbles	68	0.253	0.82	1	0.251	0.61	0	0.251	0.66
General Mills Participates but does Not Reformulate	Kellogg's	Frosted Flakes	598	0.330	2.52	571	0.330	3.10	597	0.331	2.38
	GM	Cinnamon Toast Crunch	714	0.307	2.46	643	0.308	2.45	655	0.308	2.14
	GM	Lucky Charms	0	0.316	1.21	0	0.315	1.02	0	0.316	0.86
	Kellogg's	Froot Loops	635	0.286	1.76	0	0.280	1.36	839	0.287	1.97
	Kellogg's	Apple Jacks	164	0.343	1.48	0	0.341	0.84	104	0.346	1.64
	GM	Cocoa Puffs	0	0.348	0.62	0	0.348	0.61	0	0.349	0.66
	Pepsi Co.	Quaker Cap'n Crunch	0	0.312	0.47	280	0.313	0.68	0	0.313	0.37
	Post	Fruity Pebbles	0	0.249	0.39	102	0.252	0.72	0	0.252	0.63
GM Participates & Reformulates	Kellogg's	Frosted Flakes	553	0.331	2.19	538	0.327	2.63	606	0.331	2.66
	GM	Cinnamon Toast Crunch	690	0.309	2.31	684	0.310	2.42	721	0.308	2.65
	GM	Lucky Charms	200	0.320	1.70	251	0.321	1.79	124	0.320	1.61
	Kellogg's	Froot Loops	566	0.284	1.58	0	0.281	1.28	888	0.287	1.94
	Kellogg's	Apple Jacks	174	0.344	1.17	0	0.342	0.85	649	0.347	1.48
	GM	Cocoa Puffs	171	0.351	0.98	169	0.351	1.22	102	0.350	1.11
	Pepsi Co.	Quaker Cap'n Crunch	1	0.312	0.47	2	0.311	0.54	0	0.310	0.47
	Post	Fruity Pebbles	72	0.253	0.86	11	0.250	0.73	0	0.251	0.70

Table A4. Full Awareness Payoffs of Kellogg's and General Mills in Strategic Form ($ Million)

	K (1)	K (2)	K (3)
GM (1)	(21, 20)	(18, 22)	(25, 20)
GM (2)	(25, 18)	(20, 17)	(26, 15)
GM (3)	(21, 21)	(18, 23)	(26, 22)

Note. Two players: Kellogg's (K) and General Mills (GM).
Each player has the following three strategies:
(1): Not participate;
(2): Participate, but not reformulate and with restricted advertising;
(3): Participate and reformulate;
In each parentheses, the first number is Kellogg's payoff and the second one is General Mills'.

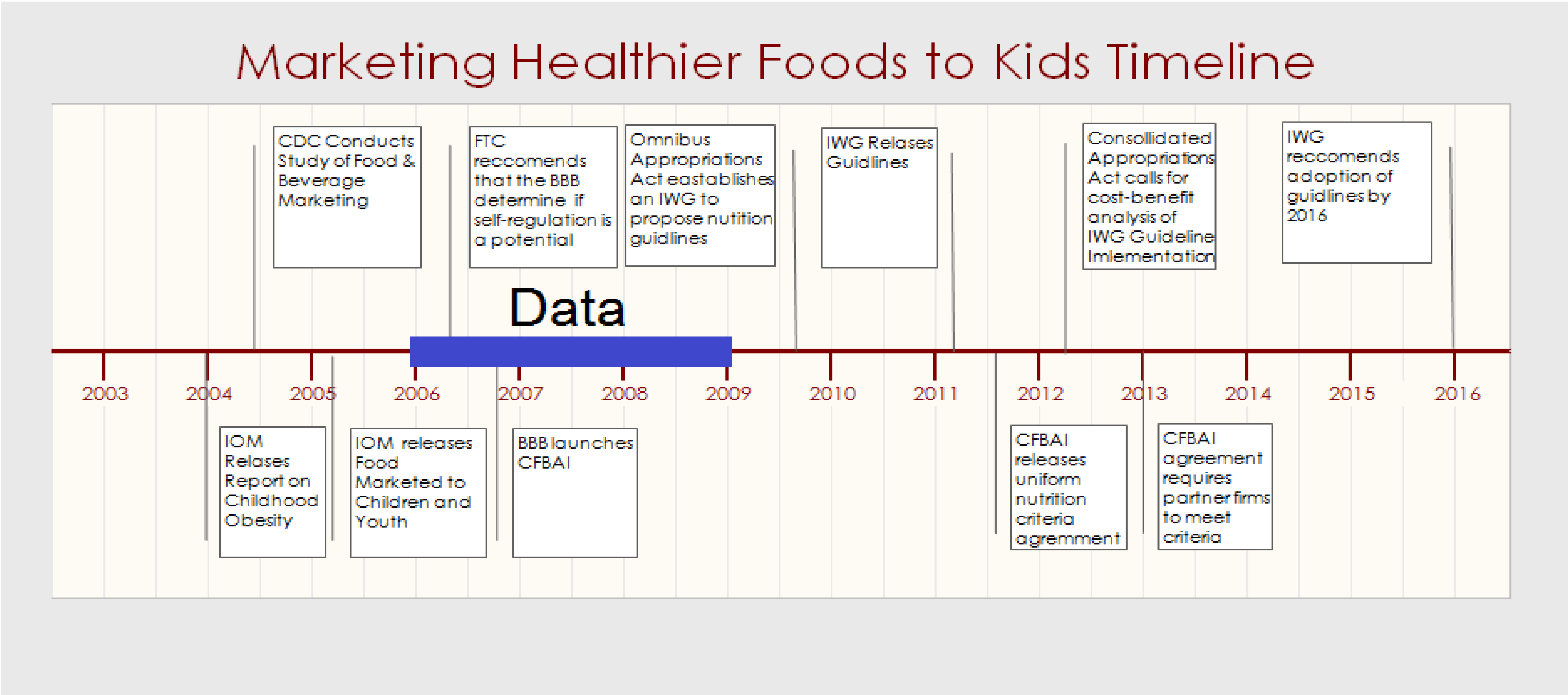

Figure 1. Chronicles of Food Marketing to Children

Figure 2. Children's Breakfast Cereals Brands Used in the Study

Note. We show the pictures of a typical front of packaging for the eight childrens' cereal brands used in this study.

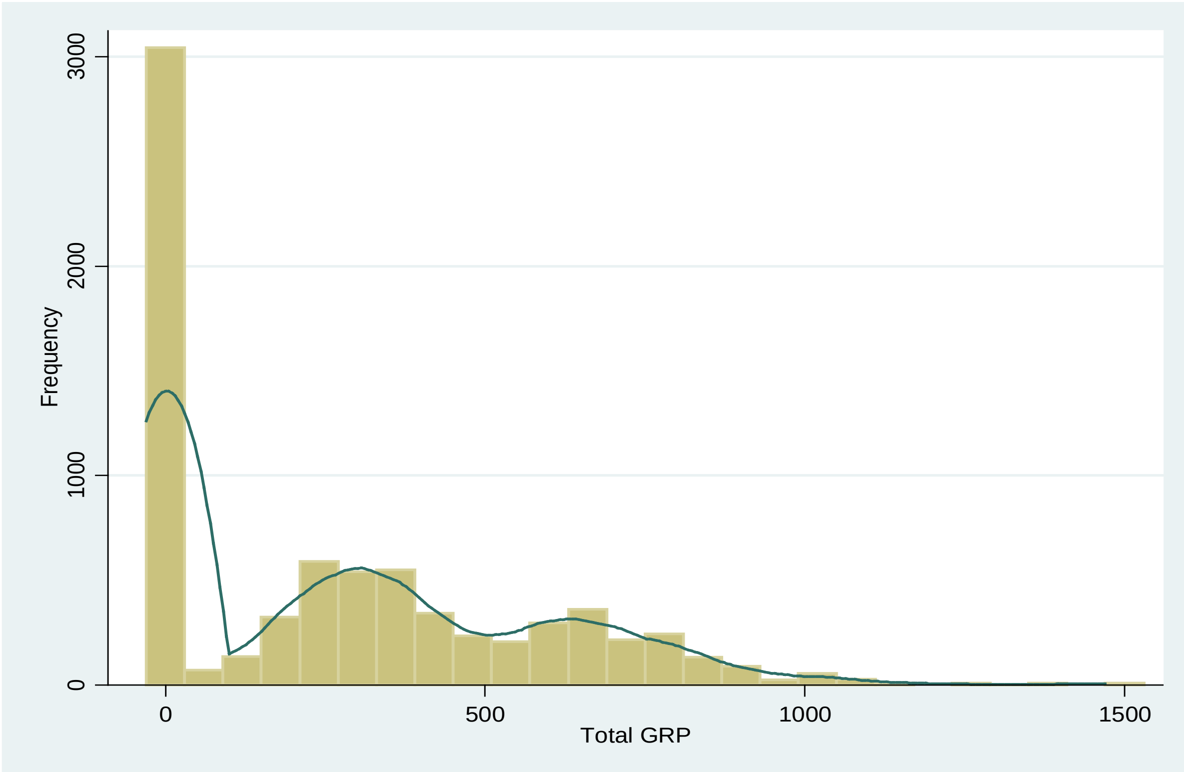

Figure 3. Frequency Distribution of GRP Levels

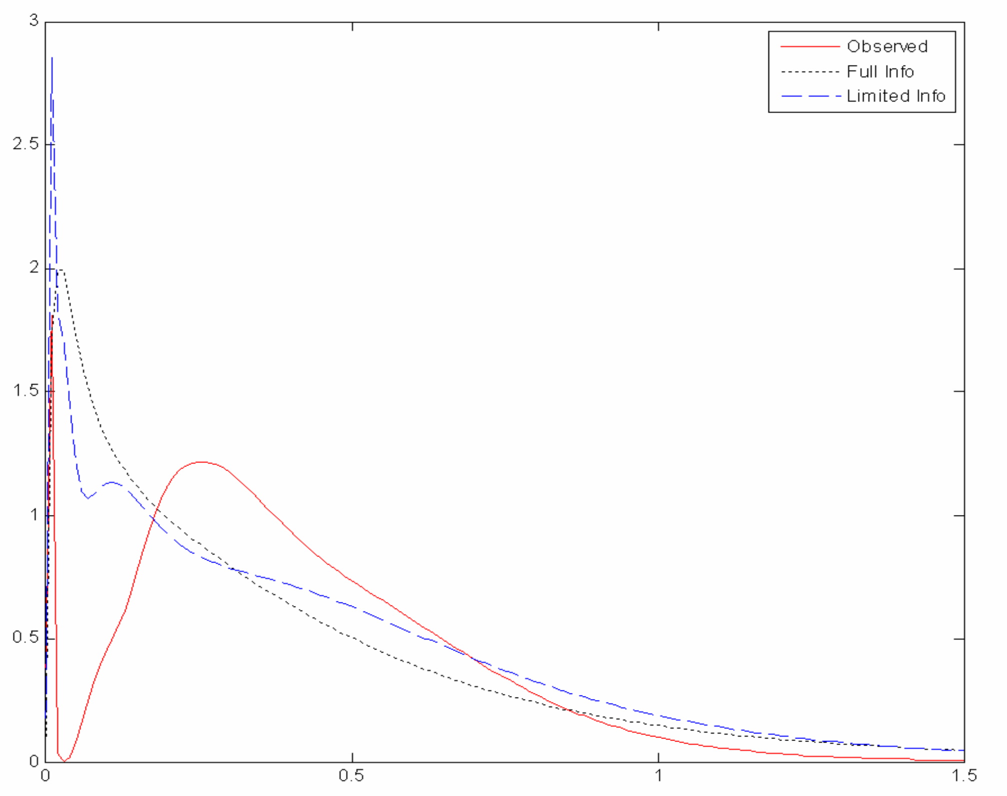

Figure 4. Kernel Density Estimates of Observed and Simulated GRP Distributions

		Affinity (KLIC)	Fit (MISE)	K-S Test
H0:	Observed GRP			
H1:	Limited Awareness	32.5705	0.2577	Reject H0
H2:	Full Awareness	54.5038	0.3617	Reject H0