Mergers Simulation and Demand Analysis for the U.S. Carbonated Soft Drink Industry

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1. Introduction

Horizontal Mergers between large firms have long attracted governmental attention (Farrell and Shapiro, 1990). In the mid-1990s, the regulatory authorities at the U.S. Federal Trade Commission (FTC) and Department of Justice (DOJ), as well as many economists, developed a new approach for exploring the potential competitive effects of a horizontal merger. This method is known as Horizontal Merger Simulation (Pofahl, 2006). Such merger simulation analysis commonly presumes, given that the analyst knows the parameters of the demand system and information is sufficiently comprehensive to calculate elasticities, it is possible to simulate the price effects or consumer welfare change of a merger. The soundness of this approach depends on how accurately the demand estimation reflects the reality and on how close the firm's pricing behavior is to the assumed game (Ashenfelter and Hosken, 2008). However, in estimating the demand of differentiated-products markets (demand-side), there are thousands products to be taken into account. That is, it is common for several hundred brands to be sold in beer or breakfast cereal market (Pinkse and Slade, 2004).

Traditional models used in demand estimation, as derived from constrained utility maximization, assume that quantity is a function of prices and income. These models such as Almost Ideal Demand System (AIDS) and Rotterdam demand model are characterized by "flexible functional forms" because they leave the own- and cross-price elasticities unrestricted to be determined by the data itself without imposing additional assumptions on substitution patterns like Independence of Irrelevant Alternatives

(Hausman, 1994). Nonetheless, if a demand equation involves the prices of all pertinent goods of differentiated products, estimation of all parameters will be a computational burden, which is what we call the curse of dimensionality (Pofahl, 2006). Arguably the direct solutions addressing the dimensionality problem are Distance Metric demand estimation method (DM) and discrete choice model (DC).

However, one of DC's obvious disadvantages is that multiple purchases by consumers cannot be studied. Discrete choice models are based on the assumption that each consumer buys only one product at each purchasing moment (Giacomo, 2004). Apparently, this assumption does not fit consumer behavior in many differentiated product markets, including Carbonated Soft Drinks (CSD). Dube (2004) showed, approximately, 31% of the shopping trips are multiple-product purchase of CSD and 61.5% of the trips are multiple-unit purchase in his dataset. It is clear that presumption of single unit purchase is inappropriate in the CSD industry.

On the other hand, Pinkse, Slade and Brett (2002) developed the distance metric (DM) estimation method to overcome the dimensionality limitation of classical demand models and the single purchase restriction of DC models by specifying the cross-price coefficients semi-parametrically, as functions of the distance between the products attribute space, projecting prices dimension into attributes dimension to reduced the number of estimated coefficients (Pofahl, 2006). For example, in the CSD industry, the distance metric $\left| Carb_i - Carb_j \right|$ could be employed, which gives the absolute distance of the carbohydrate contents between *i* and *j*.

In this essay, I incorporate the Distance Metric (DM) estimation approach in LA/AIDS model to assess the impacts of Cadbury/DPSU merger effective on March 2, 1995 in the U.S. CSD industry. The goal of this paper is to test the power of DM approach, as a basis for simulation study of merger analysis.

Notably, dynamic aspects of demand are not incorporated in DM model. Since past purchases may play a more important role in the choice of durable goods than non durable goods, we should be able to ignore this issue in the CSD industry.

2. The United States Carbonated Soft Drink Industry

Soft Drink Production is the largest component of beverage manufacturing in the U.S., with annual 2006 revenue of $42.3 billion. This industry is dominated by carbonated soft drinks (CSD), which account for around 54.3% of industry revenue. The U.S. has very high levels of CSD consumption and per capita CSD consumption in the U.S. is estimated at 51.4 gallons per person per year. [1] CSD refers to beverages manufactured by mixing flavoring concentrate, sweetener, and carbonated water. This industry has some of the highest brand recognition in the world along with a high level of sales through its vast investments in advertising and marketing. In 2006, Coca-Cola Company had 42.9 percent of the CSD market; Pepsi-Cola Company held a 31.2 percent share, and Cadbury Schweppes was ranked third, with 14.9 percent of the market share in 2006. [2]

In January 1986, Philip Morris planned to sell the Seven-Up Company to PepsiCo, while Coca-Cola was attempting to buy Dr Pepper. However, both proposed acquisitions were blocked by Federal Trade Commission (FTC) for antitrust considerations. When these acquisitions were prohibited, Dallas-based investment bank Hicks& Haas purchased Dr Pepper for $406 million in August 1986. Britain’s Cadbury Schweppes also

[1] Soft Drink Production in the US:31211. IBISWorld Industry Report. Online Edition. Available from http://www.ibisworld.com/industry/default.aspx?indid=284. Accessed October, 2008.
[2] Soft Drinks and Bottled Water. Encyclopedia of Global Industries. Online Edition. Gale, 2009. Available from http://galenet.galegroup.com. Accessed October, 2008.

joined in the buyout, earning a minority stake in Dr. Pepper. Later in 1986, Hicks & Haas again purchased the U.S. operations of Seven-Up for $240 million. Next, Hicks & Haas merged Dr Pepper and Seven-Up, forming the Dr Pepper/Seven Up Companies, Inc. (DPSU) on May 19, 1988. Overall, DPSU's share of the domestic soft drink market increased from 9.8 percent in 1991 to 11.4 percent in 1994.

Cadbury, in October 1993, was further involved in the U.S. market through the acquisition of A&W Brands Inc. The addition of A&W Brands increased Cadbury's share of the U.S. soft drink market to 5.6 percent. However, Cadbury expected to resist more aggregate competition from other international food and beverages companies, becoming the leading producer of noncola soft drinks in the world; apparently, the quickest way to achieving this goal was taking over DPSU in the U.S. market. On March 2, 1995, Cadbury Schweppes acquired the rest of DPSU for $1.7 billion. The company becomes Dr Pepper/Cadbury of North America, Inc. This company currently has renamed as Dr Pepper Snapple Group. The new company had a market share of 17 percent and a strong list of brands, including: Dr Pepper, 7 Up, Welch's, IBC, Canada Dry, Schweppes, A&W, Crush, Sunkist, Squirt, Mott's Hires, Sun Drop, Vernors, and Country Time. [3] This made Cadbury Schweppes the largest non-cola soft drink company in America. The FTC did not oppose this acquisition, possibly expecting Cadbury to be more effective competitor of Coca-Cola and PepsiCo. Afterwards, Coca-Cola, PepsiCo, and Cadbury together now account for about 90% of all CSDs sold in the U.S. (Saltzman, Levy and Hilke, 1999). [4]

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[3] Dr Pepper/Seven Up, Inc. Business & Company Resource Center. International Directory of Company Histories, Vol. 32. St. James Press, 2000. Available from http://galenet.galegroup.com. Accessed November, 2008.

[4] Cadbury reportedly has "absolutely no ambitions or intentions as far as the cola business is concerned." See *Beverage Digest* (Feb. 3, 1995 p3). Actually, a considerable portion of Cadbury's CSDs are sold by Coca-Cola and Pepsi-Cola

3. Quantitative Methods for Merger Evaluation

3.1 The Demand Model

The first step of horizontal merger simulation is to estimate the demand for CSD at the brand-level. Pinkse and Slade (2004) derived the aggregate-demand function of product sales based on normalized-quadratic indirect-utility function as

$$q_i = a_i + \sum_j b_{ij} p_j - e_i y + u_i \qquad (i=1,\ldots,n). \qquad (3.1)$$

where $B = \left[b_{ij} \right]$ is an arbitrary $n \times n$ symmetric, negative-semidefinite matrix, and normalized prices $p = \left(p_1, p_2, \ldots, p_n \right)^T$ and aggregate income *y* have been divided by p_0. Assume that both a_i and the diagonal elements of *B*, which determine the own-price elasticities, are functions of the characteristics of product *i*, $a_i = a(x_i)$ and $b_{ii} = b(x_i)$. The off-diagonal elements of *B* are assumed to be functions of the distance between products in some set of metrics, $b_{ij} = g\left(d_{ij}\right)$, $\mathrm{i} \neq \mathrm{j}$. The function $g\left(.\right)$ must be estimated semi-parametrically instead of imposing structure on that, showing how the distance measures, d_{ij}, influence the power of competition between products *i* and *j*. d_{ij} measures the closeness of the two products, *i* and *j*, in attributes space. For example, if the products were brands of bottled juice, the measures of distances might be sodium content, market share proximity, or dummy variables that indicate whether commodities belong to the same manufacturer. The random variable u_i, which captures the influence of unobserved demand and cost variables, can be heteroskedastic and correlated across observations.

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bottlers. In the late 1990s, Cadbury may be hesitant to compete with Coca-Cola and PepsiCo in the cola segment due to its all important relationship with their bottlers (Saltzman, Levy and Hilke, 1999). However, between 2006 and 2007, Cadbury Schweppes purchased the Dr Pepper/Seven Up Bottling Group (DPSUBG) and several other regional bottlers. This allowed DPS to bottle many of its own beverages but caused many Pepsi and Coke bottlers to drop Cadbury's products.

Pinkse and Slade assume u_i is mean independent of the observed characteristics, $E\left[u_i \middle| x\right]=0$. This is a strong independence assumption. If this assumption is violated, the estimator of the unknown parameter of equation (3.1) is inconsistent.

One can apply the DM approach to the Linear Approximate Almost Ideal Demand System Model (LA/AIDS). The substantial advantages of this model are that it can accommodate the non-linear aggregation across consumers and set no restrictions on the length of the panel data. As what we indicated previously, Pinkse and Slade's individual indirect-utility function is of Gorman polar form. Although it can be easily aggregated or differentiated to obtain brand-level demands, the problematic assumptions are that the change in an individual's demand for certain commodity with respect to a difference in personal income does not depend on earnings; this condition is the same for every consumer regardless of the individual's character. As a result, if a consumer does not buy a product, then the income effect for that product is assumed to be zero. Thus, it amounts to suppose that income effect for all products is zero since it would be simple to find one person who does not purchase a certain commodity, especially with long length time periods in a dataset (Rojas, 2005).

The LA/AIDS Model

Formally, let $i \in (1,\ldots,N)$ be the index of products, $t \in (1,\ldots,T)$ the set of markets which are defined as cluster-week pairs[5] in this essay, $p_t = (p_{1t},\ldots,p_{Nt})$ the vector of retail prices in market *t*, $q_t = (q_{1t},\ldots,q_{Nt})$ the vector of quantities demanded, and

[5] The cross-price elasticities are zero through markets.

$X_t = \sum_i p_{it} q_{it}$ total expenditures in market *t*. Using these notations, the LA/AIDS suggested by Deaton and Muellbauer is given as follows:

$$w_{it} = \alpha_{it} + \sum_{j=1}^{N} \gamma_{ij} \ln(p_{jt}) + \beta_i \ln\left(X_t / P_t^* \right) + \varepsilon_{it} \tag{3.2}$$

where $w_{it} = \frac{p_{it} q_{it}}{X_t}$ is the expenditure share for product *i* in market *t*, and the Stone price index is defined as follows:

$$\ln(P_t^*) \equiv \sum_{i=1}^{N} w_{it} \ln(p_{it}), \tag{3.3}$$

It was typical to use Stone price index to linearize the AIDS model. However, Moschini (1995) indicated that Stone index, varies with the variation in units of measurement of prices and quantities. For example, suppose we change the unit of the first good from bales to tons, then the corresponding price will be scaled by 4 (1 ton = 4 bales). Since such alternation does not impact the expenditure shares, the Stone index would apply unchanged weights to the scaled prices. This problem makes γ_{ij} or β_i generally biased. Among possible solutions suggested by Moschini, one feasible choice is $\ln\left(P_t^L\right)$ which is a loglinear analogue of the Laspeyres index, defined as follows:

$$\ln(P_t^*) \approx \ln(P_t^L) = \sum_i w_i^0 \ln(p_{it}), \tag{3.4}$$

where w_i^0 is product *i's* 'base' share, defined as $w_i^0 \equiv T^{-1} \sum_t w_{it}$, the average expenditure share of product *i* over *t*.

After replacing (3.3) by (3.4), the sales share form of LA/AIDS can be written as

$$w_{it} = \alpha_{it} + \sum_{j=1}^{N} \gamma_{ij} \ln(p_{jt}) + \beta_i \ln\left(X_t / P_t^L \right) + \varepsilon_{it} \tag{3.5}$$

Normally, the (N-1) equations of (3.5) can be estimated by Seemingly Unrelated Regression (SUR) method. Nevertheless, if we apply LA/AIDS model to assess the demand of numerous CSD products here, the procedure has a significantly challenge in its evaluation due to the curse of dimensionality.

Distance Metric (DM) Approach

Following Pinkse and Slade (2004) as well as Rojas (2005), we propose characteristic distance metrics are added to the LA/AIDS model to alleviate the difficulty of estimation. Briefly speaking, our objective function, (3.5), includes a vector, d, which is the distance measure of product's attributes, and the cross-price coefficients, γ_{ij}, $i \neq j$, can be prescribed as a function $g(.)$ of the distance measures, d_{ij}.

$$w_{it} = \alpha_{it} + \gamma_{ii} \ln(p_{it}) + \sum_{j \neq i} g(d_{ij}^{k}; \lambda) \ln(p_{jt}) + \beta_i \ln\left(X_t \middle/ P_t^L \right) + \varepsilon_{it}, \qquad (3.6)$$

where k equals the number of distance measures, and λ is the corresponding coefficients to each distance metric (Pofahl, 2006). The element of d is determined by researcher. Inwardly, the function g shows how difference of attributes affects the strength of product's competition (Pinkse, Slade and Brett, 2002).

The own-price parameter γ_{ii} is comprised of a constant and product i's attributes. Suppose carbohydrate content is a relevant attribute that has impact on the demand of CSD, γ_{ii} can be written as $\gamma_{ii} = \gamma_0 + \gamma_1 Carb_i$ and hence $\gamma_{ii} \ln(p_{it}) = \gamma_0 \ln(p_{it}) + \gamma_1 \ln(p_{it}) Carb_i$, including a price interacting term with the product characteristics.

Moreover, the intercept term α_{it} is modified to contain demographic variables ($Z_{1t}, ..., Z_{Mt}$) of each cluster. Besides, since advertising has noticeable effect on the growth of CSD consumption, even if we lack data for the expenditure on classical advertising channels like television, press and on-line advertisement, DFF has variable, *sales*, pointing out whether the product was sold on a promotion that week. Therefore, the percentage of stores on sales for specific brand within the same cluster (S_{it}) can be a part of intercept. Given above assumptions, α_{it} takes the form

$$\alpha_{it} = \alpha_{0i} + \sum_{m=1}^{M} c_{im} Z_{mt} + c_{i,m+1} S_{it} \tag{3.7}$$

Then, the LA/AIDS model with DM method becomes

$$w_{it} = \alpha_{0i} + \sum_{m=1}^{M} c_{im} Z_{mt} + c_{i,m+1} S_{it} + \gamma_{ii} \ln(p_{it}) + \sum_{j \neq i} g(d_{ij}^{k}; \lambda) \ln(p_{jt}) + \beta_i \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{it} \tag{3.8}$$

The theoretical restrictions contain,

$$\sum_{i=1}^{N} \alpha_{0i} = 1, \ \ \sum_{i=1}^{N} c_{im} = 0, \forall m \quad \text{for adding-up,} \tag{3.9a}$$

$$\sum_{i=1}^{N} \beta_i = 0 \quad \text{for linear homogeneity.} \tag{3.9b}$$

To have more clear insight of DM method, let’s make a simple example below. Suppose there are four commodities sold in the market, the traditional AIDS demand system is like:

$$w_{1t} = \alpha_{1t} + \gamma_{11} \ln(p_{1t}) + \gamma_{12} \ln(p_{2t}) + \gamma_{13} \ln(p_{3t}) + \gamma_{14} \ln(p_{4t}) + \beta_1 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{1t}$$

$$w_{2t} = \alpha_{2t} + \gamma_{21} \ln(p_{1t}) + \gamma_{22} \ln(p_{2t}) + \gamma_{23} \ln(p_{3t}) + \gamma_{24} \ln(p_{4t}) + \beta_2 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{2t}$$

$$w_{3t} = \alpha_{3t} + \gamma_{31} \ln(p_{1t}) + \gamma_{32} \ln(p_{2t}) + \gamma_{33} \ln(p_{3t}) + \gamma_{34} \ln(p_{4t}) + \beta_3 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{3t}$$

$$w_{4t} = \alpha_{4t} + \gamma_{41} \ln(p_{1t}) + \gamma_{42} \ln(p_{2t}) + \gamma_{43} \ln(p_{3t}) + \gamma_{44} \ln(p_{4t}) + \beta_4 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{4t},$$

If we impose symmetry on the cross-price parameters, six cross-price parameters need to be estimated. Suppose carbohydrates and sodium contents are the relevant product characteristics that have influence on the demand of CSD and let d_{ij}^{carb} and d_{ij}^{so} symbolize the distance measures of carbohydrates as well as sodium content between brand *i* and *j*. The distance metric function for cross-price coefficients can be presumed as $\lambda_0 + \lambda_1 d_{ij}^{carb} + \lambda_2 d_{ij}^{so}$. Given there are no brand attributes terms in the own-price parameter, the whole system after substitution becomes

$$w_{1t} = \alpha_{1t} + \gamma_0 \ln(p_{1t}) + \left[\lambda_0 + \lambda_1 d_{12}^{carb} + \lambda_2 d_{12}^{so}\right]\ln(p_{2t}) + \left[\lambda_0 + \lambda_1 d_{13}^{carb} + \lambda_2 d_{13}^{so}\right]\ln(p_{3t}) +$$
$$\left[\lambda_0 + \lambda_1 d_{14}^{carb} + \lambda_2 d_{14}^{so}\right]\ln(p_{4t}) + \beta_1 \ln\left(X_t / P_t^L \right) + \varepsilon_{1t}$$
$$w_{2t} = \alpha_{2t} + \left[\lambda_0 + \lambda_1 d_{21}^{carb} + \lambda_2 d_{21}^{so}\right]\ln(p_{1t}) + \gamma_0 \ln(p_{2t}) + \left[\lambda_0 + \lambda_1 d_{23}^{carb} + \lambda_2 d_{23}^{so}\right]\ln(p_{3t}) +$$
$$\left[\lambda_0 + \lambda_1 d_{24}^{carb} + \lambda_2 d_{24}^{so}\right]\ln(p_{4t}) + \beta_2 \ln\left(X_t / P_t^L \right) + \varepsilon_{2t}$$
$$w_{3t} = \alpha_{3t} + \left[\lambda_0 + \lambda_1 d_{31}^{carb} + \lambda_2 d_{31}^{so}\right]\ln(p_{1t}) + \left[\lambda_0 + \lambda_1 d_{32}^{carb} + \lambda_2 d_{32}^{so}\right]\ln(p_{2t}) + \gamma_0 \ln(p_{3t}) +$$
$$\left[\lambda_0 + \lambda_1 d_{34}^{carb} + \lambda_2 d_{34}^{so}\right]\ln(p_{4t}) + \beta_3 \ln\left(X_t / P_t^L \right) + \varepsilon_{3t}$$
$$w_{4t} = \alpha_{4t} + \left[\lambda_0 + \lambda_1 d_{41}^{carb} + \lambda_2 d_{41}^{so}\right]\ln(p_{1t}) + \left[\lambda_0 + \lambda_1 d_{42}^{carb} + \lambda_2 d_{42}^{so}\right]\ln(p_{2t}) +$$
$$\left[\lambda_0 + \lambda_1 d_{43}^{carb} + \lambda_2 d_{43}^{so}\right]\ln(p_{3t}) + \gamma_0 \ln(p_{4t}) + \beta_4 \ln\left(X_t / P_t^L \right) + \varepsilon_{4t},$$

Moreover, the demand system can be written as

$$w_{1t} = \alpha_{1t} + \gamma_0 \ln(p_{1t}) + \lambda_0 [\ln(p_{2t}) + \ln(p_{3t}) + \ln(p_{4t})] + \lambda_1 [d_{12}^{carb} \ln(p_{2t}) + d_{13}^{carb} \ln(p_{3t}) + d_{14}^{carb} \ln(p_{4t})]$$
$$+ \lambda_2 [d_{12}^{so} \ln(p_{2t}) + d_{13}^{so} \ln(p_{3t}) + d_{14}^{so} \ln(p_{4t})] + \beta_1 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{1t}$$
$$w_{2t} = \alpha_{2t} + \gamma_0 \ln(p_{2t}) + \lambda_0 [\ln(p_{1t}) + \ln(p_{3t}) + \ln(p_{4t})] + \lambda_1 [d_{21}^{carb} \ln(p_{1t}) + d_{23}^{carb} \ln(p_{3t}) + d_{24}^{carb} \ln(p_{4t})]$$
$$+ \lambda_2 [d_{21}^{so} \ln(p_{1t}) + d_{23}^{so} \ln(p_{3t}) + d_{24}^{so} \ln(p_{4t})] + \beta_2 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{2t}$$
$$w_{3t} = \alpha_{3t} + \gamma_0 \ln(p_{3t}) + \lambda_0 [\ln(p_{1t}) + \ln(p_{2t}) + \ln(p_{4t})] + \lambda_1 [d_{31}^{carb} \ln(p_{1t}) + d_{32}^{carb} \ln(p_{2t}) + d_{34}^{carb} \ln(p_{4t})]$$
$$+ \lambda_2 [d_{31}^{so} \ln(p_{1t}) + d_{32}^{so} \ln(p_{2t}) + d_{34}^{so} \ln(p_{4t})] + \beta_3 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{3t}$$
$$w_{4t} = \alpha_{4t} + \gamma_0 \ln(p_{4t}) + \lambda_0 [\ln(p_{1t}) + \ln(p_{2t}) + \ln(p_{3t})] + \lambda_1 [d_{41}^{carb} \ln(p_{1t}) + d_{42}^{carb} \ln(p_{2t}) + d_{43}^{carb} \ln(p_{3t})]$$
$$+ \lambda_2 [d_{41}^{so} \ln(p_{1t}) + d_{42}^{so} \ln(p_{2t}) + d_{43}^{so} \ln(p_{4t})] + \beta_4 \ln\left(X_t \big/ P_t^L \right) + \varepsilon_{4t}$$
(3.10)

For cross-price coefficients, only three parameters, λ_0, λ_1 and λ_2 are necessary to be estimated right now. Obviously, if there are numerous products are involved in the demand estimation, the method's effect on reducing the dimensionality will be clearer. This is why we say DM method can handle the challenge for "curse of dimensionality". [6]

Because the distance metrics are symmetric, symmetry can be required by making λ equal across all equations. Once we obtain the estimated coefficients of λ, it is simple to calculate the cross-price coefficients and elasticities. The functional form of $g(.)$ can be estimated by parametric or semiparametric methods. If the parametric assumption is correct, then choosing the semi-parametric methods will be inefficient. However, we estimate $g(.)$ semi-parametrically since it can derive as much flexibility in the pattern of substitution as possible without depend on any arbitrary parametric form according to the analyst's uncertain knowledge or beliefs. Among numerous semi-parametric estimation

[6] This example was suggested by Dr. Pofahl.

approaches, we attempt to apply additive model with B-splines in continuous metrics to get the optimal function form of $g(.)$.

Additionally, the expression of Marshallian price elasticities, uncompensated price elasticities, can be written as (Green and Alston, 1990 and Rojas, 2005)

$$\eta_{ij} = \begin{cases} -1 + \dfrac{1}{w_{it}}\left[\gamma_{ii} - \beta_i \dfrac{d \ln P_t^L}{d \ln p_{it}}\right] = -1 + \dfrac{1}{w_{it}}\left[\gamma_{ii} - \beta_i w_i^0\right], \text{ for } i = j \\ \dfrac{1}{w_{it}}\left[g\left(d_{ij}^k;\lambda\right) - \beta_i \dfrac{d \ln P_t^L}{d \ln p_{jt}}\right] = \dfrac{1}{w_{it}}\left[g\left(d_{ij}^k;\lambda\right) - \beta_i w_j^0\right], \text{ for } i \neq j \end{cases} \tag{3.11}$$

3.2 Household Demographics

In addition to demand parameter estimation, capturing variation in substitution patterns among across broad classifications of consumer groups should not be ignored in our estimation. Based on the same data resource, Hoch et al. (1995) and Chintagunta et al. (2003) indicate category-level consumer price elasticity across stores is mainly influenced by consumer demographic difference. In other words, zone-pricing through store chain is substantially activated by price discrimination on consumer's heterogeneity rather than competition between stores. Thus, consumer demographic difference between clusters will be considered as we estimate the demand of CSD.

4. Data and Preliminary Data Analysis

4.1 Demand Data

The primary data resource is the administrative Dominick Database from Kilt Center for Marketing, University of Chicago, Booth School of Business. The dataset involves weekly retail price, sold quantities, and profits for more than 3500 UPCs for over 100 stores operated by Dominick's Finer Foods (DFF) across approximately 9 years (09/14/89-05/14/97). DFF is the second-largest supermarket operator in the metropolitan

Chicago area. Safeway, which bought Dominick's in 1998, has decided to keep the chain, which was offered for sale in the early 2000s, but failed to attract a buyer. I select the products related to the Cadbury/DPSU merger from the "Soft Drink" (SDR) group.

Data Preparation

Observations were dropped if one of these variables including sold quantity, price, or profit, was missing for that observation. This essay covers the store-level scanner data for 2 years from 03/04/1993 to 03/05/1997. I segregate the data into two groups depending on the effective date of Cadbury/DPSU merger on March 2, 1995 as a dividing point. The nearest two years of pre-merger data which starts from 03/04/1993 to 03/01/1995, equivalent to recorded week #182-#285 in DFF database, is employed to simulate the price effects of this CSD merger, while the post-merger data is used to be a comparison with the simulated price changes. Nevertheless, given a lack of available price information for three brands on the selected list in week #211, we drop the observations during this period. After we decide the selected brands, if a certain brand does not have sales information in some markets during the period of interest, the whole selected brands observations are deleted in that cluster-week pair to avoid bias in estimation. Finally, 5,616 observations are taken into considerations in the analysis.

The information on nutritional facts is based on previous research, as well as collected from CSD package at local supermarkets or manufacturer websites. If the collected information from grocery stores is different from Dube (2005)[7] and McMillan's paper (2007), we will pick up the data from their search rather than information on package since some brands may have been re-formulated. For example, 7-

[7] The first version of Dube's paper (2004) was received on September 25, 2000 by Marketing Science. The products' characteristics table in that paper is the earliest data I can find for this merger case happened in 1995.

UP has replaced sodium citrate with potassium citrate to reduce the beverage's sodium content in 2006. [8] For some commodities which are unavailable through their inquiries, unless we are very sure some brands' formula was altered after 1995, we presume that the nutrition facts on current brands are consistent with the characteristic content during the related period of our research. Another difficulty faced in this research is that the element of CSD is viewed as a business secret; consumer service employees of these companies refused to offer information about ingredients. Initially, different package sizes of specific brand are viewed as different products because of the differences in storability. Also, Dube's research outcome (2005) shows that package size is a relevant attribute affecting consumer's purchase behavior. However, results of our preliminary OLS regressions before aggregation indicates most attributes related to package size are insignificant in the demand estimation despite the metrics form of size. [9] Besides, most papers applying DM method as Rojas' work in brewing industry and Pofahl's job in bottled juice category mainly focus on brand-level demand. Thus, we do the aggregate of CSD products into sixteen brands and that should be helpful to simply the demand estimation effectively.

DFF clusters its stores into four groups: A, B, C and D. I form the stores within the same cluster as the same cohort and handle these groups as separate regional markets. The demographics description and summary of statistics for each cluster of store-specific demographic data are shown in Table1 and Table2. The data are obtained from US Government (1990) census data for the Chicago metropolitan area and Market Metrics

[8] See http://www.solarnavigator.net/solar_cola/7up.htm.

[9] Preliminary OLS outcomes are shown in Table A1 and A2 in Appendix A. The t-statistic of package size (Mvol) is -0.90 in Table A1 where the package size is used to set continuous metrics while the t-statistic of package size (Msize) is 2.09 in Table A2 where package size is treated as a dummy indicator. Both of them are insignificant at 5% level.

operates this data to generate demographic profiles for each of the DFF stores. [10] Although it has been documented that Dominick's price zones are up to 16 for the whole Chicago area, for simplicity, here I assume there are only four price zones.

To further simply the analysis, CSDs with at least a 0.3% sales volume share (in fluid ounces) [11] in any cluster are taken into account, consisting of 16 brands including the top-10 soft drinks brands in 1994-1995 and some Cadbury's famous brands representing approximately 68.3% share of total CSD sales by dollar value during the relevant time period. [12] Chosen brands and their market shares as well as their characteristics are shown in Table 3 and Table 4. Coke is the most expansive while Diet A&W Root Beer is the least expensive. I do not consider regional brands here because of the comparably small nationwide sales percentage, about 3%. Additionally, we only have data throughout Chicago metropolitan region.

4.2 Distance Metrics

The brand attributes that are presumed to affect consumer's perception are comprised of: calories, milligrams of sodium, and grams of total carbohydrates content based on per 12 fluid ounce (355 ml) serving, as well as a set of binary variables for the presence of caffeine, citric acid and whether it is a cola drink. Dummy variables are constructed to identify different manufacturers. These chosen characteristics are established based on earlier work of Dube (2004 and 2005) and McMillan (2007). Noticeably, it is clear that there is high correlation between calories and carbohydrates and therefore we only choose carbohydrates, sparing calories, in setting distance matrices.

[10] See http://research.chicagogsb.edu/marketing/databases/dominicks/demo.aspx for more detail of DFF Store-Specific Demographics database.
[11] In highly competitive differentiated industry, a new product with 0.5% market share can be considered quite successful (Cotterill, 1999).
[12] The ranking of top-10 best selling brands has a slight change in 1994-1995 but the list of brand for 1994 and 1995 are the same. Database: Business Source Complete.

Coverage, the percentage of stores that sell specific brand, is utilized as a choice of continuous variable in both Pinske and Slade's (2004) as well as Rojas's (2005) research. We do not consider it here since almost all of the selected CSDs are sold at every chain store over the interested time period that makes coverage useless here.

Discrete and continuous matrices are set as an inverse of distance to make the interpretation of result easier.

Continuous Distance Measures with Continuous Brand Attributes

I create single-dimension distance metrics of carbohydrate content of CSD in continuous attribute space as:

$$d_{ij}^{carb} = \frac{1}{1 + 2\left|Carb_i - Carb_j\right|} \tag{4.1}$$

where $\left|Carb_i - Carb_j\right|$ is the absolute value for the difference of brand's rescaled-carbohydrates content and $d_{ij}^{k} \in (0,1]$. If brands *i* and *j* have the same carbohydrates attributes, this metric reaches the maximized value of 1. As the distance in carbohydrates space between brands *i* and *j* grows, the metric's value approaches to zero. Obviously, the assumption behind this formula is that the strength of the competition is influenced by how near the brand's attributes are. That is to say that we use this measure to examine if Diet Pepsi is a stronger substitution for Diet Coke than Coke. The measures of the other continuous characteristics, such as sodium as well as carbohydrates coverage are constructed following the same formula. The above one-dimensional metrics are not singular option for making distance measure; that is we can define an n-dimensional Euclidian distance measure to accommodate multiple attributes between different brands. For instance, a two-dimensional distance metrics can be written as:

$$d_{ij}^{SCB} = \frac{1}{1+2\sqrt{\left(So_i - So_j\right)^2 + \left(Carb_i - Carb_j\right)^2}} \tag{4.2}$$

However, if we want to know which characteristic plays the most influential role in determining patterns of substitution, a single-dimensional metrics cannot be neglected (Pofahl, 2006).

Discrete Distance Measures with Continuous Brands Attributes

Following Pinkse and Slade (2004), Rojas (2005) as well as Pofahl (2006), continuous commodities attributes can be used to construct two-dimensional market areas and these measures are derived from the Euclidean distance. Two kinds of metrics are considered here: the nearest-neighbor measures and the common-boundary measures.

For nearest-neighbor metrics, the distance measure in sodium/carbohydrates space can be defined exogenously that d_{ij}^{NNSC} equals to one when brands *i* as well as *j* are nearest neighbors to each other in sodium/carbohydrates space, $1/2$ if brands *i(j)* is *j*'s*(i*'s*)* nearest neighbor but not vice versa, and 0 otherwise. Brand *i*'s nearest neighbor is meant to be the brand having the shortest Euclidean distance from brand *i* in relevant attribute space. To derive more reasonable and reliable Euclidean distance between brands, continuous attributes are rescaled through dividing by its maximum value since each of these characteristics' measurement unit differs so it is better to limit the value of continuous characteristics between 0 and 1.

Moreover, for common-boundary metrics, d_{ij}^{CBSC} is set to be one when brands *i* and *j* share a common boundary in brand's sodium/carbohydrates space but are not nearest neighbors, and zero otherwise. In detail, given the coordinates of *i* and *j* as $\left(i_{so}, i_{carb}\right)$ and

(j_{so}, j_{carb}) in sodium/carbohydrates space, then a common boundary of *i* and *j* is defined as a set of variables $(Sodium, Carb)$ satisfying the next equation:

$$\sqrt{(So - i_{so})^2 + (Carb - i_{carb})^2} = \sqrt{(So - j_{so})^2 + (Carb - j_{carb})^2} \tag{4.3}$$

After solving (4.3), a linear relation between *So* and *Carb* is that:

$$So = Carb\frac{i_{carb} - j_{carb}}{j_{so} - i_{so}} + \frac{j_{so}^2 + j_{carb}^2 - i_{so}^2 - i_{carb}^2}{2(j_{so} - i_{so})} \tag{4.4}$$

Once above equation for all *i* and *j* are solved, the intersection points of the lines derived from linear equation will be determined and necessarily establish which portion of the lines are actual common boundaries (Rojas, 2005).

Additionally, another set of nearest-neighbor is developed by considering brand attributes and per fluid ounce price together. It allows a situation that consumer's purchase decision depends on both brands' attributes as well as the relative prices between competitors simultaneously (Rojas, 2005). Following Rojas, nearest-neighbor metrics is set upon the summation of square for the attributes' Euclidean distance and differential in average unit (fl.oz.) price. That is,

$$(So - i_{so})^2 + (Carb - i_{carb})^2 + p_i = (So - j_{so})^2 + (Carb - j_{carb})^2 + p_j \tag{4.5}$$

Discrete Distance Measures with Discrete Brand Attributes

Here, some categories distance measures are included. Although there is no distinct definition on classification of CSDs, according to the nutrition information for each product, the selected commodities are classified to noncola-caffeine free, noncola-caffeine, cola-caffeine free and cola-caffeine segment. In other words, d_{ij}^{seg} is equal to one if brands *i* as well as *j* are in the same segment and zero otherwise.

Besides, we have dummy variable indicating if the drinks have ingredient of citric acid and thus d_{ij}^{citric} is set to be one if brands *i* as well as *j* both contain citric acid and zero otherwise.

These products are manufactured by Coca-Cola, PepsiCo and Cadbury respectively so a discrete distance metric for manufacturer identity is created to examine if shoppers tend to substitute between brands with the same manufacturer when price change occurs. Hence, d_{ij}^{manu} 's value is one when brands *i*, as well as *j*, belong to the same manufacturer and zero otherwise.

All weighting matrices regarding brand classification can be normalized; the sum of each row is equivalent to one and thus the weighted prices of rival commodities which are in the same group will be equal to their mean (Rojas, 2005).

5. Econometric Estimation

Price Endogeneity

Dhar, Chavas and Gould (2003) shows AIDS model with retail level scanner data for differentiated products has price endogeneity, likely coming from retailer's pricing strategy or consumer heterogeneity, and that will cause inconsistent demand estimates as well as have large impact on price and expenditure elasticities. Moreover, Pinkse, Slade and Brett (2002) indicates, obviously, the instrumented variables in our case are of the form $\sum_{j\neq i} g\left(d_{ij}^{k};\lambda\right)\ln\left(p_{jt}\right)$ and thus it is intuitive to choose instruments of the form $\sum_{j\neq i} g\left(d_{ij}^{k};\lambda\right)y_{jht}$ where y_{jht} is correlated to p_{jt} but uncorrelated to ε_{it}. If y_{jht} can explain most variation in p_{jt}, then one would expect $\sum_{j\neq i} g\left(d_{ij}^{k};\lambda\right)y_{jht}$ to explain most variation in $\sum_{j \neq i} g\left(d_{ij}^{k};\lambda\right)\ln\left(p_{jt}\right)$.

An appropriate instrument is necessary for this study. The advantage of this database is that we are able to compute the real wholesale prices from gross margin that Dominick offers on the website. Following Pofahl (2006), the calculated wholesale prices are utilized as instruments for retail prices, as well as rescaled by Chicago Metropolitan's Consumer Price Index (CPI) from the Bureau of Labor Statistics (BLS). I compute the share of total sold volume for every brand in each market and then apply these as weights to get the weighted average per fluid ounce price (wholesale and retail).

6. Estimated Results

Before investigate the semi-parametric estimations, even though OLS (or IV) estimated coefficients are probably inconsistent, they are still meaningful. [13]

Preliminary OLS Regression Result before Aggregation

Prior to doing an aggregate of products by their brands, we have 16,121 observations, consisting of 47 products. Table (A.1) and (A.2) shows the estimated coefficients and t-statistics results of each distance measure when package size is treated as continuous metric and discrete metric, respectively. Regardless of the form of container size metrics, the OLS preliminary results indicate own-price coefficients are both negative and statistically significant even at 1% level. [14] We do not check the loyalty to a given product because we cannot trace specific consumer's shopping history and thus we are not able to build relevant metric for this item. On the other hand, we set a brand identity,

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[13] IV estimators may be inconsistent if presumed g function is wrong. In other words, only given right distance measures, IV estimator just could be consistent.

[14] . The t-statistic of own-price coefficient is -43.88 when the package size is used to set continuous metrics and -44.16 when package size is treated as a dummy indicator.

d_{ij}^{brand} to check if consumers are apt to choose a certain brand. As expected, the positive coefficient on brand identity shows that consumer has loyalty to specific product. In addition, both cases imply product's promotion has positive effect on purchasing behavior. [15] The estimated result of manufacturer implies consumers may not support particular firm. That is a Coke lover may not prefer Sprite to Seven-Up. The negative sign of coefficient on group segment represents a product within the same group is stronger substitute than another group's product; the competition between products with the same category is more aggressive. The comparison between our estimation result and Dube's result (2004 and 2005) is shown in Table A.3.

Preliminary OLS Regression Result after Aggregation

Results of our preliminary OLS regressions before aggregation indicates package size is not an obviously relevant attribute affecting the purchasing decision.[16] Consequently, we do the aggregate of CSD products based on their brands.

Estimation results are reported in Table 5. Most distance metrics have similar effects as the previous analysis on non-aggregated products. For example, sales activity can stimulate consumer to purchase and also brands within the same category have stronger substitution than other groups. Besides, the nearest neighbor measure with price has stronger effect than its counterparts.

7. Conclusions

In this study we have considered the performance of distance-metrics method applied in demand estimation of carbonated soft drink products. Based on preliminary OLS

[15] The t-statistic of sales coefficient is 4.02 when the package size is used to set continuous metrics and 4.00 when package size is treated as a dummy indicator.

[16] The t-statistic of can size indicator (Msize) is 1.83 which is insignificant under 95% confidence level.

outcome, the estimated coefficients are satisfied our prior expectations and results are consistent with previous research. Brand loyalty and stronger substitution between products of the same group is found in our study, as also found in Rojas and others. Our tentative conclusion is that distance metrics approach is worthy of further consideration in demand estimation and offers the potential for study of merger simulations.

TABLES

Table 1: General Traits of Typical Household in Demographic Cluster in DFF Database

Traits	Cluster			
	A	B	C	D
Description	Established Suburban Families	City Dwellers	Ethnic Neighborhoods	Prospering Suburban Families
Household Size	Medium	Small	Medium	Large
Married	Married (50% w/ children)	Few married	Married	Nuclear Families
Children	Older (6-17)	Few	Few	Many
Singles	Few	Lots	Few	Few
Education	High (36% college+)	Medium (30% college +)	Low education	High (35% college+)
Seniors	Some	Some	Many	Few
Middle Age	Lots	Few	Lots	Few
Dual Income	Lots	Few	Few	Many
Income	Higher (45% $50000+)	Lower (42% $20000-)	Lower-middle (80% $50000-)	Higher (44% $50000+)
Price Zone	Moderate competition	Low competition	Moderate	Very competitive
Ethnicity		Substantial Blacks, Hispanics		

Notes: We thank William Minseuk Cha., research assistant of James M. Kilts Center for Marketing, offering this table to us.

* Nuclear Family primarily refers a family group is comprised of most naturally, a father, a mother and their kids.

Table 2: Mean and Standard Deviation of Demographics for Store Cluster in DFF Database

		Cluster			
Variable	**Description**	**A**	**B**	**C**	**D**
Hsizeavg	Average Household Size	2.6330 (0.0960)	2.3993 (0.423)	2.6297 (0.1515)	2.8431 (0.2080)
Single	Decimal of Singles	0.2436 (0.0205)	0.4127 (0.0714)	0.2716 (0.0217)	0.2522 (0.0254)
Age9	Decimal of Population under age 9	0.1286 (0.015)	0.1304 (0.0340)	0.1271 (0.0195)	0.1599 (0.0194)
Age60	Decimal of Population over age 60	0.2018 (0.0463)	0.1585 (0.0294)	0.2312 (0.0454)	0.1090 (0.0315)
Educ	Decimal of College Graduate	0.2716 (0.1066)	0.1970 (0.1141)	0.1303 (0.0630)	0.2665 (0.095)
Workwom	Decimal of Working Women with full time jobs	0.3367 (0.0342)	0.3466 (0.0620)	0.3088 (0.0308)	0.3956 (0.044)
Ethnic	Decimal of Black & Hispanics	0.0573 (0.029)	0.4851 (0.2660)	0.1547 (0.1229)	0.0946 (0.0798)
Nwhite	Decimal of Population that is non-white	0.1103 (0.0422)	0.5490 (0.2359)	0.1848 (0.1290)	0.1357 (0.0777)
Poverty	Decimal of Population with income under $15,000	0.0329 (0.0117)	0.1425 (0.0425)	0.0694 (0.0174)	0.0293 (0.0118)
Income	Log of Median Income	10.7886 (0.1833)	10.1291 (0.15)	10.4911 (0.1078)	10.7759 (0.1699)

Source: DFF database, James M. Kilts Center, University of Chicago Booth School of Business.

Table 3. List of Brands with Aggregate Sales Volume Shares, Average Retail Price and Their Shares of Each Cluster (Ordered by Aggregate Sales Volume Shares)

Product Description	Average Retail Price ($/fl. oz.)	Cluster A	Cluster B	Cluster C	Cluster D	Total
Pepsi	0.0258	0.20864	0.26787	0.31697	0.24004	0.25508
Coke	0.027	0.15242	0.15351	0.12945	0.14540	0.14415
Diet Pepsi	0.0242	0.12888	0.10359	0.11892	0.13231	0.12430
Diet Coke	0.0251	0.13413	0.09234	0.08065	0.12005	0.11012
7 UP	0.0256	0.09030	0.13633	0.12736	0.08339	0.10334
Diet 7 UP	0.0254	0.03878	0.03464	0.03669	0.03467	0.03631
Diet Caffeine Free Pepsi	0.0257	0.03969	0.02129	0.02717	0.04124	0.03466
Dr Pepper	0.0254	0.03289	0.02446	0.03140	0.03876	0.03347
Sprite	0.0252	0.03227	0.03774	0.03108	0.03032	0.03197
Diet Caffeine Free Coke	0.0267	0.03948	0.01902	0.01569	0.03418	0.02890
Mountain Dew Soda	0.0256	0.02164	0.01962	0.01805	0.02592	0.02192
Canada Dry Ginger Ale	0.0195	0.02043	0.03315	0.02001	0.01803	0.02108
A&W Root Beer	0.0225	0.01090	0.00981	0.01036	0.01144	0.01081
Squirt Soda	0.026	0.00436	0.00596	0.00459	0.00424	0.00458
Diet A&W Root Beer	0.0144	0.00464	0.00352	0.00344	0.00396	0.00396
A&W Cream Soda	0.0214	0.00369	0.00123	0.00331	0.00382	0.00333

Table 4: Attributes of CSD Brands in the Dataset

Manufacturer	Product	Calories	Sodium (mg)	Carbohydrates (g)	Caffeine	Contain Citric Acid	Cola
Coca Cola	Coke	140	50	39	1	0	1
	Diet Coke	0	40	0	1	1	1
	Diet Caffeine Free Coke	0	40	0	0	1	1
	Sprite	140	70	38	0	1	0
PepsiCo	Pepsi	150	35	41	1	1	1
	Diet Pepsi	0	35	0	1	1	1
	Diet Caffeine Free Pepsi	0	35	0	0	1	1
	Mountain Dew Soda	170	70	46	1	1	0
Cadbury	Dr Pepper	150	55	40	1	0	0
	7 UP	140	75	39	0	1	0
	Diet 7 UP	0	35	0	0	1	0
	Canada Dry Ginger Ale	140	50	36	0	1	0
	A&W Root Beer	170	65	47	0	0	0
	Diet A&W Root Beer	0	100	0	0	0	0
	A&W Cream Soda	190	70	47	1	1	0
	Squirt Soda	140	50	39	0	1	0

Characteristics are per 12-oz serving.

Data Source:1.https://www.wegmans.com/webapp/wcs/stores/servlet/HomepageView?storeId=10052&catalogId=10002&langId=-1
2.http://www.pepsiproductfacts.com/infobycategory_print.php?pc=p1062&t=1026&s=8&i=ntrtn

Table 5: OLS regression results of Estimated Coefficient on Distance Metrics before aggregation (Metrics of Manufacturer is not included)

Distance Metrics		Cross-Price	
Continuous Distance Measures with Continuous Variables		Coeff	t-stat.
One-Dimensional			
	Carbohydrate Content (Mcarb)	11.85*	4.28
	Sodium Content (Mso)	-27.52*	-7.00
Two-Dimensional			
	Sodium/Carbohydrate Content (MSC)	11.23	1.53
Discrete Distance Measures with Continuous Variables			
Nearest Neighbor			
	Sodium/Carbohydrate Content (MNNSC)	-7.74	-1.15
	Sodium/Carbohydrate/Price Content (MNNSCP)	24.58*	4.18
Common Boundaries			
	Sodium/Carbohydrates Content (MCBSC)	-28.35*	-12.49
Discrete Distance Measures with Discrete Variables			
Product Classifications			
	Product grouping (Mgroup)	-46.38*	-5.48
	Citric Acid Containing (Mcitric)	6.54	0.43

1. All regressions include cluster, product, and year dummy indicators.
2. Coefficients have been multiplied by 1,000 for readability
3. * Significant at 1%

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APPENDIX A

Table A.1: OLS Regression Results of Estimated Coefficient on Distance Metrics before Aggregation (Package size is treated as a continuous variable)

Distance Metrics		Cross-Price	
Continuous Distance Measures with Continuous Variables		Coeff	t-stat.
One-Dimensional			
	Carbohydrate Content (Mcarb)	-2.68*	-2.85
	Sodium Content (Mso)	0.41	0.38
	Container Volume (Mvol)	-0.34	-0.90
Two-Dimensional			
	Sodium/Carbohydrate Content (MSC)	31.84*	6.45
	Sodium/Volume Content (MSV)	-23.98*	-16.05
	Carbohydrate/Volume Content (MCV)	19.20*	13.48
Discrete Distance Measures with Continuous Variables			
Nearest Neighbor			
	Sodium/Carbohydrate Content (MNNSC)	-26.86*	-5.74
	Sodium/Carbohydrate Content with Price (MNNSCP)	7.41*	4.07
	Sodium/Carbohydrate/Volume Content (MNNSCV)	-2.09	-1.2
Common Boundaries			
	Sodium/Carbohydrate Content (MCBSC)	2.09**	2.54
	Carbohydrates/Volume Content (MCBCV)	1.4	1.74
Discrete Distance Measures with Discrete Variables			
Product Classifications			
	Manufacturer Identity (Mmanu)	4.35	0.55
	Brand Identity (Mbrand)	28.24*	4.08
	Product grouping (Mgroup)	-51.07*	-5.93
	Citric Acid Containing (Mcitric)	15.53	0.98

1. All regressions include cluster, product, and year dummy indicators.
2. Coefficients have been multiplied by 1,000 for readability
3. * Significant at 1% , ** Significant at 5%

Table A.2: OLS Regression Results of Estimated Coefficient on Distance Metrics before Aggregation (Package size is treated as a dummy variable)

Distance Metrics		Cross-Price	
Continuous Distance Measures with Continuous Variables		Coeff	t-stat.
One-Dimensional			
	Carbohydrate Content (Mcarb)	2.83*	3.30
	Sodium Content (Mso)	-5.75*	-5.64
Two-Dimensional			
	Sodium/Carbohydrate Content (MSC)	20.73*	4.27
Discrete Distance Measures with Continuous Variables			
Nearest Neighbor			
	Sodium/Carbohydrate Content (MNNSC)	-16.32*	-3.58
	Sodium/Carbohydrate/Price Content (MNNSCP)	9.25*	5.17
Common Boundaries			
	Sodium/Carbohydrates Content (MCBSC)	4.79*	4.55
Discrete Distance Measures with Discrete Variables			
Product Classifications			
	Manufacturer Identity (Mmanu)	11.34	1.42
	Brand Identity (Mbrand)	29.78*	4.36
	Product grouping (Mgroup)	-54.17*	-6.21
	Size classification (Msize)	5.37	1.83
	Citric Acid Containing (Mcitric)	-2.96	-0.19

1. All regressions include cluster, product, and year dummy indicators.
2. Coefficients have been multiplied by 1,000 for readability
3.* Significant at 1%

Table A.3: The comparison between our estimation results before aggregation and Dube’s result

	Our result		Dube's result	
Variables and Distance Measures	sign	significant	sign	significant
On Promotion	positive	yes	positive	yes
Brand Loyalty	positive	yes	positive	yes
Product Loyalty	unknown	unknown	positive	no
Manufacturer Loyalty	positive	no	unknown	unknown
Package Size	either	no	positive	yes

*Dube’s result is based on his papers published in 2004 and 2005.