Competition between Private Label and National Brand for Health-differentiated Food Product: A Canadian Retailing Case

Xiongwei Ying, Sven M. Anders[1]

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013

[1] Xiongwei Ying is a research assistant in Department of Resource Economic and Environmental Sociology, University of Alberta, Edmonton, Canada. Email: xiongwei@ualberta.ca. Sven M. Anders is associate professor in Department of Resource Economic and Environmental Sociology, University of Alberta, Edmonton, Canada. Email: sven.anders@ualberta.ca.

Competition between Private Label and National Brand for Health-differentiated Food Product: A Canadian Retailing Case

Abstract: Retailers in Canada are beginning to introduce private labels to gain vertical bargaining power over manufacturers and horizontal differentiation among retailers. Product differentiation in health and wellness is an emerging trend for both private labels and national brands. This study applies a model derived from a random utility nested logit model to estimate the extent to which consumer choice of health-related food attributes has affected retailer pricing and brand-level competition, using the Distance-Matrix (DM) approach to identify the location of both private label and national brands of canned soup market in their attribute space. It suggests that private label does not have a positive effect on retailers' demand.

Key words: Private label; National brand; Health differentiation; Distance matrix; nested logit

Introduction

Private label (PL), or store brand, has been introduced by retailers to compete with national manufacturers vertically, and with other retailers horizontally. PLs have been growing fast, adopted and sold in most of North American super and hyper-super markets. According to the data released by PLMA, PL brands comprised an all-time highest of 21.3 % of unit share and 16.4% of dollar share in supermarkets in 2006 for North America (PLMA, 2007). Between 1999 and 2003, PL products in supermarkets grew at an annual rate of 17.9% compared to national brand (NB) products sales growth of 14% during that same period of time (PLMA, 2004). With the rise in their popularity, retailers' efforts to develop and introduce quality differentiated PLs have intensified both brand-level and retail-level competition in the oligopoly retailing market. For instance, several retail chains have developed health-differentiated PL lines, known as "good for you" products which largely focus on favorable nutritional properties (Anders and Moeser 2010).Though PL products were generic and low-priced which often sacrificed quality to reduce costs and prices (Colins and Bone, 2008), reports released by several marketing institutes revealed that consumers have developed preference for PLs over national brands and recognized the quality differentiation of PLs.[2] Product differentiation (including brand, flavor or quality, nutritional properties) is now becoming the main concentration of competition between retailers and manufacturers. Despite the strong effects of PL on the competitive structure of retailing oligopoly markets, few studies have been devoted to examining the competition considering the degree of product differentiation between PLs and NBs. Thus, the primary objective of this study is to estimate the structural demand for both PL and NB considering the health-related brand differentiation, providing a new insight into the vertical interaction of PL and NB competition. In doing so, this study contributes to the literature by presenting an alternative innovative approach to directly identify products' quality differentiation, which was developed by Pinkse and Slade (2002), Pinkse and Slade (2004), Richards, Hamilton and Patterson (2010).

Research on PL and NB competition up to date has stressed many contributions of PL to retailers' competing with manufacturers, such as to increase consumers' loyalty (Bontemps, Orozco, Requillart, 2008), retailers' bargaining powers with upstream suppliers (Scott-Morton and Zettekmeyer, 2000; Sayman, Hoch and Raju, 2002), and margins and profits (Mills, 1995; Bergès, Bontems and Réquillart, 2004; Kumar and Steenkamp, 2007). As reported in a French survey by LSA/Frontier (1996), the main reasons retailers develop PLs are to increase customer loyalty (16%), to improve their positioning (18%), to improve margins (25%), and to lower prices (3%). However, some studies also found some evidence on the negative effects on retailers of their PL introduction (Ailawadi and Keller, 2004; Bergès, Bontems and Réquillart, 2004; Walker, 2006; Geyskens, Gielens and Gijsbrechts, 2010). The threat of market share losses to PL also fosters the NB manufacturers to provide more attractive prices to retailers and, most importantly, offer more differentiated NB products to consumers (Richards, Hamilton and Patterson, 2010). Unfortunately, few studies has focused on the effects of product differentiation between PL and NB on their vertical interactions, which will be the main concentration of this study by adopting two

[2] For example, the Nielsen Company indicated that three-quarters of shopper cited PL products as "good alternatives" to national brands, two-thirds stating that store brands were of "equal quality" to national brands and more than 40 percent believing that "some (PL products had) better quality" than national brands (The Nielsen Company, 2011).

proprietary datasets regarding to products' sales and properties.

Moreover, preview studies have a major challenge when dealing with differentiated product structural demand in the retailing market. As suggested by Pofahl and Richards (2009), many of the most active categories in terms of PL introduction now have a large product differentiation.[3] Consequently, these categories possess many more products than are practically feasible in the traditional demand model. A lot of attempts have been made by researchers to circumvent the "dimensionality problem" (Nevo, 2001). All of these attempts were aimed at reducing the dimensions to make the estimation more flexible so that more products can be included in the model to better simulate the market structure. One of the most commonly-used approaches is the discrete-choice model, such as the multinomial logit (McFadden, 1973), the nested logit (NML) (McFadden, 1978) and random coefficient logit (Berry, 1994; Berry, Levinsohn and Pakes, 1995; Nevo, 2000; Nevo, 2001). These models circumvent the "dimensional problem" by projecting the products onto a characteristic space, hence making the product dimension the dimension of characteristics, instead of number of products (Nevo, 2001). Moreover, the multinomial logit model suffers from the well-known independent from irrelevant alternatives (*IIA*) problem for all the choice products, which in most case would lead to an unrealistic forecast (Train, 2002). And though the random coefficient (mixed) logit model circumvents the inflexibility by adopting an intuitive relationship between proximity in attribute space and competition with alternatives (Pofahl and Richards, 2010), it still lacks the direct consideration of attribute difference (Pofahl and Richards, 2009), and has a relatively high requirement for the data structure (Train, 2002) and computational complexity (Berry, 1994). Therefore, a nested logit model is comparatively appropriate for analysis of demand for oligopoly differentiated product demand to circumvent the "dimensional problem" as well as get rid of traditional "*IIA*" property.

Furthermore, the nested logit model also suffers from two major challenges. First, the substation patterns for the NML model depends on the pre-determined groupings (Berry, 1994) and substitution between two products within the same group also exhibits the "IIA" property (Train, 2002). Second, most of previous studies utilize the levels of product characteristics in the utility maximization function to derive the choice probabilities or market share equations, which cannot directly capture the fact that substitution patterns between products largely rely on the distance between two products in the characteristic space and competition between them increases with the their proximity in the characteristics space (Pinkse, Slade and Brett, 2002; Pinkse and Slade, 2004; Slade, 2004). In other words, the traditional NML model cannot capture the notion that competition is spatially determined (Pofahl and Richards, 2009). Thus, in this study, the Distance-Matrix approach developed by Pinkse and Slade (2002) will be adopted to directly consider the effects of product attribute differences on the substitution patterns between any of two products in the NML model. Moreover, Pofahl and Richards (2009) acknowledged that the DM approach "brings the issue of characteristic proximity to the surface of a demand model in a way that is easy to understand and easy to implement".

Finally, this study also contributes to the literature concerning the Canadian retailing market. Few

[3] For instance, Bocionek (2011) found 115 different kinds of salad dressing in one of Canadian retail chains, with three kinds of PL: the premium and copycat PL, respectively.

studies have focused primarily on the Canadian retailing markets of PL and NB competition, even though PL development has been growing for decades and reports show that penetration of PL in consumers' shopping trips has reached approximately 100% in Canada (Mintel, 2011).

This study estimates the structural demand for canned soup products (both PL and NB brands) in one of the largest retail chains in Canada, which is based on the nested logit (NML) model to derive the market share equation. We hypothesize that product characteristics are pre-determined by a prior and unknown stage of game and consumers possess a perfectly subjective assessment of product differentiation that is based on the product characteristics (Richards, Hamilton and Patterson). More specifically, the Distance-Matrix approach is used as a new and innovative insight to identify products' locations in their characteristics space and circumvent the inflexibility and limitation of traditional demand models. Furthermore, two proprietary sets of data are utilized to describe the canned soup market in this Canadian national retail chain. The canned soup category is selected in this study for several reasons. First of all, canned soup is a category which enjoys a high penetration of PL introduction in the retailing markets. Secondly, the canned soup markets are comparatively concentrated with a leading NB and other following brands (including PL) so that competition between PL and NB can be more strategic. Third, the retail channel dominates in the sales of canned soup, with 70.2% of market share in 2011 (Datamonitor, 2012). Finally, manufacturers compete with each other by introducing varieties of products to differentiate their products in flavours, packaging, ingredients, processing and even labelling strategies. This results in the fact that the characteristics space occupied by all the canned soup products is significantly large and sparse, which benefits the construction of distance matrix in this study.

Our finding shows that consumers have a strong preference for a set of nutritional attributes and flavor. However, as opposed to many of previous studies, this study found that PL has a negative effect on this concentrated canned soup market in Canada, which can be explained by the market characteristics. Also a mixed effect of the nutritional properties on the products' demand has been discovered. Our findings provide a new insight for both policy makers and industrial institutes.

Data

Two proprietary sets of data are used in this study. The first dataset is scanned sales data (SIEPR-Giannini Data Center 2012) from one of the largest retail corporations in North America, which currently operates now 1678 stores in United States and western Canada with more than 178,000 employees. The available dataset covers product-level sales for over 200 grocery categories with over 60,000 items in total. These items are identified by their unique UPC (Universal Product Code) numbers, which is a barcode system that is widely used in North America, and in countries such as Australia, UK and New Zealand for stores to track items.

The available dataset contains sales data from the 1st week of 2004 to the 22nd week of 2007. Furthermore, it consists of observations with their week/store/ category identification, UPC identification, weekly net revenue, gross revenue, sold quantities and adjusted gross profit (AGP). The dataset also consists of information for stores operated by the national retail chain corporation, including their location, total building size, total selling area and division identification. In the case of Canada, the retail chain corporation operates, in total, 220 stores in the Canadian provinces of British Columbia, Alberta, Saskatchewan, Manitoba, and Ontario. Although it is better to have sale data from more retail chains in Canada, Pinkse and Slade (2004) indicated that most of the food retailers behave as local monopolists. Thus, as Chintagunta, Bonfrer and Song (2002) and Pofahl and Richards (2009) indicated, it is reasonable to exclude other food retailers in the study and only include one of the largest as our case study.

The second proprietary dataset in this study is obtained from Mintel Global New Product Database (GNPD) (Mintel, 2012), which contains the information of items sold in this national retailing corporation in both United States and Canada. It consists of UPC identification, UPC description, subclass name, category number and some other minor sectors. In the canned soup category investigated, there were 2707 kinds of canned soup (defined by their UPCs) sold in both United States and Canada and 200 kinds of canned soup products sold exclusively in Canada during the investigated period. However, information for a few products are missing in this database. Hence, we collected the product information by inspecting the stores or the manufacturers' websites based on the products' UPC codes. Except for the prices and quantities, products' nutritional information regarding calories, fat, cholesterol, sodium, carbohydrates, fiber, sugar and protein is readily available on the products' labels and were obtained from in-store visits or website investigation. We s assume that there have been no changes to the products' characteristics since the year of 2004. Even this is not exactly a fact, it seems a first and reasonable approximation (Nevo, 2001).

During the investigated period (W1/2004-W22/2007), the national retailer sold one PL brand under its chain name in all of its stores for canned soup category and 14 other NB brands. As opposed to other categories investigated by previous studies, the canned soup market in Canada was dominated by one NB brand with approximately 69.69% of unit share, followed by PL brand with 11.41%. What's more, on average, PL is priced at $0.85/cup, which is almost 40% lower than the NB that is priced at $1.42/cup. And relative retail margins for PL are valued at $0.45/cup, nearly 15.6% higher than NB. Also PL enjoys a much higher percentage margin (51.77%) than that of NB (27.62%). In addition, however, statistics show that NBs tend to offer more promotion depth and frequency, thus giving up some of their profits to keep competing with PLs. Moreover, there is a distinct difference in the product characteristics, mainly nutritional attributes between PL and NB, as well as among flavors. For instance, PL does better in containing 26.43% less fat than NB on average and NB does better in containing 17.75% less sodium than PL. Hence, the fact that prices and market share vary significantly by brand and flavor indicates that products' characteristics play a vital role in the competition between PL and NB.

Although the retailer in the study sold hundreds of unique canned soup SKUs, we should focus on an important subset of brands that are available on shelves (Richards, Hamilton and Patterson, 2010).[4] These five brands have both the largest market shares and the most flavor varieties: *Campbell (NB1)*, *Safeway (PL)*, *Habitant (NB2)*, *Primo (NB3)* and *Imagine (NB4)*, among which *Safeway* is a PL and others national brands. These five brands account for more than 90% of the

[4] This is particularly important for the construction of distance matrix as the sizes of spatial distance matrix increase with square of the number of products. For instance, if 10 products are selected, the distance matrix (nutritional distance matrix, etc.) will be 10*10 matrix, with 100 elements in this matrix.

total canned soup market volume in the panel. The sub-sample data also includes the top five flavors by category share within each brand. We also include an “others” category including all other brands and flavors that are not presented in our focus sub-sample. The detailed category share for each brand and each flavor is presented in Table 1, in which relative price is measured as the price of per cup (250 ml) of canned soup. The top five flavors offered by each brand tend to be very similar, but not identical.

Table 1: Summary of Prices and Market Shares for Selected Canned Soup Products

Brand	Flavor	Mean Absolute Price($)	Mean Relative Price($)	Mean Dollar Share (%)	Mean Cups Share (%)
Safeway	Tomato	0.86	0.76	1.70	2.42
Safeway	Cream of Mushroom	0.90	0.79	1.75	2.35
Safeway	Chicken Broth	1.12	0.31	0.44	1.50
Safeway	Chicken Noodle	0.90	0.79	0.97	1.31
Safeway	Vegetable	0.90	0.79	0.62	0.84
Campbell	Cream of Mushroom	5.22	4.59	8.11	6.17
Campbell	Tomato	0.97	0.85	3.94	5.04
Campbell	Chunky New England Clam Chowder	2.39	1.11	2.35	2.37
Campbell	Chicken Noodle	1.75	0.95	4.02	4.62
Campbell	Chunky Beef	2.24	1.04	3.47	3.60
Primo	Beef Barley	2.12	0.98	1.01	1.24
Primo	Chicken	2.11	1.00	0.79	0.94
Primo	Lentil	2.12	0.98	0.72	0.84
Primo	Grilled Chicken with Rice	2.09	0.93	0.56	0.73
Primo	Chicken Noodle	2.09	0.97	0.54	0.68
Imagine	Tomato	4.52	1.13	0.51	0.68
Imagine	Butternut Squash	4.38	1.46	0.31	0.37
Imagine	Sweet Potato	4.92	1.23	0.26	0.24
Imagine	Potato Leek	4.92	1.23	0.16	0.13
Imagine	Sweet Corn	4.89	1.23	0.13	0.12
Habitant	Pea and Ham	2.18	0.68	1.21	2.03
Habitant	Pea	2.18	0.68	1.07	1.78
Habitant	Chicken Noodle	2.16	0.68	0.73	1.27
Habitant	Minestrone Traditional	2.15	0.68	0.69	1.18
Habitant	Vegetable	2.16	0.68	0.66	1.12
Others	Others	2.13	1.44	63.28	56.43

Besides the product sales and nutritional information data, some input prices or price indexes were collected to act as the instrumental variables for the prices and conditional shares in the demand equation, which will be addressed below. These prices (or price indexes) include diesel price, interest rate, vegetable price index, energy price index, electricity price index, canned soup industry price index and weekly wage. Table 2 provides an overview of summary statistics for some major variables used in this study.

Table 2: Summary for Selected Canned Soup Market in Canada (N=337598)

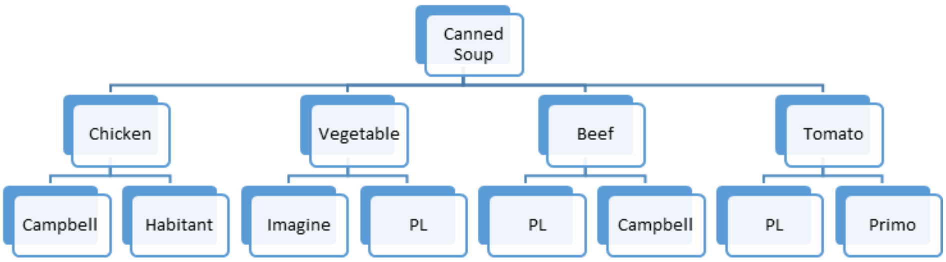
Variables	Mean	Std. Dev.	Min	Max
Absolute Price ($/can)	2.29	1.90	0.15	29.85
Relative Price ($/cup)	1.17	1.54	0.13	26.28
Absolute Margin ($/can)	0.64	0.75	-6.82	29.36
Relative Margin ($/cup)	0.30	0.49	-6	25.85
PL Indicator	0.19	0.39	0.00	1.00
Probability of Discount	0.26	0.44	0.00	1.00
Calories (per cup)	132.14	53.17	20.00	250.00
Fat (g/cup)	3.64	3.92	0.00	15.00
Cholesterol (mg/cup)	7.91	7.64	0.00	20.00
Sodium (mg/cup)	846.60	377.13	360.00	1700.00
Carbohydrate (g/cup)	19.18	7.54	2.00	34.00
Fiber (g/cup)	2.56	3.01	0.00	10.00
Sugar (g/cup)	5.09	5.44	0.00	20.00
Protein (g/cup)	5.19	2.22	1.00	9.00
Number of Health Claims	1.07	1.03	0.00	3.00
Diesel Price[1]	56.23	9.95	36.10	74.50
Interest Rate[2]	3.12	0.86	2.00	4.25
Vegetable Price Index[3]	90.89	7.13	81.20	104.70
Energy Price Index[3]	238.76	48.50	158.60	388.00
Electricity Price Index[3]	99.76	4.65	90.80	110.70
Canned Soup IPI[3]	113.12	3.37	105.90	117.10
Wage[4]	833.90	32.97	771.90	887.83

Note: 1. Source: Natural Resource Canada. Price in cents/liter. 2. Source: Bank of Canada. Target for overnight rate is selected here. 3. Source: Statistics Canada. 2002=100. 4. Source: Statistics of Canada. Average weekly earnings for food manufacturing section is selected. Wages in $/week.

Model

The model used in this study to estimate the structural demand for the canned soup category follows the MNL model developed by Berry (1994), which has been utilized by some researchers to investigate the demand for oligopoly differentiated products (Chintagunta, Bonfrer and Song, 2002; Villas-Boas and Zhao, 2005; Pham and Prentice, 2010). In addition to the advantages talked about above, there is one more reason to use the MNL model. The standard multinomial discrete choice model assumes that consumers choose their preferred products directly, without any hierarchical purchase decisions. However, this may not be true. Shopping trips always involve significant search and travel costs; consumers first choose where to buy their preferred products and decide among the available superstores, or outlets and convenient stores. And then consumers tend to choose among brands and flavors to decide which specific product to buy. It is natural for us to follow this hierarchical step for consumers since it is easier for consumers to substitute among brands and flavors within a store than among stores within brands and flavors. It is assumed in this study that consumers choose flavor first and then decide among brands in their preferred flavor. Figure 1 is able to show the hierarchical decision consumers make when they decide which canned soup product to purchase.

Figure 1: Consumers Decision Tree Example



It is assumed that utility of consumers choosing individual soup product depends on the characteristics of this product, and also characteristics of consumers. There are *I* brands, *J* flavors. To be more specific, the mean utility of consumer *h* choosing soup brand *i* for flavor *j* in store m in week *t* (the time subscript is suppressed below) is represented by:

(1) $$u_{ijh} = \delta_{ij} + \epsilon_{ijh},$$

where $\delta_{ij} = X_{ij}\beta - \alpha p_{ij} + \xi_{ij}$ is the total mean utility, X_{ij} is observed product characteristics by the econometrician, p_{ij} is the shelf price, ξ_{ij} represents the unobserved product characteristics that is believed to influence consumer's purchase utility, and ϵ_{ijh} captures the consumer-specific term that are not observed by the econometrician. The product attribute vector X_{ij} includes the seasonal dummy (*se*), store division dummy (*div_id*), binary indicators for private label (*pl*), brand (*b*), an binary indicator whether the product is offered in an in-store discount (*promotion*), and product's nutritional content variables (*cal* for calories, *fat* for fat, *cho* for cholesterol, *sod* for sodium, *carb* for carbohydrate, *fib* for fiber, *sug* for sugar and *pro* for protein) and an indicator (*hc*) showing the number of health claims in the front-facing label of this product. As opposed to other studies concerned about seasonal dummies, we define *se*=0 for the first and fourth quarter and *se*=1 otherwise. The justification to use this definition is that canned soup sales are strongly related to seasonal changes, staying high on cold days and low on hot days. Due to its geography and climate patterns, Canada always has the lowest temperature in the first and fourth quarter and the highest in the second and third quarters. Furthermore, Berry (1994) noted that ξ_{ij} might be thought of as the mean of consumers' valuations of an observed product characteristic such as brand premium and product quality, while ϵ_{ijh} represents the distribution of consumer preferences about this mean, which captures the heterogeneity of consumers' preferences. To investigate more about consumers' preference for brand and flavor, following Berry (1994), we adopted variance component formulation of nested logit model used by Cardell (1997) and Richards, Patterson and Hamilton (2010). In the demand model,

(2) $$\epsilon_{ijh} = \nu_{jh} + (1-\sigma)\psi_{ij},$$

where ε_{ijh} is identically and independently extreme-value distributed, which captures the unobserved consumer-specific characteristics and ν_{jh} is common to all products branded by *i*, specifically for consumer *h*, whose distribution relies on the parameter of σ $(0 \le \sigma < 1)$ (Berry, 1994; Cardell, 1997; Villas-Boas and Zhao, 2005). Cardell (1997) showed that ν_{jh} possesses a unique distribution so that $\nu_{jh} + (1-\sigma)\psi_{ij}$ is also extreme-value distributed. Consistent with

Berry (1994) and Richards, Patterson and Hamilton's (2010) arguments, the parameter of σ is the inverse measure of brand heterogeneity, which captures the intra-brand substitution pattern. For instance, if σ approaches 1, the within brand group correlation goes to one, indicating that brands are taken as perfect substitutes for consumers and as σ approaches 0, the within brand correlations goes to 0, which reduces the nested logit model to a standard logit model (Train, 2003). Thus, adoption of variance component formulation allows us to interpret correlation within groups of similar products, and also allows correlation patterns to depend only on groupings of products that are determined prior to estimation (Berry, 1994).

For simpler notation, we assign a unique identifier to every product according to their brand identifier (say, brand *i*) and flavor identifier (say, flavor *j*). The market share of product *ij* in the above nested logit model is the product of the conditional market share of brand *i* given that flavor is *j* *I* ($s_{i|j}$), and the marginal share of flavor *j* in the total canned soup retailing market (s_j) (Berry, 1994; Train, 2003). This can be expressed in arithmetic term as:

(3) $$s_{ij} = (s_{ij|j})(s_j).$$

The well-known formula for the conditional market share of brand *i* given the flavor is in *j*th group is

(4) $$s_{ij|j} = \frac{e^{\delta_{ij}/(1-\sigma)}}{E_I},$$

where the denominator of this expression is

(5) $$E_j = \sum_{i\in j} e^{\delta_{ij}/(1-\sigma)},$$

with $ln\, E_j$ being the inclusive value term for the brand choice. And furthermore, the marginal market share of flavor *j* in the canned soup retailing market is

(6) $$s_j = \frac{E_j^{1-\sigma}}{\sum_j E_j^{1-\sigma}}.$$

Thus, the market share of product *ij* is

(7) $$s_{ij} = \left(s_{i|j}\right)\left(s_j\right) = \frac{e^{\delta_{ij}/(1-\sigma)}}{E_j^{\sigma} \sum_j E_j^{1-\sigma}}.$$

Additionally, an outside good is included in the model, allowing for the possibility of consumers not purchasing any of the brands included in the sub-sample. Its price is not set in response to the prices of the available products (Berto Villas-Boas, 2007), which means that preference ordering over brands available in the sub-sample is not affected by preference orderings over brands that consist of the outside good group (Chintagunta, Bonfrer and Song, 2002). The outside good is assumed to be all the other canned soup products sold in this retail chain, including some other brands which have lower market shares. With the outside good as the only product in the group zero and with $\delta_0 = 0, E_0 = D_0 = 1,$ we have

(8) $$s_0 = 1 \Big/ \sum_j E_j^{1-\sigma_j}.$$

Based on the basic model, we are able to derive a simple model for mean utility levels. Taking logs of the market share equation shows

(9) $$ln\, s_{ij} - ln\, s_0 = \frac{\delta_{ij}}{(1-\sigma)} - \sigma\, ln\, E_j.$$

This equation depends on the unknown parameter E_j, which makes it difficult to estimate. After some simple calculation and substitution, we can get our demand model as

(10) $$ln\, s_{ij} - ln\, s_0 = X_{ij}\beta - \alpha p_{ij} + \sigma lns_{ij|j} + \xi_{ij}.$$[5]

The Distance-Matrix (DM) Approach

In the NML model, the cross-price elasticity between product *i* and *j* ($i \neq j$) depends only on the characteristics of *I* within the same nest (group). However, as Pofahl and Richards (2009) noted, the DM approach allows the substitution patterns to be spatially determined, which captures the notion that distance between two products in their multi-dimensional attribute space should influence their competition, or more precisely, cross-price elasticity.

First of all, we should define the distance between two products. Distance, or its analog described in Pinkse, Slade and Brett (2002) and Richards, Hamilton and Patterson (2010), proximity, can be measured in five major ways: (1) brand distance (**db**) (two products belong to the same brand, *i*=*l*); (2) flavor distance (**df**) (two products belong to the same flavor, *j*=*m*); (3) company distance (**dc**) (two products are manufactured by the same company); (4) nutrient content distance (**dn**) (how far two products are in the multi-nutrient attribute space, which will be discussed below). All four measurements of distance, brand distance, flavor distance, and company distance are discrete, while nutrient content distance is continuous. We define a separate element, *d*, for each of these five different measurements, *d*=1 for brand distance and 2, 3, 4 for company, flavor and nutrient, respectively. Since what we are concerned about is the distance between any two product pair in their attribute space, we should further define a distance function for these two products *ij* and *lm*, that is, $g_{\,ij,lm}(d_n)$, in which *n*=1 to measure the distance in brand perception, and 2 for company distance, 3 for flavor distance, 4 for nutrient distance, respectively.

For the four discrete distance measurements, we can create the zero-one DM function as follows:

(11) $$g_{il,lm}(d_n) = \begin{cases} 1, & \text{if product } ij \text{ and } lm \text{ share the same level for attribute } d_n \\ 0, & \text{otherwise} \end{cases},$$

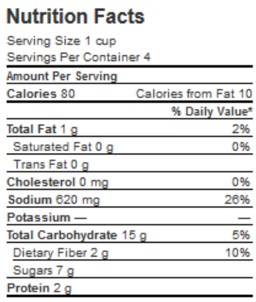
where $d_n \in \{\text{brand}, \text{flavor}, \text{company}\}$. While Pinkse and Slade (2004) pointed out that other notions can be used in addition to the discrete notion already defined above, such as Voronoi diagrams mapping, Pofahl and Richards (2009) argued that this definition is straightforward in intuition. For example, d_1 is able to capture the within brand substitution patterns if most shoppers are brand loyal. Similar intuition applies to other dimensions (Pofahl and Richards, 2009). In addition, specifically, as an example of brand distance, if canned soup *ij* is branded by *NB1* and *lm* is also branded by *NB1*, the brand distance element for *ij* and *lm* takes the value 1, namely $g_{ij,lm}(d_1) = 1$. However, if canned soup *ij* is the chicken flavor, and canned soup *lm* is the beef flavor, the flavor distance element for *ij* and *lm* takes the value 0, namely $g_{ij,lm}(d_2) = 0$. Similar specification applies to other distance elements for company (d_2) and for flavor (d_3).

The continuous distance measurements (nutrient distance) represent patterns of global competition within the canned soup category (Pinkse, Slade and Brett, 2002). Euclidian distance was often constructed in previous studies to measure how far apart two products are in their attribute space, since it is a perfect multi-dimensional measure for continuous attribute. However, Pinkse and Slade (2004) suggested that using an inverse Euclidian distance measure can be of great significance so

[5] For more detailed calculation and derivation, see Berry (1994).

that it is a reflection of how close two products are, rather than how far apart they are. In this study, we still follow this method by Pinkse and Slade (2004) and Pofahl and Richards (2009). The relevant canned soup nutrients included in our study are calories, fat, cholesterol, sodium, carbohydrates, fiber, sugar and protein. The set of nutrients consists of all calories, fat (gram), cholesterol (milligram), sodium (milligram), carbohydrates (gram), fiber (gram), sugar (gram), and protein (gram) in per cup (250 ml). Specifically, the nutrient distance (proximity) for canned soup *ij* and *lm* given their coordinates in the nutrient attribute space is calculated as

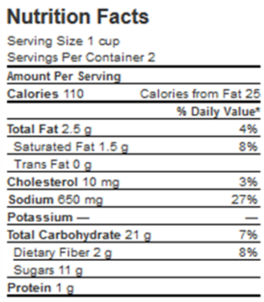
(12) $$g_{ij,lm}(d_4) = \left(1 + 2\sqrt{\sum_k \left(n_{ij,k} - n_{lm,k}\right)^2}\right)^{-1},$$



Nutrition Facts

Serving Size 1 cup
Servings Per Container 4

Amount Per Serving	
Calories 80	Calories from Fat 10
	% Daily Value*
Total Fat 1 g	2%
Saturated Fat 0 g	0%
Trans Fat 0 g	
Cholesterol 0 mg	0%
Sodium 620 mg	26%
Potassium —	—
Total Carbohydrate 15 g	5%
Dietary Fiber 2 g	10%
Sugars 7 g	
Protein 2 g	



Nutrition Facts

Serving Size 1 cup
Servings Per Container 2

Amount Per Serving	
Calories 110	Calories from Fat 25
	% Daily Value*
Total Fat 2.5 g	4%
Saturated Fat 1.5 g	8%
Trans Fat 0 g	
Cholesterol 10 mg	3%
Sodium 650 mg	27%
Potassium —	—
Total Carbohydrate 21 g	7%
Dietary Fiber 2 g	8%
Sugars 11 g	
Protein 1 g	

where k=8 represents the continuous nutrients from calories to protein, n is the nutrient content. As an example of nutrient proximity in this study, we can calculate the proximity between two canned soup products (expressed 12 and 34) in our database, with their nutrition fact table shown below. The nutrient proximity for these two products is calculated as

(13) $$g_{12,34}(d_4) = \frac{1}{1+2\sqrt{(80-110)^2+(1-2.5)^2+(0-10)^2+(620-650)^2+(15-21)^2+(2-2)^2+(7-11)^2+(2-1)^2}} = 0.0112.$$

As noted before, it is assumed that consumers possess a subjective assessment of product differentiation that is measured by the distance between two products given their coordinates in the attribute space. Consequently, Pinkse, Slade and Brett (2002) created an arbitrary matrix, which consists of measures of the distance between two products, which is multiplied by the product shelf price so that shelf prices are adjusted according to consumers' subjective perception of one product's differentiation from others. This idea has also been developed by Pinkse and Slade (2004) and Richards, Hamilton and Patterson (2010). Following this method, we create a separate attribute-distance-adjusted price vector for each of these five measures, P_{d_n} for n=1 (brand), 2 (flavor), 3 (company), and 4 (nutrient). The vector consists of the adjusted attribute-related price given consumers' judgment of product differentiation in terms of a given product attribute, which is obtained by multiplying the shelf price vector P by the attribute-distance-differentiation matrix G_{d_n}. The distance-differentiation matrix consists of the distance function defined above, that is, $G_{d_n} = \left[g_{\,ij,lm}(d_n)\right]_{ij*lm}$, which is a $IJ \times IJ$ symmetric matrix. To sum up, $\widehat{P_{d_n}} = G_{d_n}P$. The distance-differentiation matrix for each attribute was normalized so that the elements of each row sum to one. Pinkse and Slade (2004) explained that the normalization is performed so that when the price vector is multiplied by the distance-differentiation matrix, the corresponding element in the distance-adjusted price vector is the average price of products of the same type. Finally, to account for all the attribute-distance effects on consumers' judgment of shelf prices, a linear sum is conducted to form the adjusted price vector. In addition, adding a constant term to account for own-price elasticities, the adjusted price vector is expressed in matrix notation as:

(14) $\widehat{\mathrm{P}} = \Psi_0\widehat{P_{d_0}} + \Psi_1\widehat{P_{d_1}} + \Psi_2\widehat{P_{d_2}} + \Psi_3\widehat{P_{d_3}} + \Psi_4\widehat{P_{d_4}}$,

where $\boldsymbol{P_{d_0}}$ is an identity matrix and $\boldsymbol{\Psi_n}$ is interpreted as spatial-autoregressive coefficients (Richards, et al, 2010). Using typical elements in each of the matrix in the notation, the adjusted price for products which is branded by i and flavored in j is calculated as:

(15) $\widehat{p_{ijt}} = \psi_0 \sum_l \sum_m g_{\,ij,lm}(d_0)p_{lmt} + \psi_1 \sum_l \sum_m g_{\,ij,lm}(d_1)p_{lmt} + \psi_2 \sum_l \sum_m g_{\,ij,lm}(d_2)p_{lmt} + \psi_3 \sum_l \sum_m g_{\,ij,lm}(d_3)p_{lmt} + \psi_4 \sum_l \sum_m g_{\,ij,lm}(d_4)p_{lmt}$,

where $g_{\,ij,lm}(d_1)$, $g_{\,ij,lm}(d_2)$, $g_{\,ij,lm}(d_3)$, $g_{\,ij,lm}(d_4)$ are elements of the brand, flavor, company, and nutrient distance differentiation matrix, respectively, whose definitions are indicated above, and ψ_n is the estimate to be estimated. This adjusted price will be adopted into the demand equation, which not only accounts for the effects of product differentiation on the brand-level demand, but also reduces the number of estimates that need to be estimated without any a priori, compared to traditional differentiated product demand functions.

Instruments

The share equation cannot be estimated using the traditional OLS method because some elements in the error term may be correlated with the prices and conditional share. Thus, we need to find two sets of instrumental variables to identify the variations.

The first issue which must be addressed in estimating equation (10) is the endogeneity of retail prices, as well as the distance-weighted price index, $\widehat{p_{ijt}}$. Retailers take all the product characteristics into account when setting retail prices for canned soup products. That is, both the observed product characteristics X_{ij} and unobserved product characteristics ξ_{ij} are considered by the retailers, as well as their changes and valuations (Berto Villas-Boas, 2007). As in equation (6), we include a brand fixed variable to capture the unobserved brand effect that is constant over time, and a dummy quarterly variable to capture unobserved seasonal effects which are quite important for demand of canned soup products. The econometric residuals that remain in the error term ξ_{ij} only include some no-seasonal unobserved product characteristics that are difficult to quantify, such as shelf placement, in-store advertising, changes in consumer preference and some other non-quantifiable product characteristics that are not available in our data such as reputation, style and prestige (Berry, Levinsohn and Pakes, 1995). Therefore, prices in equation (6) are correlated with the unobserved product characteristics that affect demand, which will make the estimates for demand parameters biased and inconsistent. Thus, in order to obtain precise demand estimates, instrumental variables (*IV*) are used, which are correlated with product prices in equation (6) but uncorrelated with the unobserved product characteristics in the error term, ξ_{ij}. The set of instrumental variables is constructed by interacting the manufacturers' input prices (or input price indexes) with the brand dummy variables (similar to Nevo, 2001; Chintagunta, Bonfrer and Song, 2002; Berto Villas-Boas, 2007). The selected input prices and price indexes are average weekly earnings in food manufacturing section, non-residential electric power selling price index, raw material price index of vegetable products, and energy price index, which are listed in Table 2. All the original input cost data came in monthly sets, which have been transformed into weekly sets by using the spline interpolation. Moreover, it is reasonable to assume that manufacturers' input prices or price indexes are uncorrelated with unobserved product characteristics in the error term, ξ_{ij}. For instance, changes in the in-store advertising for canned soup products is more likely not correlated with manufacturers' input prices such as prices for elasticities, labor and capital. In addition, the intuition to interact manufacturers' input prices with brand dummy variables is to allow each input to enter the production function of each brand differently (Berto Villas-Boas, 2007). Berto Villas-Boas also provided another alternative set of instrumental variables which interact the input prices with product dummies. However, in our study, we assume that manufacturer marginal cost depends on the brand, indicating that marginal cost for producing the same brand of canned soup product is the same.

The second issue is also about endogeneity of conditional shares in equation (6). It is reasonable to consider that unobserved changes in product characteristics (by econometrician) are correlated with the conditional market share for a given brand. For example, it is more likely that in-store advertising for a given brand will increase its attraction to consumers and thus improve its market share. Thus, an optimal instrument variable is needed to exclude this variation. Berry, Levinsohn and Pakes (1995) indicated that the market share of a given product is affected by the varying characteristics of its competing products in the market, so characteristics of competing products can be adopted as instruments. Following Pinkse and Slade (2004) and Richards, Hamilton and Patterson (2010), the weighted average nutritional attributes of other brands/flavors are constructed by multiplying the vector of continuous nutritional contents by the nutrient weighting matrix G_{d_4}, which is defined above. To illustrate, for example, let F represent the vector of fat content of all the brands/flavors, and then $G_{d_4}F$ should contain the weighted average fat content of competing products. Instruments of additional nutritional attributes are created in such a way that the model is over-identified (Pinkse and Slade, 2004).

Results and Discussion

The results of NML/DM model is presented in Table 3. In doing so, we test (a) the justification of nesting structure (NML); (b) the validity of instrumental variables for prices and conditional share; (c) the importance of DM approach to identify products' locations in their attribute space; and (d) the effects of products' health-related attributes on the market demand for both private label and national brands. Table 3 shows the results for the structural demand model in four different specifications. Regression results in column (i) derived from the most basic model do not include the instrumental variables and DM approach. Regression results in column (ii) and (iii) include the instrumental variables and DM approach, respectively. Column (iv) presents the regression results which include both instrumental variables and the DM approach.

First of all, we evaluate the justification of nesting structure (NML) in the canned soup product demand. The coefficient of conditional share is negative and significant at any rational significance level. More importantly, it always lies between 0 and 1, indicating that consumers do substitute among brands within group. This finding is consistent with other studies such as Pham and Prentice (2010) which showed that consumers choose between "Discount" and "Mainstream"

Table 3: Estimation Results

Variables	i		ii		iii		iv	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	z-ratio
Seasonal	−0.111	−56.77	−0.125	−48.42	−0.125	−62.13	−0.058	−23.68
Division	−0.060	−333.04	−0.058	−265.52	0.001	2.53	0.055	49.23
Promotion	−0.583	−195.56	−0.600	−137.12	−0.493	−180.60	0.180	16.37
Brand	−0.082	−118.54	−0.150	−171.90	−0.184	−271.16	−0.103	−38.66
Private Label	−0.947	−95.29	−1.446	−101.59	−1.239	−111.20	−1.353	−47.18
Calorie	−0.011	−30.58	−0.016	−42.44	0.024	17.96	−0.142	−7.51
Fat	0.069	20.73	0.159	47.88	−0.130	−11.66	1.523	10.46
Cholesterol	0.038	70.32	0.041	78.49	−0.044	−32.15	−0.207	−27.77
Sodium	0.001	161.51	0.002	83.55	−0.001	−41.39	−0.003	−26.64
Carbohydrates	−0.015	−8.59	0.013	7.56	−0.204	−35.80	0.466	6.88
Fiber	0.054	27.94	0.132	69.22	0.061	33.25	−0.185	−30.46
Sugar	0.111	170.07	0.105	164.84	0.116	147.64	0.031	22.73
Protein	0.200	110.81	0.111	58.34	0.206	32.64	1.258	12.35
Health Claims	−0.241	−137.82	−0.337	−136.81	−0.389	−222.34	0.001	0.09
Brand-Distance	−	−	−	−	−0.794	−114.32	0.294	21.64
Flavor-Distance	−	−	−	−	0.120	17.69	0.289	29.98
Nutrient-Distance	−	−	−	−	−0.075	−12.10	−0.315	−14.26
Price	−0.026	−34.80	−0.369	−57.10	−2.543	−113.50	−6.914	−60.99
Price-Calorie	−	−	−	−	−0.019	−14.26	0.147	6.85
Price-Fat	−	−	−	−	0.138	11.66	−1.629	−9.39
Price-Cholesterol	−	−	−	−	0.578	15.68	0.252	38.27
Price-Sodium	−	−	−	−	0.062	47.75	0.005	31.15
Price-Carbohydrates	−	−	−	−	0.148	26.65	−0.475	−6.11
Price-Protein	−	−	−	−	−0.116	−18.33	−1.235	−12.23
σ	0.445	204.25	0.223	72.54	0.545	288.47	0.590	132.70
Adjusted R-squared	0.9795		0.9990		0.9784		0.9999	

cigarettes. Moreover the significance of both brand and flavor distance parameters also addresses the justification of nested structure in the canned soup category demand, which is consistent with finding in Richards, Hamilton and Patterson (2010).

Second, we need to test the validity of instrumental variables for prices and conditional share. Comparing the results in the basic and 2sls model would give a first impression on the bias of endogeneity problem. First, the robust standard errors in the 2sls model are much higher than those in the basic model since the basic model amounts to use the price and conditional share themselves as instrumental variables. This finding has also been theoretically reported by Greene (2007) and theoretically found by Stock and Yogo (2005). Second, price has a larger effect on the demand and demand is much more price sensitive, which is consistent with findings by Villas-Boas and Zhao (1995) and Richards, Hamilton and Patterson (2010). Last, in the basic model, it is surprising to find negative promotion effects on the demand, while it is positively negative in the

2sls demand model, indicating that temporary promotion would foster products' sales. More specifically and theoretically, the well-known Durbin-Wu-Hausman (Greene, 2008) test for endogeneity is used in this study, which shows the statistic of 394.9. Thus, we reject the null hypothesis that there is no endogeneity in the structural demand model and verify the two-stage-least-square method in the estimation.

Third, we evaluate the importance of Distance-Matrix approach in defining product differentiation considering health-related attributes. Although the importance of distance differentiation is suggested by the significance of all the distance-related parameters, some other evidence could be found by directly comparing the parameters in column (i) and (ii) to (iii) and (iv). Failing to account for product differentiation considering the health-related attributes not only underestimated the price effects and within-flavor substitution for the canned soup category, but also reverts the signs of coefficients for some important health-related attributes, such as sodium and cholesterol. Similar findings by Richard, Hamilton and Patterson (2010) also confirms the importance of the DM approach.

As discussed above, all the distance-related parameters are significantly different from zero. We can easily find corresponding rationale for the interpretation of these distance-related parameters. Recall that shelf prices are multiplied by the continuous and discrete distances to show consumers' assessment of product differentiation, so if there is more of the same brand within the flavor, the distance weighted prices will be larger. Hence, as to the interpretation of distance-related parameters, for instance, conditional on prices and other product's characteristics, the positive brand distance parameter shows that if the retailer carries more of the same brand within the flavor would foster the market share. Similar interpretation applies to the discrete-distance parameter of flavor. This is consistent with finding by Feinberg, Kahn and McAlister (1992) that product varieties generally help boost the market share. Moreover, a different interpretation should apply to the nutrient distance parameter. Recall that the nutrient distance shows the proximity of two products in their health-related attributes. The strongly negative parameter implies that conditional on prices, flavor and brand, if one product is closer in the characteristics space with others, its market share will be lower. This finding is different from that of Sayman, Hoch and Raju (2002) who found that mimicking national brand characteristics would cannibalize NB sales and increase PL shares. However, this finding is consistent with Richards, Hamilton and Patterson (2010). This result indicates that in terms of nutritional property, consumers tend to prefer nutritional varieties and attach importance to products' health-related attributes.

Another important parameter in the structural demand model is the PL indicator. As opposed to many other findings (Hoch and Banerji, 1992; Mill, 1995; Sayman, Hoch and Raju, 2002; etc.), we find a strong and consistent negative effect of PL on the market share. While it seems somewhat counterintuitive compared to other empirical and theoretical findings, it is likely explained by the fact that the canned soup market consists of a large number of NBs and statistics above show that there is strong price and promotion competition among NBs in this category. This is consistent with findings by Raju, Sethuraman and Dhar (1995), who theoretically and empirically found that in a category with a large number of NBs, even though introducing a PL may increase category profits, it does not necessarily increase market share. Moreover, they highlighted the argument that in large volume category (where the canned soup category lies), higher price competition among NBs (or higher cross-price sensitivity among NBs) makes the introduction of PL less attractive and decrease PL's market share (Raju, Sethuraman and Dhar, 1995). Furthermore, Sethuraman (1992) found empirical evidence that there exists a strong negative relationship between NB's promotion strategies (such as retailers' in-store discounts and manufacturers' coupons) and PL's market share, which indicates that price competition among national brands may inhibit private label introduction and growth. Similar findings were also discovered by Dhar and Hoch (1997) and Narasimhan and Wilcox (1998). The strong price and promotion competition among NBs (including the leading NB brand) leaves no place for the introduction of PL. While many previous findings believed the contention that PL introduction is beneficial to retailers due to case study difference or cross-category aggregation, this finding is especially important in the managerial perspective. The success of PL introduction by retailers depend not only on the retailers' marketing strategies; but also heavily on the market characteristics of the corresponding category.

Price-nutrient response parameters in the structural demand model suggest that nutrition properties and elasticities are closely related. Consistent with findings by and Richards et al. (2010), it is observed that consumers tend to be more price-elastic for high fat and high protein canned soup products since high fat and high protein canned soup products have less steep (i.e., more negative or positive) slopes that other nutrients. It is a reasonable result which has also been reported by Huang (1996) who indicated similar relationship between price and nutrient for beef products. Moreover, contrary to previous content that sodium is a big concern in the canned soup category, we find that, however, sodium has the steepest slope of all nutrients, showing its lowest price elasticity. While this result may be somewhat counterintuitive, it is probably strong evidence that consumers' perception of healthy nutrients deviates from scientific indication, which will be addressed again below. Allowing the slope (or the own price-elasticities) to vary with its own nutritional characteristics is therefore important in the perspective of manufacturers (Slade, 2004).

The health-nutrient parameters present a mixed result. All parameters are strongly significant in the demand model, indicting their strong relationship with market share. However, of all selected nutrients, we find that cholesterol, sodium and protein, are consistent with our hypothesis that consumers prefer less "bad for you" nutrients in their shopping basket. Other nutrients, especially fat, fiber and sugar, are estimated to have opposite effects on demand as hypothesized. For instance, the strongly positive coefficient for fat suggests consumers prefer high-fat canned soup. Similar results have been found by Nevo (2001), yet without further interpretation. Nayga, Tepper and Rosenzweig (1999), who found increased consumption of higher fat meat and sugar sweets, and deceased consumption of grains and fruit and vegetables coming with increased consumers' self-perception of health and health knowledge, argued the importance of taste attributes to the intriguing finding. It suggests that consumers' food consumption has been motivated more by their taste preference than "desirable eating habits based on established dietary guidelines" (Nayga, Tepper and Rosenzweig, 1999). Intuitively, for instance, a shopper trying to decide between noodle soup and beef noodle soup will probably pick up the beef noodle soup due to taste preference even though it has a higher level of fat and sugar. This interesting finding suggests that regardless of hype about health and nutrients, taste still plays an important role in determining consumers' purchasing decisions and manufacturers should make a trade-off between the adoption of healthy nutrients and taste (Blaylock, et. al, 1999 and Binkley and Golub, 1999).

Other parameters provide evidence on how market share varies with seasonal change, store location, promotion and brand. These parameters capture the fixed product effects that influence products' market share. The seasonal parameter suggests that canned soup products have a 5.8% higher market share in winter than summer on average. This is consistent with the statistical finding from our data. Moreover, accounting for the product differentiation considering health-related attributes and endogeneity problems reverts the sign for promotion parameter, which is consistent with most of some previous findings (Hoch and Banerji, 1993; Mills, 1995; Chintagunta, Bonfrer and Song, 2002).

Concluding Remarks

This study estimates the structural demand for canned soup products (both PL and NB) in the Canadian retailing market, considering product differentiation based on the products' characteristics, mainly health-related nutritional properties. Nested logit (MNL) model was adopted to derive the structural demand equation, in which the Distance-Matrix approach was used to identify products' location in their characteristics space and address product' differentiation. This method circumvents the traditional "*IIA*" and "dimensional" problem and makes it more flexible to estimate demand based on discrete choice model. Our empirical results show that both the DM approach and Nested Logit (MNL) model are appropriate for estimating demand for the canned soup category.

This study finds an intriguing result that in the canned soup category, retailers' introduction of PL does not help increase its market share. The strong price competition among incumbent NBs and large numbers of brands are theoretically believed to be the barrier for the success and performance of PL. Moreover, products' distance parameters also shows that retailers' carrying more of the same brand and flavor do benefit the retail sales. And PL's strategies to mimic NB's characteristics (locate PL close to NB in the characteristics space) would decrease its market share. It is also suggested that, contrary to common convention, consumers' perception of healthy nutrients deviates from scientific indication. More specifically, taste plays an important role in determining consumers' purchasing decisions and consumers' food consumption has been motivated more by their taste preference than "desirable eating habits based on established dietary guidelines" (Nayga, Tepper and Rosenzweig, 1999). This intriguing result would certainly bring an insight for both retailers and manufacturers to make a trade-off between adoption of healthy nutrients and tastes.

Limitations and Area of Future Research

Though the method in this study circumvents the traditional "*IIA*" and "dimensional" problem, it still have three major limitations. First of all, it is assumed that products' characteristics are pre-determined in an unobserved game and regarded as exogenous variations. However, products' characteristics may also be related to retailers' and manufacturers' pricing behaviors. Thus, a detailed investigation of determinants of products' characteristics would reveal more in the retailing market. Second, this study is focused on one-retailer case, in which this retailer is assumed to be market monopolist and represent the entire Canadian market. However, PL has been introduced not only for vertical competition between NBs, but also horizontal differentiation from other stores. Including more retailers would be helpful to better simulate the market competition. Finally, this study concentrates only on the demand side from the perspective of retailers. However, competition between PL and NB begins exactly from the upstream supply side, or margins (both manufacturing and retailing margins). To make the study more general, an investigation of supply side competition must be estimated. Thus, the most important area of future research lies in the evaluation of cost and price margins between manufacturers and retailers.

References

Aliswadi, K. L. and K. L. Keller. 2004. Understanding Retail Branding: Conceptual Insights and Research Priorities. *Journal of Retailing*. 80: 331-342.

Anders, S. and W. Ahmad. 2011. Private Label and National Brand Pricing and Promotional Strategies in Health Differentiated Product Categories: Canadian Evidence. Paper presented for EAAE 2-11 Congress.

Bergès-Sennou, F., P. Bontems and V. Réquillart. 2004. Economics of Private Labels: A Survey of Literature. *Journal of Agricultural & Food Industrial Organization.* 2(1): 1-23.

Berry, S. T. 1994. Estimating Discrete-Choice Models of Product Differentiation. *Rand Journal of Economics*. 25(2): 242-262.

Berry, S. T., J. Levinsohn, and A. Pakes. 1995. Automobile Prices in Market Equilibrium. *Econometrica*. 63(4): 841-890.

Berto Villas Boas, S. 2007. Vertical Relationships Between Manufacturers and Retailers: Inference with Limited Data. *Review of Economic Studies*. 74(2): 625-652.

Bocionek, M. 2012. Price Rigidity in the Context of Private Label-National Brand Competition in Canadian Retailing. M.Sc. Dissertation, the Justus Liebig University, Giessen, Germany.

Bontemps, C., V. Orozco and V. Réquillart. 2008. Private Labels, National Brands and Food Prices. *Review of Industrial Organization*. 33(1): 1-22.

Cardell, N. S. 1997. Variance Components Structures for the Extreme Value and Logistics Distribution. *Econometric Theory*. 13(2): 185-213.

Chamberlin, E. H. (1033 and 1956). The Theory of Monopolistic Competition. Cambridge, MA, US: Harvard University Press.

Chintagunta, P. K., A. Bonfrer and I. Song. 2002. Investigating the Effects of Store Brand Introduction on Retailer Demand and Pricing Behavior. *Management Science*. 48(10): 1242-1267.

Choi, S. C. and A. T. Coughlan. 2004. Private Label Positioning: Vertical vs. Horizontal Differentiation from the National Brand. Working paper, Marketing Department, Rutgers Business School, Newark, NJ, US.

Collins, K. and D. Bone. 2008. Private Label Shopping Trends in Food and Non-Alcoholic Beverages: Effectively Targeting Value Conscious Shoppers and Understanding Consumers' Attachment to Food and Drink Brands. Datamonitor, New Consumer Insight Series.

Datamonitor. 2011(September). Soup in Canada. Proprietary market report available at http://www.datamonitor.com/.

Dhar, S. K. and S. J. Hoch. 1997. Why Store Brand Penetration Varies by Retailer? *Marketing Science*. 16(3): 208-227.

Feinberg, F. M., B. E. Kahn and L. McAlister. 1992. Market Share Response When Consumers Seek Variety. *Journal of Marketing*

Research. 29(5): 227-237.

Greene, W. H. 2008. Econometric Analysis. Sixth Edition. Upper Saddle River, N. J., USA: Pearson/Prentice Hall.

Hoch, S.J. and S. Banerji. 1993. When Do Private Label Succeed? *Sloan Management Review.* 34(3): 57-67.

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

Kumar, N. and J. Steenkamp. 2007. Private Label Strategy: How to Meet the Store Brand Challenge. Boston, MA, US: Harvard Business School Press.

LSA/Frontier. 1996. Les Marques de Distributeurs. *Libre Service Actualites*, 1472: 10-15.

McFadden, D. 1974. The Measurement of Urban Travel Demand. *Journal of Public Economics*. 3(4): 303-328.

McFadden, D. 1976. The Mathematical Theory of Demand Models. D. C. Health and Co.: Lexington, MA, US.

McFadden, D. 1978. Modeling the Choice of Residential Location. In *Spatial Interaction Theory and Planning Models*, eds., A. Karlqvist, L. Lundqvist, F. Snickars, and J. W. Weibull. Amsterdam: North-Holland.

Mills, D. 1995. Why Retailers Sell Private Labels. *Journal of Economics and Management Strategy*. 4(3): 509-528.

Mintel. 2013. Global New Product Database. Proprietary market database available at http://gnpd.mintel.com.

Narasimhan, C. and R. T. Wilcox. 1998. Private Labels and the Channel Relationships: A Cross-Category Analysis. *Journal of Business*. 71(4): 573-600.

Nayga, R. M., B. J. Tepper and L. Rosenzweig. 1999. Assessing the Importance of Health and Nutrition Related Factors on Food Demand: A Variable Preference Investigation. *Applied Economics.* 31(12): 1541-1549.

Nevo, A. 2000. A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand. *Journal of Economics and Management Strategy*. 9(4): 513-548.

Nevo, A. 2001. Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica*. 69(2): 307-342.

Pham, V. and D. Prentice. 2010. An Empirical Analysis of the Counterfactural: A Merger and Divestiture in the Australian Cigarette Industry. MPRA paper publicly available at http://mpra.ub.uni-muenchen.de/26713/1/MPRA_paper_26713.pdf.

Pinkse, J. and M. E. Slade. 2004. Mergers, Brand Competition, and the Price of a Pint. *European Economic Review*. 48(3): 617-643.

Pinkse, J., M. E. Slade and C. Brett. 2002. Spatial Price Competition: A Semiparametric Approach. *Econometrica*. 70(3): 1111-1153.

Private Label Manufacturers Association (PLMA) (2004): PLMA's 2004 Private Label Yearbook. PLMA, New York, NY.

Private Label Manufacturers Association (PLMA) (2007): PLMA's 2007 Private Label Yearbook. PLMA, New York, NY.

Pofahl, G. and T. J. Richards. 2009. Valuation of New Products in Attribute Space. *American Journal of Agricultural Economics*. 91(2): 402-415.

Raju, J. S., R. Sethuraman and S. K. Dhar. 1995. The Introduction and Performance of Store Brands. *Management Science.* 41(6): 957-978.

Richards, T. J., S. F. Hamilton and P. M. Patterson. 2010. Spatial Competition and Private Labels. *Journal of Agricultural and Resource Economics*. 35(2): 183-208.

Sayman, S., S. J. Hoch and J. S. Raju. 2002. Positioning of Store Brand. *Marketing Science*. 21(4): 378-397.

Schmalensee, R. 1978. Entry Deterrence in the Ready-To-eat Breakfast Cereal Industry. *Bell Journal of Economics*. 9(2): 305-327.

Scott-Morton, F. and F. Zettelmeyer. 2004. The Strategic Positioning of Store Brands in Retailer-Manufacturer Negotiations. *Review of Industrial Organization*. 24(2): 161-194.

Sethuraman, R. 1992. The Effects of Marketplace Factors on Private Label Penetration in Grocery Products. Working Paper: 92-128. Marketing Science Institute, Cambridge, MA, USA.

Slade, M. E. 2004. Market Power and Joint Dominance in U.K. *Journal of Industrial Organization*. 52(1): 133-163.

Stanford Institute for Economic Policy Research (SIEPR). 2012. SIEPR-Giannini Data Center. http://are.berkeley.edu/sgdc.

Stock, J. H. and M. Yogo. 2005. Testing for Weak Instruments in Linear IV Regression. In: Andrews DWK Identification and Inference for Econometric Models. New York: Cambridge University Press; 2005. p. 80-108. Publicly available at http://scholar.harvard.edu/files/stock/files/testing_for_weak_instruments_in_linear_iv_regression.pdf.

Train, K. E. 2003. Discrete Choice Methods with Simulation. First Edition published by Cambridge University Press.

Turner, P. 2010. Aggregate Advertising, Sales Volume and Relative Prices in the Long Run. *Applied Economics Letters*. 7(8): 505-508.

Urban, T. L. 1998. An Inventory-Theoretic Approach to Product Assortment and Shelf-Space Allocation. *Journal of Retailing*. 74(1): 15-36.

Villas-Boas, J.M. and Y. Zhao. 2005. Retailer, Manufacturers, and Individual Consumers: Modeling the Supply Side in the Ketchup Marketplace. *Journal of Marketing Research*. 42(1): 83-95.