Valuation of New Products in the Face of Consumer Income Disparity

Geoffrey M. Pofahl, Timothy J. Richards, & Glynn T. Tonsor[1]

Selected Paper prepared for presentation a the Agricultural & Applied Economics Association

Annual Meeting, Milwaukee, WI, July 26-28, 2009

[1] Authors are Assistant Professor, Morrison School of Management & Agribusiness, Arizona State University, Mesa, AZ; Morrison Chair of Agribusiness, Morrison School of Management & Agribusiness, Arizona State University, Mesa, AZ; and Assistant Professor, Department of Agricultural Economics, Michigan State University, East Lansing, MI. Contact author: Pofahl. email gpofahl@asu.edu. Support from the Economic Research Service of the USDA Cooperative Agreement No. 10.253 is gratefully acknowledged. All opinions and findings described herein are, however, the authors' and do no reflect the official position of USDA.

I. Introduction

Understanding the determinants of consumer food choices is complicated by constant change in the marketplace (Blaylock et al. 1999). On the demand-side, the ever changing status of age distribution, educational attainment, immigration rates, and other cultural phenomena means that food choice determinants and consequences continue to be difficult to pin down (Kinsey and Senauer 1996; Variyam and Golan 2002). Likewise, on the supply-side, greater competition has led to alternative retail formats, consolidation, production efficiencies and growing pressure to provide distinct products and shopping experiences that will secure consumer loyalty (Jekanowski and Binkley 2000). While much has been written about relationships between and amongst these market changes, we are not aware of any research that explores potential linkages between two contemporary issues of notable importance: (1) the widening income gap between rich and poor U.S. households (Browning 2003), and (2) the consistently high rate of new food product introduction.

Consumers benefit from new product introductions in at least two possible ways. First, if new products are notably different from those that are already being sold, consumers may experience an increase in welfare due to the extra variety offered by the new product (Draganska and Jain 2005). On the other hand, new products could have a negative variety effect if no notable innovations are presented and the new product simple increases the number of alternatives consumers must assess at the retail shelf. Second, new product introductions can cause existing product prices to increase or decrease. For example, if a company introduces a product that is very similar to existing products of a competing supplier, then consumers are likely to benefit from greater price competition between the rival firms. On the other hand, if the new product is more likely to compete with existing products from the same firm, the manufacturer or retailer (in the case of private label introductions) may be able to raise the prices of its whole line of competing products, thus creating a negative welfare effect for consumers. The net impact of price and variety effects can be either positive or negative.

The objective of this research is to begin exploring the welfare effects of new food product introductions and to determine whether such effects vary depending on the income classification of the customer base to which the products are introduced. In other words, when new products are introduced to both high- and low-income markets, is there a significant difference in estimated welfare effects that can be attributed to differences in consumer-base income levels? In an application involving new bottled juice introductions, we do, in fact, find notable differences in welfare effects accruing to different income-class cohorts. Our results provide important evidence of the need for an even greater understanding of new product welfare effects and how these effects vary across population groups and certain new product claims.

The remaining sections are organized as follows. In section two we highlight relevant literature surrounding consumer food choices as well as factors that influence manufacturer and retailer decisions to introduce and maintain food products on store shelves. Next, section three contains an outline of our modeling approach. We describe our empirical application and data source in section four. In section five and six we provide a discussion of our results, conclusions, and implications for future research.

II. Background

Several areas of literature establish the needs underlying our research objective. First is literature that explores the importance of income disparity in describing overall food choices and the potential health consequences of such choices. Second, significant research suggests that supply-side decisions as to which new products to introduce is increasingly being determined by automated processes that place notably higher value on financial measures than on consumers' possible appreciation for nutritional alternatives. Finally, there is a growing body of research aimed at estimating consumer and producer welfare effects resulting from new product introductions. It is this final body of work that will be used to link the previous two. Each of these research areas is discussed in turn below.

The link between household income and food choice is well established in the literature. For example, in Blaylock et al. (1999) income is emphasized as one of the most well-grounded determinants of food demand in theory and in practice. Other studies regularly refer to changes in income inequality to explain or predict changes in the food choice landscape (Kinsey and Senauer 1996). The rapidly expanding literature on obesity has also focused considerable attention on the role of income in affecting food choices that contribute to overweight. Drewnowski and Spector (2004), for example, show that the affordability of high-energy-density foods may be a plausible explanation for higher rates of overweight and obesity in low-income households. On the other hand, Zenk et al. (2005) provide evidence suggesting a negative relationship between household income and fruit and vegetable intake among certain consumer groups. Other research has even targeted the food-stamp program as a potential contributor to higher rates of obesity in low-income households (Ver Ploeg and Ralston 2008; Meyerhoeffer and Pylypchuk 2008; Chen, Yen, and Eastwood 2005). Studies of new product introduction and diffusion also highlight the importance of household income variety in determining the acceptance and potential success of new products (Horsky 1990; Song and Chintagunta 2003).

Another vein of literature suggests the important role of food suppliers in determining household food choices. Increased consumption of calories, refined carbohydrates and fats is not surprising considering the increased supply of such nutrients (Putnam et al. 2002). Likewise, numerous studies have shown that unhealthy food choices and subsequent obesity prevalence can be partially attributed to the available supply of foods from which consumers choose. For example, Morland et al. (2006) show that consumers' relative accessibility to supermarkets, as opposed to convenience stores, had negative effects on rates of obesity and overweight. In other words, consumer access to high-assortment supermarkets may be attributed to healthier food choices and lower rates of obesity. Similar studies demonstrate linkages between areas of differing income status, access to small- medium- or large-format food stores, product pricing, product assortments, and subsequent health measures (see e.g. Morris et al. 1992; Chung and Meyers. 1996; Horowitz et al. 2004; Block and Kouba 2006; and Inagami et al. 2006). An extensive review of these studies can be found in Ford and Dzewaltowski (2008).

Despite the many contributions of the supply-related studies above, none of them have addressed growing trends regarding automated management of retail assortments and how such practices will likely exacerbate the role of food suppliers in determining household food choices. Research in the area of category assortment and shelf space allocation continues to grow (e.g. Borin, Farris, and Freeland 1994; Bai and Kendall 2005; Kok and Fisher 2007) and retailers are rapidly investing in new technology solutions aimed at automating and optimizing store-level assortments and space allocations (Millstein 2005; Howell 2006; Amato-McCoy 2007; Progressive Grocer 2008).[2] Thus, retailers' increasing ability to make data-driven assortment decisions means that historical product selections could have a greater impact on future

[2] For example, see http://www.galleria-rts.com/ .

assortment change decisions. In other words, if consumer's do not show a historical preference for, say, healthy foods it may be less likely that an automated assortment plan ever recommends that a healthy new product be made available to those consumers. The literature also suggests that most automated assortment models are based on financial measures such as profit margins, inventory costs, etc., and pay relatively less attention to consumer satisfaction and preference change indicators that are difficult to measure (Borin, Farris, and Freeland 1994; Bai and Kendall 2005). Despite this, academic research and trade-press alike suggest that retailers are eager to develop data-driven measures that will improve their ability to understand consumer choices and potential preference changes.

A possible solution to retailers' difficultly in measuring consumer welfare changes associated with product assortment decisions can be found in the relatively new literature on new product valuation. There are only a handful of published papers that estimate the effects of new product introduction in food product categories.[3] The first is a study by Hausman (1994), who, motivated by the hypothesis that the CPI for food is biased by lack of consideration for new products, evaluated changes to consumer welfare and price index calculations due to the introduction of the ready-to-eat cereal, Apple-Cinnamon Cheerios. He found that consumer benefits from the new product introduction were quite significant. However, his research did not explore the effects of product introduction on the supply side of the market, e.g. firm profitability. In 2004, Kim estimated the changes in consumer and producer welfare due to the introduction of three processed cheese products. He decomposed his consumer welfare measure into portions attributable to changes in category variety and prices, respectively. He finds that

[3] Other industries which have benefited from research on the effects of new product introduction are tomography scanners (Trajtenberg 1989), automobiles (Petrin 2002), bath tissue (Hausman and Leonard 2002), and personal computers (Bayus, Erickson, and Jacobson 2003).

consumers benefit from the added variety associated with the three new cheese products but are harmed by subsequent price changes. He also finds that producers observe an increase in profits that can be attributed to the newly introduced products. Research in this area continues to grow with a study by Pofahl and Richards (2008) who introduce a new model of new product valuation that directly accounts for differences in product attributes and is capable of accommodating large demand choice sets.

Our review of the literature draws attention to the need for research that explores the potential usefulness of estimated welfare effects of new food product introductions in informing retail product assortment decisions. These potential welfare effects will likely vary across consumer groups and retailers that reside in geographies characterized by vastly different income classes. Understanding the welfare effects of new product introduction on different income groups could play a major role in management and planning decisions made by both private and political organizations. For example, government food assistance program administrators would be better able to anticipate the impact of emerging food trends on groups at risk for food insecurity or obesity.

Additional support for our proposed research can be seen in industry facts and census data that draw attention to the potential food choice implications we outline above. As can be seen in figure 1, the total number of new food products introduced has remained relatively steady at over 10,000 per year on average. When considering new food products that carry health related claims, introductions have increased from around 4,000 in 2002 to nearly 12,000 in 2007. Health related claims associated with these products include those that are classified as “Food-minus” or “Food-plus.” “Food-minus” claims include those such as “Low/no/Reduced Fat”, “Low/no/Reduced Sodium”, or “No Additives or Preservatives.” “Food-plus” claims include statements such as “Wholegrain,” “Organic,” “All Natural,” or “Vitamin/Mineral Fortified.” As can be seen in figure 2, both types of health related claims have seen increased use in new product introductions. A more detailed example of specific health related claims can be seen in figure 3. While all of the claims in this figure have appeared on a greater number of new products over the last five years, it is easy to see that claims of “Low/no/Reduced Transfat” have increased more than others in the three categories represented.

A probable explanation for these trends is the constant evolution of American consumers. An aging population, better education on the links between diet and health, immigration of ethnic populations, a greater need for convenience, and changes in income distribution all contribute to the food industry’s “mad dash” to develop “the next big thing” (Harris 2002; Variyam and Golan 2002; Blisard et al. 2002; Jekanowski and Binkley 2000). Since the effects of income inequality on the welfare effects of new product introductions is a major focal point of our proposed research, we provide information in figure 4 that emphasizes the widening gap between rich and poor Americans. This figure shows that the only income class that has seen an increase in its share of total household income from 1975 to 2005 is the wealthiest fifth of the population. On the other hand, the bottom four fifths have all experienced a decline in their share of total household income over the same 30 year period.

While it is reassuring to observe the increasing number of new product introductions that carry potential health changing messages, as alluded to in our literature review above, it may be the case that these products and their corresponding messages are not being sent to the stores in which low-income households shop. Even if these products are currently being introduced to stores that serve low-income populations, lower education levels associated with these populations may mean that such products are not as eagerly embraced as they would be in stores that serve high-income/high-education shoppers. Thus, in stores that serve low-income consumers it is possible that such products will not meet the financial threshold levels that retailers are using more and more to determine shelf space allocation. Through this study and future research in the area, we will contribute to the establishment of consumer welfare metrics that may assist retailers in better understanding the implications of product introductions and assortment decisions on objectives other than short-run profitability. For example, even if a new product does not meet acceptable financial standards for success, retailers could use our proposed welfare measures to infer whether or not consumers have benefited from the additional variety brought about by the introduction. In the future, it may be the case that retailers will begin to place greater weight on consumer welfare effects stemming from healthy new products as they realize that sustainable long-run financial success could depend on the overall health of a growing population.[4]

III. Model of New Product Valuation[5]

Welfare Measures

Changes in consumer welfare due to new product introduction are estimated using a common economic measure called compensating variation (CV). CV is defined as the difference

---

[4] In recent conversations with Wal-Mart's sustainability team we discovered that much of their sustainability objectives are not just focused on eco-friendly initiatives but are also aimed at encouraging healthier diets and lifestyle changes. For example, to participate in their own unique ways with the sustainability trend, many Wal-Mart Associates have set goals such as "stop smoking," "go on a diet," "eat locally grown fruits and vegetables," etc.

[5] This section is based on Pofahl and Richards (2009)

between pre- and post-introduction expenditure levels where utility is held constant at the post-introduction level. Specifically, CV is expressed as

(1) $$CV = e(p_1, p_N, u_1) - e(p_0, p_N^*(p_0), u_1),$$

where p_0 and p_1 are pre- and post-introduction price vectors for competing products, p_N is the observed price of the new product, $p_N^*(p_0)$ is a function defining the reservation price of the new product, i.e. the price at which demand for the product is equal to zero, and u_1 is post-introduction utility.[6] Hausman and Leonard (2002) and Kim (2004) show that (1) can be decomposed into a variety effect and a price effect as follows:

(2) $$\begin{aligned} CV = & \left[e(p_1, p_N, u_1) - e(p_1, p_N^*(p_1), u_1) \right] + \\ & \left[e(p_1, p_N^*(p_1), u_1) - e(p_0, p_N^*(p_0), u_1) \right], \end{aligned}$$

where the first bracketed term is the variety effect, or the increase in consumer welfare due to the availability of a new brand or brands, and the second bracketed term is the price effect.

To derive an empirical version of (2), a category demand model is required. To represent category demand we use the following log-linear relationship:

(3) $$Q_t(P_t, Y) = Y_t^{\theta} P_t^{\eta} \exp(\mu_t + Z_t \phi)$$

[6] We follow Hausman and Leonard (2002) by referring to (1) as CV, as opposed to –EV (equivalent variation). The reasoning here is simply a matter of what one labels as "new" and "old." In our scenario, the "new" price is the observed actual price, whereas the "old" price is partially constructed from estimated reservation prices. Thus, utility at the actual (post-introduction) price is used as the base.

where Q_t is category-level demand[7], Y_t is disposable income (or some proxy), P_t is a category-level price index, Z_t is a vector of seasonal indicator variables, θ is the income elasticity, and η is the category-level price elasticity.

Using Roy's identity we generate a partial differential equation which can then be solved by separation of variables integration for the indirect utility function:

$$(4) \qquad v(P_t, Y_t) = \left(\frac{Y_t^{(1-\theta)}}{1-\theta} \right) - A \left(\frac{P_t^{(1+\eta)}}{1+\eta} \right),$$

where $A = \exp(\mu + Z\phi)$. Solving for Y_t we obtain the following expenditure function:

$$(5) \qquad e\left(P, u\right) = \left[(1-\theta) \left(u + \frac{AP_t^{(1+\eta)}}{1+\eta} \right) \right]^{\frac{1}{(1+\theta)}}.$$

Substituting (3) and (4) into (1) and rearranging terms we get the following expression for CV (Hausman 1981):

$$(6) \qquad CV = \left[\frac{1-\theta}{(1+\eta)Y_1^{\theta}} \left(P_0 Q_0 - P_1 Q_1 \right) + Y_1^{1-\theta} \right]^{\frac{1}{1-\theta}} - Y_1,$$

where P_0 and P_1 are pre- and post- introduction price indices, Q_0 and Q_1 are pre- and post-introduction category demands, and Y_1 is post-introduction income. Following the decomposition in (2) we get the following expressions for the variety and price effects, respectively:

[7] i.e. the weekly sum of sales over all selected products in the category.

(7) $$VE = \left[\frac{1-\theta}{(1+\eta)Y_1^{\theta}} \left(P_1^* Q_1 - P_1 Q_1 \right) + Y_1^{1-\theta} \right]^{\frac{1}{1-\theta}} - Y_1$$

(8) $$PE = CV - VE,$$

where P_1^* is the post-introduction price index calculated using virtual, or reservation prices of the new products as opposed to their observed post-introduction values.

Calculating (5) requires that we first estimate (3) using observations from the post-introduction price and quantity information. However, computing (6) also requires information regarding pre-introduction prices and category-level sales. Aggregate sales are easily obtained by simply summing the sales for products being considered in the pre-introduction environment. Development of a pre-introduction price index, however, requires additional analysis.

Demand Model

Hausman (1994) indicates that the correct price to use for new products in the pre-introduction period is their “virtual” or “reservation” price. This is the price that sets demand for these products equal to zero. Since these prices are unobserved, they must be estimated using UPC-level demand or share equations. Using post-introduction data, we first estimate a UPC-level demand model for all products (old and new) in the category that are being considered. Using estimated parameters as well as mean prices for the existing products, we set the share or demand equations for new products equal to zero and solve for the reservation prices.

As with many other applications in marketing and industrial organization, new product valuation is inherently dependent on the estimation of substitution patterns between similar products within a category. Thus, whether or not the conclusions of such applications are of any value crucially depends on the quality of the underlying demand specification (Nevo 2000b).

We use a novel approach to demand estimation that explicitly incorporates product differentiation.[8] This framework is called the DM approach of Pinkse, Slade, and Brett (2002) and Pinkse and Slade (2004). The DM approach highlights the fact that differentiated products compete along many dimensions. While price remains the most obvious platform for competition, it is also quite obvious that the relative strength of competition in pricing is directly related to how similar products are in terms of real or perceived attributes. For example, the degree to which consumers respond to a price increase for, say, a 64oz bottle of Mott's apple juice depends not only on the number of other apple juice products in the category, but on how similar those products are along dimensions such as size, packaging, % juice content, and numerous other nutritional characteristics. Furthermore, we should also expect demand substitution between products to be determined by their relative proximity within some multidimensional attribute space. In other words, substitution patterns are spatially determined. Continuing with our example, if size is an important attribute for apple juice consumers then we should expect to see greater substitution between apple juice products that are a short distance from one another along that attribute dimension. However, it may be that size is not as important a characteristic as, say, brand. In that case, we would expect substitution patterns to reflect a much higher degree of brand, as opposed to size, loyalty.

To construct share equations required for virtual price estimation, we utilize distance metrics within the framework of the popular Linear Approximate Almost Ideal Demand System

[8] A full discussion of alternative demand models for differentiated product categories can be found in numerous published sources (e.g., Nevo, 2000; Pinkse & Slade, 2004, etc.)

(LA/AIDS) of Deaton and Muellbauer (1980). Formally, let $i \in (1,...,N)$ be the index of brands, $t \in (1,...,T)$ the time index, $p_t = (p_{1t},..., p_{Nt})$ the vector of retail prices, $q_t = (q_{1t},..., q_{Nt})$ the vector of brand quantities demanded, and $X_t = \sum_i p_{it} q_{it}$ total expenditure in time *t*. This information leads to the following share equations:

(9) $$w_{it} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} \ln(p_{jt}) + \beta_i \ln(X_t / P_t^*)$$

where $w_{it} = \dfrac{p_{jt} q_{jt}}{X_t}$ is the expenditure share for product *i* in time *t*, $\ln P_t^*$ is a log linear analogue of the Laspeyeres price index which is similar to Stone's price index (Moschini 1995), and α_i, γ_{ij}, and β_i are parameters.

The standard way to estimate (6) is to select (N-1) equations to which Seemingly Unrelated Regression (SUR) is applied. However, due to the large number of parameters that would have to be estimated, this procedure is problematic when applied to large choice sets. To reduce the number of model parameters, we replace all cross-price coefficients (γ_{ij}) in the model with a function of distance metrics. Specifically, defining γ_{ij} in (6) as $g(d_{ij}; \lambda_k)$ gives:

(10) $$w_{it} = \alpha_i + \gamma_{ii} \ln(p_{it}) + \sum_{j \neq i}^{N} g_{ij}(d_{ij}; \lambda) \ln(p_{jt}) + \beta_i \ln(X_t / P_t^*)$$

where $g_{ij}(\cdot)$ is a function of d_{ij}, a vector of distance metrics, and λ is a vector of parameters corresponding to each distance metric.

The function $g(\cdot)$ is chosen by the researcher. However, to allow for as much flexibility in substitution as possible, Pinkse, Slade, and Brett (2002) advocate the use of semi-parametric techniques such as series expansion methods (Li and Racine 2006). For example, assuming we have only two continuously defined metrics, a power series expansion of $g(\cdot)$ gives:

$$g(d^1, d^2; \lambda) = \sum_{r=0}^{R} \sum_{s=0}^{R} \lambda_{rs} (d^1)^r (d^2)^s \tag{11}$$

where R, the degree of the power series expansion, is determined by the data. In practice however, this procedure is complicated by the fact that some of the distance metrics are not continuous, but are 0-1 variables. Pinkse and Slade (2004) recommend that this problem be addressed by dividing $g(\cdot)$ into separate parts corresponding to each value of a compound discrete metric. Thus, a more general version of (8) is:

$$g(d; \lambda) = \sum_{m}^{D*} I(d^D = m) g_m(d^C) \tag{12}$$

where $I(\cdot)$ is an indicator function that equals 1 when the expression in parentheses is true and zero otherwise, d^D is a compound discrete measure taking $m = 1, ..., D*$ different values, and d^C is a vector of continuous metrics.

Substituting (9) into (7) gives us our final share expressions for each product under consideration. After estimating this system of equations we use average values of each variable along with the estimated model parameters to solve for the prices that set the new product shares equal to zero.[9]

[9] Uncompensated elasticities can be calculated just as with the original LA/AIDS model, but with the function of distance metrics used in place of the cross-price coefficients (Green and Alston 1990). This substitution creates the

In addition to virtual price estimates, we need to allow for the possibility that new product introductions affect the prices of other products as well (Hausman 1994; Hausman and Leonard 2002). One way to achieve this is to create a structural pricing model using parameter estimates from our post-introduction demand model. However, this approach requires additional assumptions regarding strategic interactions and equilibrium conditions that could be problematic (Hausman & Leonard 2002). Instead, we directly estimate the relationship between pre-existing product prices and new product introductions while controlling for other factors (e.g. cost changes) that might cause retail prices to shift. The exact specification we use for this task is given in the empirical model section below.

In our empirical example, we construct and estimate the new product valuation model for two notably different market segments – one that is characterized by high income consumers and another that is characterized by low income consumers. Identification of these different markets is discussed below.

IV. An Empirical Example

The Data

To conduct our study we use publicly available data from the Kilts Center for Marketing, University of Chicago. Specifically, we use data from the shelf-stable bottled juice category. Our application includes the top 44 juice products, as determined by revenue shares. These 44

expression $\varepsilon_{ij} = -\delta_{ij} + \left(g(d;\lambda) - \beta_i w_j \right) / w_i$, where δ_{ij} is Kronecker's delta which equals 1 when $i=j$ and zero otherwise. Elasticities are not essential to the completion of our objectives. However, they are estimated and partially reported as a check on whether or not the model produces reasonable results.

products represent roughly 80% of dollars sales within the juice category. Of these products, 41 are present for the duration of the time period, whereas the remaining three are introduced almost midway through the series. The three new products are as follows: Minute Maid Apple, Gatorade Watermelon, and Gatorade Raspberry. All three products were introduced at the same time in our data. The data include weekly store level transaction prices, quantities, percent markups, and discount information for over 100 stores operated by Dominick's Finer Foods.[10] Although it would be useful to have data for more than one chain, Slade (1995) showed that most food retailers behave as local monopolies. Thus, it is likely that inclusion of other chains in our study would have little effect on our estimation of substitution patterns (Sudhir 2001; Chintagunta, Dube, and Singh 2003).

Along with standard marketing mix information, our data includes zip codes for every store in the market. Linking the zip codes with U.S. census data we are able to segment the stores into ones that are located in high income neighborhoods and those that are located in low-income neighborhoods. For this study we define "high" and "low" income neighborhoods as those where average household income is greater than $100 thousand and less than $50 thousand, respectively. Table 1 provides a breakdown of the number of stores within each zip code as well as some characteristics of the population served.

Our exercise uses 50 weeks of pre-introduction data and 65 weeks of post-introduction data for a total of 115 weeks from August 1994 to November 1996.[11] In addition to prices and weekly unit sales, nutritional information regarding sugar, carbohydrates, juice, vitamin C, and

[10] During the time-frame covered by the data, Dominick's was the number two retail chain in the greater Chicago area.
[11] Note that all estimation procedures are based on the 65 weeks of post-introduction data. The pre-introduction data is only used to obtain average prices of the pre-introduction products.

sodium content was obtained for each product included in the analysis. This information is readily available on the nutritional labels of each product and was retrieved from in-store-visits or manufacturer websites. For a summary of information used in this analysis see tables 1 and 2 below.

To create an empirical specification of (7), we begin by forming both continuous and discrete attribute distance metrics. Our continuous distance metrics are defined as follows:

$$(13) \qquad d_{ij}^{C} = \left(1 + 2\sqrt{\sum_k \left(z_{ik} - z_{jk}\right)^2}\right)^{-1},$$

Where the z's are continuously defined product attributes (e.g., sugar, calories, etc.) and $\sqrt{\sum_k \left(z_{ik} - z_{jk}\right)^2}$ is the Euclidian distance between the values of z for two distinct products. To account for within brand or within flavor competition, we use two discrete distance metrics expressed as:

$$(14) \qquad d_{ij}^{D} = \begin{cases} 1, & \text{if products } i \text{ and } j \text{ share the same qualitative status} \\ & \text{or level for attribute D} \\ 0, & \text{otherwise} \end{cases} .$$

Combining these two notions of attribute distance, we create a distance metric function that is used to replace all cross-price parameters in (7). After experimenting with numerous functional form possibilities we settle on the following:[12]

$$(15) \qquad g_{ij}(d;\lambda) = \sum_{m}^{D^*} I(d^D = m)(\lambda_{0,m} + \lambda_{1,m} d_{ij}^{C} + \lambda_{2,m} (d_{ij}^{C})^2)$$

[12] In preliminary model runs we found that DM functions using 3rd and 4th order series expansions had only minor effects on estimation outcomes.

where d_{ij}^{C} is a continuous metric in sugar, juice, and discount frequency space, the λs are parameters to be estimated, $I(\cdot)$ is an indicator function that equals 1 when the expression in parentheses is true and zero otherwise, d^{D} is a compound discrete measure representing four possible scenarios; same flavor/same brand, same flavor/different brand, different flavor/same brand, and different flavor/different brand.

Demand System Estimation

We take an instrumental variables approach to estimate our system of 43 share equations. For our instruments, we take advantage of a rare feature of our data – the availability of wholesale price information. Each wholesale price is assumed to be exogenous and is used as an instrumental variable. In addition, we use producer price index data for high fructose corn syrup, refined sugar, plastic bottles, frozen juices and ades, commercial energy, and gas, so that our system is overidentified.[13]

Our choice of instruments is reasonable for several reasons. First, we find a high level of correlation between our set of instruments and retail prices. Second, given that Dominick's accounts for only 20% of Chicago grocery sales, it is reasonable to assume that unobserved marketing activities (e.g. in-store promotions, shelf placement, ect.) of this single chain are unlikely to have a large impact on wholesale prices. This argument is further supported by regulations such as the Robinson-Patman Act that constrain fluctuations in wholesale prices to market-level as opposed to individual chain-level phenomena (Chintagunta 2002; Chintagunta, Dubé, and Singh 2003). Moreover, our use of wholesale price instruments is consistent with

[13] In addition to price endogeneity, we find that several of our original share equations suffer from serial correlation. Thus, to reduce bias in the standard errors of our estimates we add an AR(1) term to each equation.

other published studies that use the Dominick's database (Chintagunta 2002; Chintagunta, Dubé, and Singh 2003; Sriram, and Kalwani 2007). Furthermore, we conduct a Hausman test of the hypothesis that the parameter estimates from standard SUR estimation are statistically equivalent with those obtained via three stage least squares. We do this twice – once when applying our demand model to stores that cater to higher income households and a second time when applying our model to stores that cater to lower income households. In both cases, we easily reject this hypothesis with test statistic of 82,707 and 5,257,253 respectively.

Rival Price Changes

To account for the fact that prices of rival products also may change as a result of new product introductions, we must infer these potential price changes. One approach is to directly estimate the effects of new product introductions on rival prices while controlling for other potential price shifters. An example of this approach can be found in Pofahl and Richards (2009) who use the following price equations:

(16) $$\ln p_t = \delta + \phi \ln v_t + \theta_1 qtr1_t + \theta_2 qtr2_t + \theta_3 qtr3_t + \zeta NP_t + \varepsilon_t,$$

where $\ln p_t$ is the log price in week *t*, δ are product specific constant terms, and ε_t are mean-zero error terms. To capture the effects of possible cost fluctuations on retail prices three quarterly indicator variables are included as well as a vector of supply-side input cost indexes, v_t. The variable NP_t is a "post-introduction" indicator variable that equals 1 for weeks in which the new products are in existence and zero otherwise. Given our accounting of potential changes in cost conditions, the parameter ζ captures the direct effect of new product introductions on prices of existing products. Other studies use a similar approach (Hausman and Leonard 2002; Besanko, Dubé, and Gupta 2005). Percentage changes to pre-existing prices resulting from new product introductions are then generated with the expression $(\exp(\zeta)-1)$.

V. Results

Demand Parameter Estimates

Due to the large number of products considered in our analysis we provide only a basic discussion of regression diagnostics in text.[14] As indicated in Table 3, our demand model explained roughly 70% of the variation in product shares on average over 43 equations and two retail zones. Though not reported here, the distance metric parameter estimates are reflective of intuitive substitution patterns which are subsequently seen in corresponding cross-price elasticities. In other words, the parameter estimates reflect the fact that stronger cross-price competition exists between products that are similar to one another (e.g., share the same flavor). For a full discussion of distance metric parameters, readers are referred to Pofahl and Richards (2009).

Although demand elasticities are not essential for the completion of our objective, we briefly report the own-price estimates in Table 4. Demand for every bottled juice product in our study is highly elastic. This is to be expected given the large number of closely related substitutes within the category. We can also see that most of the own-price elasticities are larger in absolute value for the low-income stores, indicating the higher degree of price sensitivity one would expect to observe amongst low income populations. Based on these estimates alone, we

[14] A full set of results can be provided upon request

can expect the welfare effects of new product introductions to have a larger impact on low income consumers to the extent that a new product results in category price fluctuations.

Using estimated demand parameters we are able to solve for the virtual prices that set demand for the new products equal to zero. In table 5 we see that the virtual price estimate for Minute Maid Apple juice is \$0.059 and \$0.061 for low and high income populations, respectively. This means that for high income consumers, the price of this product would have to increase roughly 17% before demand fell to zero. For low income consumers the price a price increase of 15% would have the same effect. Using equation (16) and data from each consumer zone we estimate the direct price effects associated the new product introductions. We find that 22 of the 44 products experience statistically significant price changes due to the introduction of new products. Some of these price changes are positive (e.g., Ocean Spray Cranberry [2.75%, 3.48%], and Dominick's Cranberry [4.58%, 4.40%]) but most are negative (e.g., Indian Summer Apple [-6.20%, -6.12%]).

Finally, table 6 contains estimated welfare effects associated with the three new product introductions. Overall, all welfare estimates are statistically significant. Price effects are positive for both high and low-income consumers: \$213 and \$1,122 respectively. On the other hand, the variety effect is negative for both groups: -\$616 and -\$177 respectively. The pattern of these results seem quite reasonable from a logical standpoint: they suggest that low income shoppers experience a greater welfare increase due to additional price competition than their high income counterparts. This makes perfect sense. For both groups we see that the addition of three new products has a negative effect on welfare, i.e., the additional variety is not appreciated by high or low income consumers. This could reflect the fact that the bottled juice category is already highly saturated with a large variety of products. One of the new products introduced is another apple juice product – there were already 7 apple juice alternatives on the shelf before this new variety arrived. Perhaps the most interesting feature of the negative variety effect is that it is more pronounced with high income consumers. It is not difficult to image why higher income households might be more frustrated with redundant new product additions. They are likely to be more pressed for time due to longer work hours. Also, given their higher earnings potential, it makes sense that they would be more aware of the concept “time is money,” which could be reflected in an unwillingness to sort through large sets of choice alternatives.

VI. Conclusions

In this study, we evaluate the welfare effects of new product introductions to notably different cohorts of the population. Using an application involving the introduction of three shelf-stable bottled juice products, we find that consumer shopping at stores in low-income neighborhoods do in fact experience different welfare effects than consumers who shop at stores in high-income neighborhoods. While these results alone are interesting, they also provide an important justification for studying such welfare effects even further. Extensions of this research will consider the welfare effects of new product introductions to retailers as well. Furthermore, we intend to identify and evaluate new product introductions in categories characterized by innovative health claims. Understanding how different segments of the population respond to such claims through their purchase behavior could play a substantial role in shaping retail management decisions as well as the development of food assistance programs.

References

Amato-McCoy, D., 2007, ‘Leaping into Localization,’ *Chain Store Age*, July, 84, p. 55

Bai, R., and G. Kendall, 2005, ‘An Investigation of Automated Planograms Using a Simulated Annealing Based Hyper-Heuristic,’ in Ibaraki, T., K. Nonobe, and M. Yagiura (Eds), *Metaheuristics: Progress as Real Problem Solvers – (Operations Research/Computer Science Interface, Vol. 32), Berlin, Heidelberg, New York, Springer*

Bayus, B.L., G. Erickson, and R. Jacobson, 2003, 'The Financial Rewards of New Product Introductions in the Personal Computer Industry,' *Management Science*, 49, pp. 197-210

Besanko, D, J. Dubé, and S. Gupta, 2005, ‘Own-Brand and Cross-Brand Retail Pass-Through,’ *Marketing Science*, 24, pp. 123-137

Blaylock, J., D. Smallwood, K. Kassel, J. Variyam, and L. Aldrich, 1999, ‘Economics, Food Choices, and Nutrition,’ *Food Policy*, 24, pp. 269-286

Blisard, N., B. Lin, J. Cromartie, and N. Ballenger, 2002, 'America's Changing Appetite: Food Consumption and Spending to 2020,’ *Food Review*, 25, pp. 2-9.

Block, D., and J. Kouba, 2006, ‘A Comparison of the Availability and Affordability of a Market Basket in Two Communities in the Chicago Area,’ *Public Health Nutrition*, 9, pp. 837-845

Borin, N., P. Farris, and J. Freeland, 1994, ‘A Model for Determining Retail Product Category Assortment and Shelf Space Allocation,’ *Decision Sciences*, 25, pp. 359-383

Browning, L, ‘U.S. Income Gap Widening, Study Says,’ *New York Times*, Business Section, September 25, 2003

Chen, Z., S. T. Yen, and D. Eastwood, 2005, ‘Effects of Food Stamp Participation on Body Weight and Obesity, *American Journal of Agricultural Economics*, 87, pp. 1167-1173

Chintagunta, P.K. 2002. “Investigating Category Pricing Behavior at a Retail Chain.” *Journal of Marketing Research*, Vol. 39(2), pp. 141-154.

Chintagunta, P.K., J.P. Dubé, and V. Singh, 2003, 'Balancing Profitability and Customer Welfare in a Supermarket Chain,' *Quantitative Marketing and Economics,* 1, pp. 111-147

Chung, C, S. Meyers, 1996, ‘Do the Poor Pay More for Food? An Analysis of Grocery Store Availability and Food Price Disparities,’ *Journal of Consumer Affairs*, 33, pp. 276-296

Deaton, A., and J. Muellbauer, 1980, ‘An Almost Ideal Demand System,’ *American Economic Review*, 70, pp. 312-326

Draganska, M., and D. Jain, 2005, ‘Product-Line Length as a Competitive Tool, *Journal of Economics and Management Strategy*, 14, pp. 1-28

Drewnowski, A., and S. Spector, 2004, ‘Poverty and Obesity: The Role of Energy Density and Energy Costs,’ *American Journal of Clinical Nutrition*, 79, pp. 6-16

Ford, P. B., and D. A. Dzewaltowski, 2008, ‘Disparities in Obesity Prevalence Due to Variation in the Retail Food Environment: Three Testable Hypotheses,’ *Nutrition Reviews*, 66, pp. 216-228

Green, R., and Alston, J. 1990. “Elasticities in AIDS Models.” *American Journal of Agricultural Economics*, Vol. 72(2), pp. 442-445.

Harris, M., 2002, 'Food Product Introductions Continue to Decline in 2000,' *Food Review*, 25, pp. 24-27

Hausman, J., 1981, ‘Exact Consumer’s Surplus and Deadweight Loss,’ *American Economic Review*, Vol. 71, pp. 662-676

Hausman, J.A., 1994, *Valuation of New Goods Under Perfect and Imperfect Competition*, Working Paper, no. 4970, NBER

Hausman, J.A., and G. Leonard, 2002, 'The Competitive Effects of a New Product Introduction: A Case Study,' *Journal of Industrial Economics*, 50, pp. 237-263

Horowitz, C., K. A. Colson, P. L. Hebert, and K. Lancaster, 2004, ‘Barriers to Buying Healthy Foods for People With Diabetes: Evidence of Environmental Disparities,’ *American Journal of Public Health*, 94, pp. 1449-1554

Horsky, D., 1990, ‘A Diffusion Model Incorporating Product Benefits, Price, Income and Information,’ *Marketing Science*, 9, pp. 342-364

Howell, D., 2006, ‘Driving Satisfaction,’ *Chain Store Age*, 82, p. 8a

Inagami, S., D. Cohen, B. Finch, and S. Asch, 2006, ‘You Are Where You Shop: Grocery Store Locations, Weight, and Neighborhoods,’ *American Journal of Preventive Medicine*, 31, pp. 10-17

Jekanowski, M., and J. Binkley, 2000, 'Food Purchase Diversity Across U.S. Markets,' *Agribusiness*, 16, pp. 417-433

Kim, D., 2004, 'Estimation of the Effects of New Brands on Incumbents’ Profits and Consumer Welfare: The US Processed Cheese Market Case,' *Review of Industrial Organization*, 25, pp. 275-293

Kinsey, J., and B. Senauer, 1996, 'Consumer Trends and Changing Food Retailing Formats,' *American Journal of Agricultural Economics*, 78, pp. 1187-1191

Kok, A., and M. Fisher, 2007, 'Demand Estimation and Assortment Optimization Under Substitution: Methodology and Application,' *Operations Research*, 55, pp. 1001-1021

Li, Q., and Racine, Jeffrey S. 2006. *Nonparametric Econometrics Theory and Practice*, Princeton, NJ: Princeton University Press

Meyerhoeffer, C. and Y. Pylypchuk, 2008, 'Does Participation in the Food Stamp Program Increase the Prevalence of Obesity and Health Care Spending?' *American Journal of Agricultural Economics*, 90, pp. 287-305

Millstein, M., 'Bringing Science to Sales Results; Optimization Software Calls for Retailers to Trust in Technology to Forecast Demand and Predict Trends,' *DNR*, New York, February 28, 2005, 35, pp. 6-9

Morland, K., A. V. Diez Roux, and S. Wing, 2006, 'Supermarkets, Other Food Stores, and Obesity: The Atherosclerosis Risk in Communities Study,' *American Journal of Preventive Medicine*, 30, pp. 333-339

Moschini, G. 1995. "Units of Measurement and the Stone Index in Demand System Estimation." *American Journal of Agricultural Economics*, Vol. 77(1), pp. 63-68

Morris, P., L. Neuhauser, and C. Campbell, 1992, 'Food Security in Rural America: A Study of the Availability and Costs of Food,' *Journal of Nutrition Education*, 24(suppl): pp. S52-S58

Nevo, A., 2000, 'A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand,' *Journal of Economics & Management Strategy*, 9, pp. 513-548

Petrin, A., 2002, 'Quantifying the Benefits of New Products: The Case of the Minivan,' *Journal of Political Economy*, 110, pp. 705-729

Pinkse, J., and M. Slade, 2004, 'Mergers, Brand Competition and the Price of a Pint,' *European Economic Review*, 48, pp. 617-643.

Pinkse, J., M. Slade and C. Brett, 2002, 'Spatial Price Competition: A Semiparametric Approach,' *Econometrica*, 70, pp. 1111-1153.

Progressive Grocer, "Giant Eagle Selects Galleria to Enhance Assortment Planning and Optimize Space,' January 15, 2008

Pofahl, G. M., and T. J. Richards, 2009, 'Valuation of New Products in Attribute Space,' *American Journal of Agricultural Economics*, Vol. 91(2), pp. 402-415.

Putnam, J., J. Allshouse, and L. S. Kantor, 2002, 'U.S. Per Capita Food Supply Trends: More Calories, Refined Carbohydrates, and Fats,' *Food Review*, 25, pp. 2-14, Economic Research Services, USDA

Slade, M. 1995. "Product Rivalry with Multiple Strategic Weapons: an Analysis of Price and Advertising Competition." *Journal of Economics and Management Strategy*, Vol. 4(3), pp. 445-476

Song, I., and P. K. Chintagunta, 2003, 'A Micromodel of New Product Adoption with Heterogeneous and Forward-Looking Consumers: Application to the Digital Camera Category,' *Quantitative Marketing and Economics*, 1, pp. 371-407

Sriram, S., and Kalwani, M. 2007. “Optimal Advertising and Promotion Budgets in Dynamic Markets with Brand Equity as a Mediating Variable.” *Management Science*, Vol. 53(1), pp. 46-60

Sudhir, K. 2001. “Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer.” *International Journal of Research in Marketing*, Vol. 20(3), pp. 244-264

Variyam, J., and E. Golan, 2002, ‘New Health Information is Reshaping Food Choices,’ *Food Review*, Spring, Economic Research Services, USDA

Ver Ploeg, M., and K. Ralston, 2008, ‘Food Stamps and Obesity: What Do We Know?’ *Economic Information Bulletin*, No-34, Economic Research Services, USDA

Zenk, S., A. Schulz, T. Hollis-Neely, R. Campbell, N. Holmes, G. Watkins, R. Nwankwo, and A. Odoms-Young, 2005, ‘Fruit and Vegetable Intake in African Americans: Income and Store Characteristics,’ *American Journal of Preventive Medicine*, 29, pp. 1-9

Table 1. Zip Codes, Select Demographics, and the Number of Dominick's Stores within Each Price Zone

Zip Code	Population	Median Family Income	% of Households Below Poverty	Store Numbers	Price Zone
60093	19,528	162,607	1.3	1	1
60305	11,635	122,155	2.5	1	1
60521	37,496	114,584	3	1	1
60015	27,224	113,663	1.5	1	1
60558	12,539	108,867	0.7	1	1
60047	38,168	107,105	2	1	1
60062	40,392	106,020	1.3	1	1
60540	42,065	100,789	1.5	2	1
60160	23,034	47,200	8.5	1	2
60153	26,863	47,135	11.1	1	2
60409	39,065	46,071	9.7	1	2
60629	113,984	44,965	12.1	1	2
60618	98,147	44,566	11.7	2	2
60625	91,351	43,729	13.5	1	2
60620	85,771	41,449	16.3	1	2
60632	87,577	40,935	13.1	1	2
60660	47,726	40,863	14.8	1	2
60617	96,288	39,604	17.3	1	2
60640	74,030	37,766	20.3	1	2
60649	54,823	31,228	23.3	1	2

Source: U.S. Census Bureau, Summary File 1 (SF 1) and Summary File 3 (SF 3), 2000

Table 2.Bottled Juice Products, Expenditure Shares, and Attribute Information

#	Product Name	Revenue Share	Sugar (g.) per 8 oz.	Percent Juice	Discount Frequency
1	Dominick's Apple Juice	8.15%	28	100	24.81%
2	Ocean Spray Cranberry Juice Cocktail	7.19%	33	27	9.52%
3	Mott's Regular Apple Juice	6.85%	28	100	7.75%
4	Gatorade Lemon-Lime	3.89%	14	0	8.70%
5	Welch's White Grape	2.94%	37	100	37.06%
6	Ocean Spray Ruby Red	2.67%	30	30	15.14%
7	Dominick's Cranberry Juice	2.50%	35	100	17.52%
8	Musselman Apple Juice	2.45%	26	100	17.67%
9	Ocean Spray Cranapple Drink	2.39%	35	15	11.72%
10	Ocean Spray Cranraspberry Drink	2.37%	30	15	11.71%
11	Gatorade Orange	2.22%	14	0	9.21%
12	Hawaiian Punch	2.12%	28	5	10.99%
13	Gatorade Fruit Punch	1.96%	14	0	9.12%
14	Indian Summer Apple Juice	1.90%	25	100	27.65%
15	Gatorade Lemon-Ice Punch	1.86%	14	0	8.92%
16	Welch's Regular Grape	1.81%	40	100	34.55%
17	Mott's Natural Apple Juice	1.61%	27	100	7.15%
18	Ocean Spray Ruby Red & Tangerine	1.60%	31	20	14.00%
19	Treetop Apple Juice	1.58%	26	100	17.99%
20	Gatorade Tropical Burst	1.39%	14	0	8.43%
21	Ocean Spray Low Calorie Cranberry	1.39%	10	27	16.15%
22	Gatorade Lemon	1.36%	14	0	8.66%
23	HI-C Fruit Punch	1.10%	29	5	21.51%
24	Minute Maid Apple Juice	1.06%	26	100	15.99%
25	Ocean Spray Grapefruit Juice	1.05%	21	100	13.25%

26 Ocean Spray Crancherry Drink	0.99%	32	15	12.17%
27 HI-C Orange	0.99%	31	5	21.06%
28 Gatorade Watermelon	0.98%	14	0	9.41%
29 Dominick's Ruby Red Grapefruit	0.95%	35	30	22.39%
30 Gatorade Cool Blue Raspberry	0.91%	14	0	7.65%
31 Ocean Spray Crangrape Drink	0.90%	35	15	9.13%
32 Gatorade Grape	0.85%	14	0	9.17%
33 Ocean Spray Cranraspberry Light	0.84%	10	20	16.38%
34 Dominick's Cranraspberry Drink	0.83%	35	100	19.93%
35 Libby Punch	0.78%	26	100	29.97%
36 Dominick's Cranapple Drink	0.76%	40	27	21.10%
37 Ocean Spray Pink Grapefruit	0.75%	25	100	13.69%
38 Dominick's Reg. Grapefruit	0.71%	24	100	26.55%
39 Libby Berry	0.69%	26	100	29.71%
40 HI-C Ecto Cooler	0.67%	31	5	20.10%
41 Libby Cherry	0.59%	27	100	29.53%
42 Libby Grape	0.57%	28	100	32.81%
43 Ocean Spray Cranstrawberry	0.57%	30	15	10.13%
44 Veryfine 100% Apple Juice	0.57%	32	100	12.00%

Table 3. Demand System Estimation Diagnostics

	--High Income--		--Low Income--	
	Adjusted R2	Durbin-Watson	Adjusted R2	Durbin-Watson
Average (over 43 equations)	0.70	2.42	0.68	2.42
Hausman Test	82707.66		5257253.19	

Table 4. Own-price Demand Elasticities

Product Name	--High Income-- Estimate	t-statistic	--Low Income-- Estimate	t-statistic
Dominick's Apple Juice	-3.84	-46.67	-3.89	-49.00
Ocean Spray Cranberry Juice Cocktail	-3.62	-40.08	-3.48	-31.91
Mott's Regular Apple Juice	-4.64	-51.96	-5.55	-52.36
Gatorade Lemon-Lime	-3.41	-23.79	-4.24	-30.49
Welch's White Grape	-3.46	-8.91	-5.61	-12.93
Ocean Spray Ruby Red	-2.87	-25.40	-3.13	-23.68
Dominick's Cranberry Juice	-5.20	-28.91	-5.68	-36.53
Musselman Apple Juice	-12.37	-45.73	-13.35	-33.14
Ocean Spray Cranapple Drink	-3.46	-37.20	-3.71	-29.63
Ocean Spray Cranraspberry Drink	-3.80	-33.70	-3.89	-32.41
Gatorade Orange	-3.73	-43.98	-4.35	-40.14
Hawaiian Punch	-4.74	-24.95	-5.10	-40.82
Gatorade Fruit Punch	-3.19	-25.42	-4.64	-28.09
Indian Summer Apple Juice	-14.23	-42.27	-14.68	-50.27
Gatorade Lemon-Ice Punch	-4.34	-28.63	-5.69	-36.44
Welch's Regular Grape	-5.06	-10.28	-5.31	-11.61
Mott's Natural Apple Juice	-4.05	-35.69	-5.08	-34.30
Ocean Spray Ruby Red & Tangerine	-5.40	-20.27	-5.35	-20.27
Treetop Apple Juice	-6.57	-7.88	-8.41	-11.46
Gatorade Tropical Burst	-6.84	-33.95	-7.27	-33.70
Ocean Spray Low Calorie Cranberry	-3.49	-31.03	-3.70	-24.07
Gatorade Lemon	-6.06	-17.98	-7.24	-18.84
HI-C Fruit Punch	-7.65	-17.09	-6.47	-11.03
Minute Maid Apple Juice	-6.68	-21.47	-8.23	-19.30
Ocean Spray Grapefruit Juice	-4.86	-22.08	-5.15	-22.89
Ocean Spray Crancherry Drink	-3.51	-11.61	-4.15	-14.46
HI-C Orange	-7.33	-16.68	-9.89	-26.01
Gatorade Watermelon	-4.56	-28.00	-5.68	-32.07
Dominick's Ruby Red Grapefruit	-3.87	-19.79	-4.58	-22.44
Gatorade Cool Blue Raspberry	-4.28	-20.40	-5.31	-25.04
Ocean Spray Crangrape Drink	-3.23	-18.19	-3.48	-22.82
Gatorade Grape	-5.46	-22.69	-5.82	-13.43
Ocean Spray Cranraspberry Light	-3.88	-27.52	-4.20	-15.55
Dominick's Cranraspberry Drink	-8.11	-26.73	-9.02	-30.92
Libby Punch	-10.73	-17.52	-10.54	-14.44
Dominick's Cranapple Drink	-9.09	-29.26	-9.88	-39.98
Ocean Spray Pink Grapefruit	-5.45	-13.61	-6.14	-15.62
Dominick's Reg. Grapefruit	-3.20	-15.58	-3.39	-13.75
Libby Berry	-10.18	-19.47	-11.98	-18.63
HI-C Ecto Cooler	-11.78	-21.61	-12.79	-21.56
Libby Cherry	-12.64	-19.46	-11.27	-13.64
Libby Grape	-13.20	-17.85	-12.69	-14.68
Ocean Spray Cranstrawberry	-3.12	-15.52	-3.86	-18.41

Table 5. Virtual Price and Direct Price Effect Estimates

New Product	Virtual Price	Actual Price	% Difference
--Low Income Zone--			
Minute Maid Apple Juice	$0.059	$0.050	-14.59%
Gatorade Watermelon	$0.047	$0.038	-18.57%
Gatorade Cool Blue Raspberry	$0.053	$0.041	-22.83%
--High Income Zone--			
Minute Maid Apple Juice	$0.061	$0.050	-17.12%
Gatorade Watermelon	$0.050	$0.038	-24.44%
Gatorade Cool Blue Raspberry	$0.057	$0.041	-28.15%

--Direct Price Effects--

	High Income		Low Income	
	Change	S.E.	Change	S.E.
Ocean Spray Cranberry Juice Cocktail	2.75%	0.012	3.48%	0.013
Mott's Regular Apple Juice	-5.36%	0.024	-4.87%	0.024
Gatorade Lemon-Lime	-2.16%	0.009	-1.92%	0.010
Dominick's Cranberry Juice	4.58%	0.017	4.40%	0.016
Gatorade Orange	-1.59%	0.010	-	-
Indian Summer Apple Juice	-6.20%	0.024	-6.12%	0.024
Gatorade Lemon-Ice Punch	-2.38%	0.014	-	-
Welch's Regular Grape	-2.54%	0.018	-2.65%	0.017
Treetop Apple Juice	-3.82%	0.021	-3.47%	0.023
Gatorade Tropical Burst	-3.52%	0.010	-3.50%	0.011
HI-C Fruit Punch	3.70%	0.015	3.78%	0.015
Ocean Spray Grapefruit Juice	-1.73%	0.008	-1.57%	0.009
HI-C Orange	3.20%	0.016	3.99%	0.018
Gatorade Grape	-2.21%	0.008	-2.11%	0.008
Dominick's Cranraspberry Drink	3.82%	0.019	4.53%	0.020
Libby Punch	-	-	2.30%	0.016
Ocean Spray Pink Grapefruit	-1.21%	0.009	-	-
HI-C Ecto Cooler	-	-	4.27%	0.020
Libby Cherry	1.68%	0.016	2.05%	0.016
Libby Grape	2.17%	0.015	2.59%	0.016
Ocean Spray Cranstrawberry	-1.79%	0.012	-1.81%	0.012
Veryfine 100% Apple Juice	-2.76%	0.017	-3.31%	0.018

	High Income	Low Income
Actual Category Price Change	-3.78%	-4.40%
Change due to NPIs	-1.61%	-0.63%

Table 6. Welfare Effects of New Product Introductions

	High Income		Low Income	
Variety Effect	-$616.95	(42.25)	-$177.98	(10.39)
Price Effect	$213.01	(14.44)	$1,122.50	(66.44)
CV	-$403.94	(27.82)	$944.52	(56.07)
% of Category Sales	-0.37%	-	1.84%	-
CV per 8oz. Serving	-$0.0011	-	$0.0055	-

Note: standard errors are in parentheses

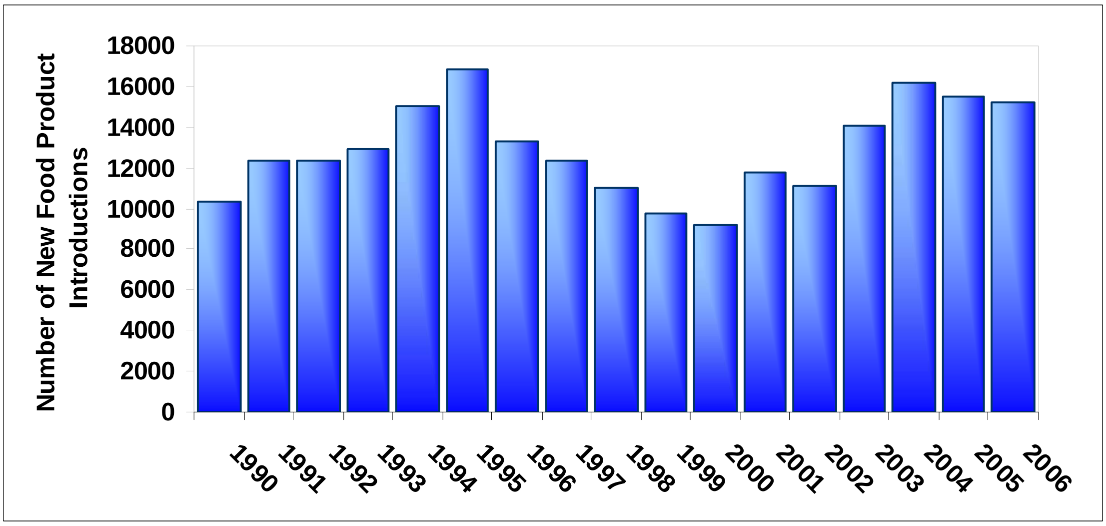

FIGURE 1. New Product Introductions in the U.S. Food Industry
Source: 1990-2000 data – Harris (2002); 2001-2006 data – Mintel, GNPD

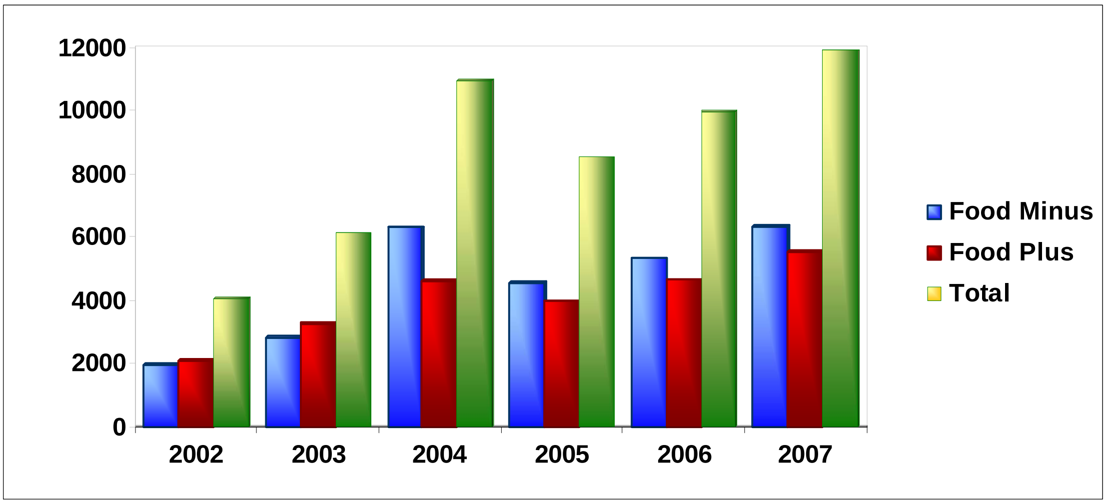

FIGURE 2. New Food Product Introductions That Involve Health Related Claims
Source: Mintel, GNPD

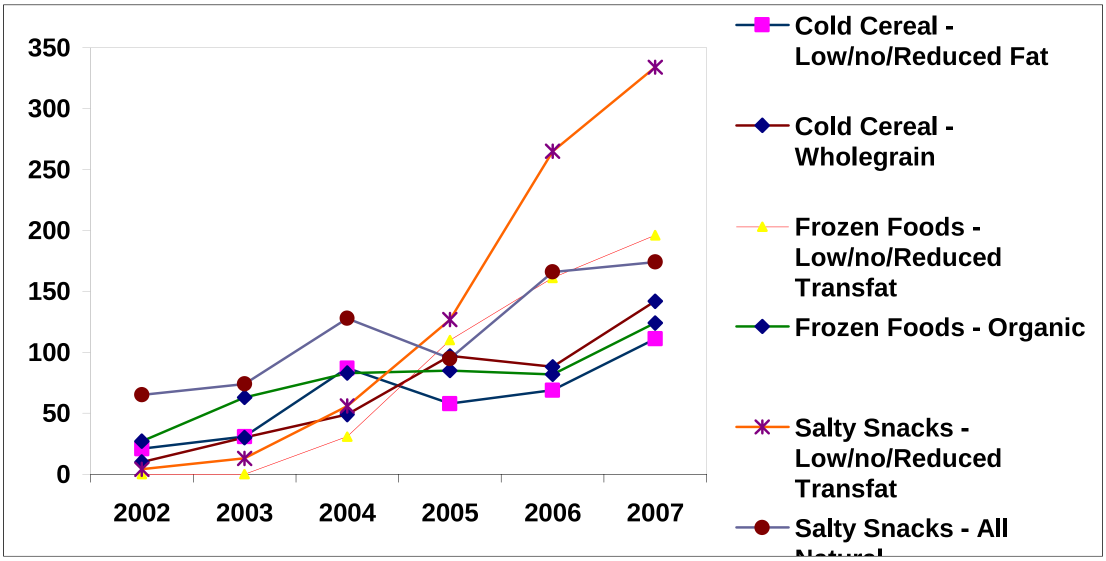

FIGURE 3. New Product Introductions with Health Related Claims for Specific Product Categories
Source: Mintel, GNPD