Identifying Competition Structure from Cross Price Elasticity Matrix

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Abstract

Analysis of competition structure among products in a product category has been an important issue in the marketing area since the accurate assessment of market structure is critical in developing competitive advantages of a firm. The meaningful characterization of competition structure among products in a market helps firms evaluate the effectiveness of marketing efforts and identify new opportunities. I develop a simple procedure for obtaining brand positions from aggregate sales data by imposing some restrictions on cross price elasticity matrix. The proposed procedure provides useful information on vulnerability and clout structure among products in a market and the cross price elasticity matrix is the only input for obtaining such information. So the input requirement in implementing the proposed model is relatively minimal since the cross price elasticity information is easily obtained from standard syndicated data sets.

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I. Introduction

Analysis of competition structure among products in a product category has been an important issue in the marketing area since the accurate assessment of market structure is critical in developing the competitive advantage of a firm. The meaningful characterization of competition structure among products in a market helps firms evaluate the effectiveness of marketing efforts and identify new opportunities. A number of models for estimating the competition structure of a market have been proposed in the marketing literature. Some of the models such as multidimensional scaling require consumers' *stated* preference data as the input of the models. It has been pointed out that the stated preferences may fail to reflect correctly actual consumer behaviors in several occasions. Cooper and Inoue (1996) utilizes two different data types in their study. They present a model that utilizes switching probabilities and attribute rating data in identifying the market structure. Models using revealed preference data have been proposed in the marketing literature. Typically, studies would utilize individual household level data and build consumer choice models based as random utility models such as logit and probit. Elrod (1988), Chintagunta (1994), and Erdem (1996) can be regarded as representative examples of such approach. Their main idea is to obtain brand positioning map by representing the brand specific intercept in the choice model as a linear combination of the brand's M-dimensional attributes. In their models, cross price elasticities among products are not utilized in analyzing brand positions and household level panel data were used. Russell and Kamakura (1994) utilizes the cross elasticity information to analyze product competition, combining consumer level choice data and store level volume data. Allenby (1989) proposed a model for identifying demand structures using aggregate data. His model is based on the unique mathematical properties of multinomial logit model called *proportional draw* property and *proportional influence* property. These two properties play a role as restrictions in identifying market structure. According to his model, the estimated cross price elasticities should satisfy the above two restrictions if the true demand can be represented by the nested logit model. Thus the identification of market structure involves finding the combination of submarkets in which the observed elasticities are the closest to the implied elasticities. that fits the observed elasticities the best. However, those two restrictive properties are no longer valid under other types of choice models such as probit. Thus, the validity of his model may be threatened if the true stochastic nature of consumer choice process is far from the nature of the logit model. Nevertheless, his model casts a valuable insight on using cross price elasticities in identifying market structure.

In this study, I will develop a simple procedure for identifying brand positions or competition structure based on a natural intuition that the cross elasticities among close substitutes (or among highly competing products) should be higher than those among not-so-close substitutes. When the price of BMW increases, the demand for Toyota Tercel will not be influenced much. It is more likely that the consumers who otherwise buy BMW will end up with choosing other luxury brands such as Mercedes or Lexus. Thus the cross price elasticities should be bigger for the pair {BMW, Mercedes} than for the pair {BMW, Tercel}. Therefore, once we have estimates for the cross price elasticities, we already have information on market structure. In other words, *a relatively large elasticity between two products implies that they are close* in attributes space. And a relatively small elasticity between two products can also be interpreted as low substitutability between the pair. By representing the cross elasticity as a function of distance between products, I can identify the relative position of products in the attribute space.

This paper is organized as follows. In section 2, the econometric model for demand function and the procedure of obtaining brand positions are developed. And the estimation and identification strategy will also be discussed. A description of the data and the estimation results will be provided in section 3. And section 4 will conclude the paper.

II. Model and Estimation Procedure

I start with specifying demand functions. Suppose there are J products in a category or in a market. Since I try to utilize elasticity information in identifying market structure, I use a multiplicative demand function in which elasticity is easily obtained from the parameters of demand functions. The multiplicative demand function is specified as follows:

$$(1)\quad Q_{it} = e^{\alpha_i} P_{1t}^{\eta_{i1}} P_{2t}^{\eta_{i2}} \cdots P_{Jt}^{\eta_{iJ}} e^{x_{it}\beta_i + \varepsilon_{it}}, \quad i = 1, \ldots, J$$

where Q_{it} is the sales volume of product i of observation t and P_{jt} is the price of product j of observation t, x_{it} is the vector of demand shifter such as deal variables and seasonal dummy variables for product i at time t. Due to this multiplicative nature of the demand model, the parameters η's are nothing but price elasticities, i.e., since $\eta_{ij} = \dfrac{\partial \log Q_i}{\partial \log P_j}$. Let $q_{it} = \log Q_{it}$ and $p_{jt} = \log P_{jt}$. Using this transformation, I linearize the demand model as follows:

$$(2)\quad q_{it} = \alpha_i + \eta_{i1} p_{1t} + \eta_{i2} p_{2t} + \cdots + \eta_{iJ} p_{Jt} + x_{it}' \beta_i + \varepsilon_{it}, \quad i = 1, \ldots, J.$$

Once the demand function is specified, the next step is to build a model for identifying competition structure. Suppose each brand can be characterized by a 2-dimensional attribute vector. I choose the 2-dimension setup not only because it is easy for managers to understand and to graphically represent but also because it has been extensively demonstrated that such a simple setup can provide managerially valuable insights. Denote the position of product i as $z_i = (z_{1i}, z_{2i})'$. The distance between product i and product j is defined as Euclidean distance, i.e., $d_{ij} = \|z_i - z_j\|, i \neq j$. Note that the distance is symmetric, i.e. $d_{ij} = d_{ji}$ while it is possible (and usual) that $\eta_{ij} \neq \eta_{ji}$ in so-called Marshallian demand. The asymmetry of cross price elasticity is due to the income effect which is specific to a product. So I posit that the cross price elasticity between a pair of products has a product- specific element as well as a pair-specific element, distance. I model the cross price elasticity as follows:

$$(3)\quad \eta_{ij} = a_i b_j e^{-d_{ij}}, \quad i \neq j, \quad a_i, b_j > 0.$$

According to this specification, the cross price elasticity is inversely related to the distance between i and j and the effect of distance on cross elasticity is moderated by two coefficients a and b which are product specific. As the distance between two products gets larger, the cross elasticity between the products goes zero. As the parameter a_i gets larger, the demand for product i, other things being equal, will be more influenced by the prices of other products because $\eta_{i\cdot}$ gets larger. I label a_i as the vulnerability parameter of product i. Meanwhile, a large value of b_j implies that the price of product j, other things being equal, is much influential on the demands for other products. I label b_j as the clout parameter of product j. The clout parameter is conceptually identical to Russell and Kamakura's (1994) *momentum* parameter. Compared to Russell and Kamakura (1994), the decomposition in my model is richer because it explicitly recognizes the vulnerability parameter as well. By estimating $\{a_i, b_i, z_i\}_{i=1,\cdots,J}$, I can identify brand locations in a 2-dimensional attribute space, get information on general vulnerability and clout, and recover cross price elasticity matrix.

In order to estimate the location of the brands, I need some identification restrictions. First, I need to fix the origin and the axes of the position map because the distance if not changed by shifting the origin or by rotating the axes of the map. To fix the origin, I need to fix the location of a product. To fix the direction of the axes, I need to fix the location of another product along an axe. Second, I need to fix one of a's to 1 because multiplying a constant to all a's and as the same time dividing all b's by the same constant would not change the implied elasticity matrix.

If I allow for free correlations among ε's within an observation, the econometric representation of the demand model is a system of regression equations with J response variables. One can estimate the parameters of the model by two step procedure. In the first step, all $\{\alpha, \eta, \beta\}$ parameters would be estimated using standard methods such as seemingly unrelated regression (SUR) method. And in the second stage, $\{a, b, z\}$ are estimated from the estimated $\hat{\eta}$ using classical minimum distance procedure (CMD).[1] As long as the estimates of the first step are consistent, the estimates of the second step of CMD are consistent (Newey and McFadden 1994). Since the first step consists of linear regressions, the two step approach is not computationally costly. However, in my application, such two-step procedure is practically unattractive. It is likely that researchers will have several negative $\hat{\eta}_{ij}$ in the first step as reported in many applications of the multiplicative demand function, which is likely to lead to unreasonable estimates in the second step. To avoid such problems, I estimate all parameters in one step with restriction implied by equation (3).

With restriction of (3), the demand model in (2) is nonlinear in parameters even though it is linear in variables. I use the generalized method of moment (GMM) estimation. Suppose that there are a set of instrumental variables w_t such that

(4) $E(w_t \varepsilon_{it}) = 0, \quad t = 1,...,T, \quad i = 1,....,J.$

With the multivariate nature of the response vectors, our optimal GMM criterion function is constructed with a consideration on the cross-equation covariance among error terms. Denote ε_j as the stacked vector of error terms for equation j. As in Greene (1997), let

$$\frac{1}{T} W'\Omega_{ij} W = E[W'\varepsilon_i \varepsilon_j' W].$$

The GMM objective function of parameter vector $\Theta = \{\alpha, \beta, a, b, z\}$ is given by

(5) $$f(\theta) = \sum_{i=1}^{J}\sum_{j=1}^{J} \left(\varepsilon_i(\theta)'W\right)\left[W'\Omega_{ij}W\right]^{ij}\left(W'\varepsilon_i(\theta)\right)$$

1) In the classical minimum distance procedure, the estimated are obtained by minimizing the distance between the estimated price elasticity and the implied elasticity of the model as follows:

$$\{\hat{a},\hat{b},\hat{z}\} = \underset{\{a,b,z\}}{\arg\min}[\hat{\eta} - \eta(a,b,z)]' w [\hat{\eta} - \eta(a,b,z)]$$

where w is a weight matrix which is usually the inverse of the variance covariance matrix of the first step estimates.

where $\left[W'\Omega_{ij}W\right]^{ij}$ is the (i,j)th block of the *inverse* of the matrix whose (i,j)th block is given by $W'\Omega_{ij}W$.

Ⅲ. Data and Results

A chain level weekly data set on ready-to-eat cereal category is used to illustrate the proposed procedure. The data are from Dominicks' Finer Food (DFF) grocery chain. DFF has more than 80 stores around Chicagoland area. I aggregate the data into chain level. The data set contain observations of 180 weeks from June 7, 1990 to November 17, 1993. And 11 UPCs are selected. The data set consists of sales volume, retail price, wholesale price, and a dummy variable for deal for UPC. It also includes customer count data and seasonal dummy variables. Specifically, the deal dummy for a UPC is set to 1 if there is any of bonus buy, coupon, or simple price discount for the UPC at a week. Customer count is the chain level store traffic. I have two seasonality variables. One is a dummy variable indicating summer season and the other is the indicator for important holidays such as Christmas or Thanksgiving day. I use deal variable, seasonality variables, and consumer count for demand shifters. Since the data were collected over three years, I need to take into account the inflation level in prices. I use consumer price index to deflate retail price and wholesale price series. The instrumental variables I use include constant, lagged wholesale prices, lagged deal variable, lagged seasonality, and lagged customer count.

The descriptive statistics of the selected UPCs are provided in 〈Table 1〉. Among the 11 UPCs, five are General Mills brands and the other six are from Kellogg. As we see in 〈Table 1〉, the average prices per ounce vary across same brands. For example, the unit price of Kellogg Corn Flakes 12oz is \$0.129 while that of Kellogg Corn Flakes 24oz is %0.1012. Such significant difference in prices may imply different consumers' valuation on different package sizes of same products.

I estimate the demand model without any restriction imposed. Without any restriction, the model is nothing but a set of demand equations. I estimated the model with the seemingly unrelated regression (SUR) procedure. The results of SUR estimation are presented in ⟨Table 2⟩. While the signs of effects of the deal variable and the customer count appear reasonable, there are a number of negative cross price elasticity estimates. As discussed earlier, there negative cross elasticity estimates would make it impractical to use the two-step approach discussed in the earlier section.

In ⟨Table 3⟩, the estimation results of the proposed model are presented. For identification purpose, I fix the location of product 11. I also fix the location of product 2 along dimension 1 and the vulnerability parameter of product 1 is fixed to 1. The effect of deal and customer count on demand appears reasonably signed. The resulting cross price elasticity matrix is presented in ⟨Table 4⟩. The unrestricted cross elasticity matrix appears different from the elasticity matrix of the proposed model. One may want to test the validity of the restrictions imposed in the model. Although the estimation method is not likelihood based, I test the validity of the model using three different statistics as in Allenby (1989). ⟨Table 5⟩ contains the test results. The likelihood ratio test and AIC favor rejecting the proposed model. But BIC is in favor of the proposed model. This phenomenon was also reported in Allenby (1989). As in Allenby (1989), the problem in testing sharp hypotheses with a large sample is also highlighted in my case since the data set has 1969 observations.[2] The BIC indicates that the proposed model which has 70 less parameters than the unrestricted demand model is a reasonable way of representing demands compared to the unrestricted model. According to the cross price elasticity matrix implied by the proposed model, within-brand substitution is stronger than inter-brand substitution. This result is intuitive since consumers who like Kellogg brand are more likely to switch to another Kellogg product than to switch to a General Mills product when facing a price increase in a Kellogg product.

The estimates of vulnerability, clout, and product locations appear insignificant, which might be partly due to the high nonlinearity of those parameters as seen in

2) Since I use lagged prices for instrument, the number of the effective observations used in the estimation is 179. As the data set contains 11 products, the total number of entire observations is 11*179=1969.

equation (3). The problem of large standard errors associated with those parameters needs to be resolved in further research. In ⟨Figure 1⟩, I present the estimated product positioning map. It appears that Kellogg's Frosted Flakes 20oz and Raisin Brand 20oz have positioned separately from other Kellogg products. And it also appears that Kellogg Frosted Flakes 15oz has not been successfully differentiated from Kellogg Corn Flakes products. This it is likely that Kellogg's Frosted Flakes 15oz is cannibalizing its Corn Flakes products. As seen in ⟨Table 4⟩, 1% price reduction in Kellogg Frosted Flakes 15oz will result in 3.3% decrease in the demand for Corn Flakes 24oz and 1.3% decrease in the demand for Corn Flakes 12oz. However, Kellogg Frosted Flakes 20oz appears more effective in competing with General Mills products. By reducing its price by 1%, it can reduce demand for General Mills Cheerios 10oz by 1.16%

General Mills Honey Nut Cheerios 14oz looks not much differentiated form Cheerios products. Although it is not as clear as in Kellogg products case, General Mills Cheerios 10oz and Wheaties 18oz seem to be positioned differentiated from other General Mills products. If one is interested in identifying submarkets, two tentative solutions are available. In a solution with two submarkets, Kelloggs' Frosted Flakes 165oz, and Corn Flakes 12oz, 18oz, and 24oz will constitute a submarket and the other submarket consists of remaining products. If we are going to have a 3-submarket solution, we can get the solution by further dividing the second submarket in the 2-submarket solution into a submarket consisting of General Mills Cheerios 15oz and 20oz and Honey Nut Cheerios 20oz and the other submarket with remaining products. The estimated product positioning map seems inconsistent with typical prior beliefs. Nevo (2001) suggests a simple product segment scheme even though the segmentation was not the focus of his study. According to Nevo (2001), Kellogg Corn Flakes, General Mills Cheerios, and General Mills Wheaties belong to *all family/basic segment*, Kellogg Raisin Bran belongs *to taste enhanced wholesome segment*, and Kellogg Frosted Flakes and General Mills Honey Nut Cheerios are in *kids segment*. But my results indicate that Kellogg Frosted Flakes 20oz, Raisin Bran 20oz, and General Mills Wheaties 18oz are closely positioned. The main difference

〈Table 1〉 Descriptive Statistics

Number	Product Description	Sales Volume (10,000oz) Mean	Sales Volume (10,000oz) Std	Retail Price (cents per ounce) Mean	Retail Price (cents per ounce) Std	Wholesale price (cents per ounce) Mean	Wholesale price (cents per ounce) Std	Deal Dummuy Mean	Deal Dummuy Std
1	GM Wheaties 18oz	3.95	4.49	16.57	0.91	13.97	0.67	0.11	0.30
2	GM Cheerios 10oz	4.99	4.84	21.37	1.40	18.23	0.94	0.07	0.23
3	GM Honey Nut Cheerios 14oz	5.45	7.50	21.31	1.35	18.13	1.01	0.08	0.25
4	GM Cheerios 15oz	8.13	11.65	19.87	1.22	16.81	0.81	0.13	0.28
5	GM Cheerios 20oz	4.24	1.93	18.59	0.95	16.29	0.72	0.08	0.26
6	Kellogg Corn Flakes 12oz	4.11	2.56	12.90	0.70	11.16	0.54	0.02	0.13
7	Kellogg Corn Flakes 18oz	9.15	17.12	10.78	0.79	8.81	0.98	0.14	0.32
8	Kellogg Corn Flakes 24oz	8.19	22.43	10.12	0.69	8.89	1.96	0.08	0.25
9	Kellogg Raisin Bran 20oz	5.04	8.05	14.96	0.95	12.64	0.82	0.10	0.29
10	Kellogg Frosted Flakes 15oz	4.43	6.20	17.22	0.46	14.83	0.70	0.04	0.18
11	Kellogg Frosted Flakes 20oz	6.91	8.50	15.96	0.75	13.70	0.92	0.11	0.28

	Mean	Std
Customer Count (Million)	1.61	0.11

〈Table 2〉 Estimation Results for Proposed Model

	Intercept	own	vulnerability	clout	deal	summer	holiday	customer count	Dim1 (z_1)	Dim2 (z_2)
GM Wheaties 18oz	**-1.2878**	**-1.1278**	1 (fixed)	0.1592	**0.6951**	**0.3845**	**-0.0332**	**0.6212**	1 (fixed)	1.0681
GM Cheerios 10oz	**6.2408**	**-4.2643**	21.2175	5.8357	**0.1784**	-0.0120	**-0.0322**	**0.3508**	2.2726	2.0295
GM Honey Nut Cheerios 14oz	**8.9743**	**-5.5041**	4.4084	0.3853	**0.6769**	**-0.0307**	**-0.0757**	0.2158	4.9895	7.5983
GM Cheerios 15oz	**17.8366**	**-5.6104**	5.6246	3.0851	**0.5350**	0.0237	**-0.1507**	**-0.9178**	2.1996	6.9703
GM Cheerios 20oz	**11.5359**	**-4.3584**	9.0144	4.8035	**0.2747**	0.0001	**-0.0060**	-0.1366	6.4004	5.8321
Kellogg Corn Flakes 12oz	-0.4195	**-2.3692**	8.4813	0.2684	**0.8820**	0.0032	**0.0296**	**0.5716**	11.8978	-9.8302
Kellogg Corn Flakes 18oz	**5.3732**	**-2.3875**	0.1603	0.6844	**0.9794**	**-0.0311**	**-0.0605**	**0.4657**	9.4422	-8.2359
Kellogg Corn Flakes 24oz	**-3.4223**	**-3.7901**	4.7500	0.6109	**0.9396**	**0.1100**	**-0.2112**	**1.0876**	10.4436	-9.1796
Kellogg Raisin Bran 20oz	**11.4613**	**-4.7971**	8.6440	0.0536	**0.4089**	**-0.0431**	**-0.1480**	0.1178	-1.8880	-1.8037
Kellogg Frosted Flakes 15oz	**9.4813**	**-2.8708**	0.0018	3.1558	**0.9230**	**0.0202**	**-0.1296**	0.0168	9.4856	-8.0114
Kellogg Frosted Flakes 20oz	**0.2732**	**-0.9405**	0.8919	1.1569	**0.8158**	**-0.1503**	**-0.0596**	**1.9570**	0 (fixed)	0 (fixed)
GMM objective function value	0.0275									

* Numbers in bold face are significant at 5% level.

〈Table 3〉 Estimation Results for Unrestricted Demand Function (SUR)

	intercept	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	deal	summer	event	cc
q1	-1.5889	**-1.9750**	0.5238	-0.3904	0.2187	0.6766	-1.5695	-0.3938	0.1772	**-1.3539**	4.2551	0.3207	**0.6758**	**0.4253**	-0.0673	0.1456
q2	**6.3531**	0.2976	**-3.9230**	-0.6762	**1.8105**	**1.4296**	**-1.7277**	0.0102	**1.0118**	-0.0613	-0.2781	0.3341	0.1941	-0.0301	-0.0392	**0.5255**
q3	**8.9130**	0.2264	-0.0899	**-5.6935**	**0.9926**	**2.9501**	1.4299	**-0.9744**	0.1532	-0.2540	-0.9912	-0.1417	**0.6691**	-0.0004	-0.0800	0.1149
q4	**18.4231**	-0.8271	0.1128	0.2617	**-3.8607**	**1.8171**	2.3501	**-1.1465**	0.2495	-0.4201	-3.4459	-0.8036	**0.5845**	-0.0440	-0.1173	0.0173
q5	**11.8108**	0.2181	0.4253	-0.5871	**1.4908**	**-3.5552**	**-2.0003**	0.2720	0.0220	0.0002	0.1881	-0.4465	**0.3051**	-0.0284	-0.0009	0.3002
q6	-0.4060	-0.5545	-0.2811	**-0.9765**	**0.6703**	**0.6978**	-2.3345	0.2510	**0.4467**	0.0216	**2.8305**	-0.5916	**0.8803**	0.0163	0.0349	**0.5947**
q7	5.3869	-0.4031	-0.4477	-0.0913	0.6991	1.1631	0.0934	**-2.3690**	0.5606	0.3061	-0.9830	-0.4111	**1.0316**	-0.0687	-0.0698	0.4815
q8	-3.5440	-0.5301	**0.7214**	-0.4317	0.5933	0.1162	-1.6847	**0.6288**	**-4.0226**	0.1368	**5.3505**	-0.4758	**0.9333**	**0.1593**	**-0.2188**	**0.8995**
q9	**11.6148**	-0.4531	**-1.0397**	0.1285	0.4237	0.4470	0.9609	-0.3866	1.3749	**-4.4514**	-1.4143	0.7209	**0.5861**	**-0.1297**	**-0.1580**	0.3463
q10	**9.6587**	-0.7261	-0.3858	-0.6251	**1.3330**	0.3003	-0.3552	-0.0739	0.2910	-0.1471	-2.3645	-0.3524	**0.9292**	-0.0255	**-0.1306**	0.2987
q11	-0.6232	-0.0002	-0.7572	-0.5676	0.5748	0.8568	**-2.8200**	-0.4740	**1.4085**	0.6679	**4.9510**	**-3.4493**	**0.7755**	-0.0400	-0.1174	**0.5287**

- Numbers in bold face are significant at 5% level.
- The ordering of products are the same as in 〈Table 1〉.

〈Table 4〉 Cross Elasticity Matrix Implied by the Proposed Model

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11
Q1	-1.1278	1.1842	0.0002	0.0075	0.0036	0.0000	0.0000	0.0000	0.0009	0.0000	0.2678
Q2	0.6853	-4.2643	0.0167	0.4677	0.3722	0.0000	0.0001	0.0000	0.0040	0.0003	1.1661
Q3	0.0003	0.0524	-5.5041	0.7791	2.2086	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006
Q4	0.0022	0.2345	0.1241	-5.6104	0.3479	0.0000	0.0000	0.0000	0.0000	0.0000	0.0044
Q5	0.0011	0.1921	0.3623	0.3581	-4.3584	0.0000	0.0000	0.0000	0.0000	0.0000	0.0018
Q6	0.0000	0.0000	0.0000	0.0000	0.0000	-2.3692	0.3106	1.0534	0.0000	1.3048	0.0000
Q7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0023	-2.3875	0.0247	0.0000	0.4025	0.0000
Q8	0.0000	0.0000	0.0000	0.0000	0.0000	0.2592	0.8211	-3.7901	0.0000	3.3089	0.0000
Q9	0.0234	0.1762	0.0000	0.0017	0.0005	0.0000	0.0000	0.0000	-4.7971	0.0001	0.7346
Q10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010	0.0002	0.0000	-2.8708	0.0000
Q11	0.0329	0.2472	0.0000	0.0018	0.0007	0.0000	0.0000	0.0000	0.0035	0.0000	-0.9405

- Effect of column prices on row quantities.
- Product ordering is the same in 〈Table 1〉.

〈Table 5〉 Test Results

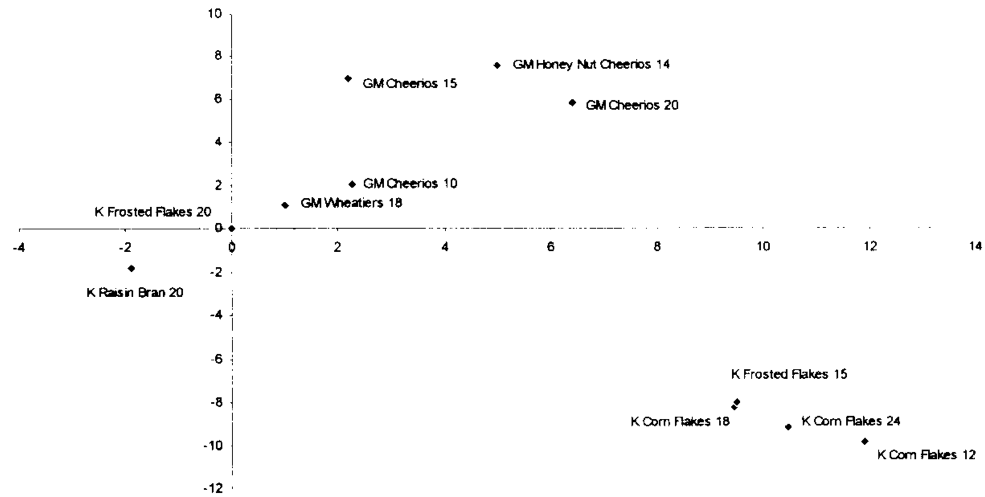
	Unrestricted	Restricted
Likelihood ratio statistic		332.8865
AIC(without constant)	2112.4545	2016.0112
BIC(without constant)	1620.9497	1719.9913

is that I use UPC level data. As seen from my results, aggregation of UPCs into brand level may end up with very different results.

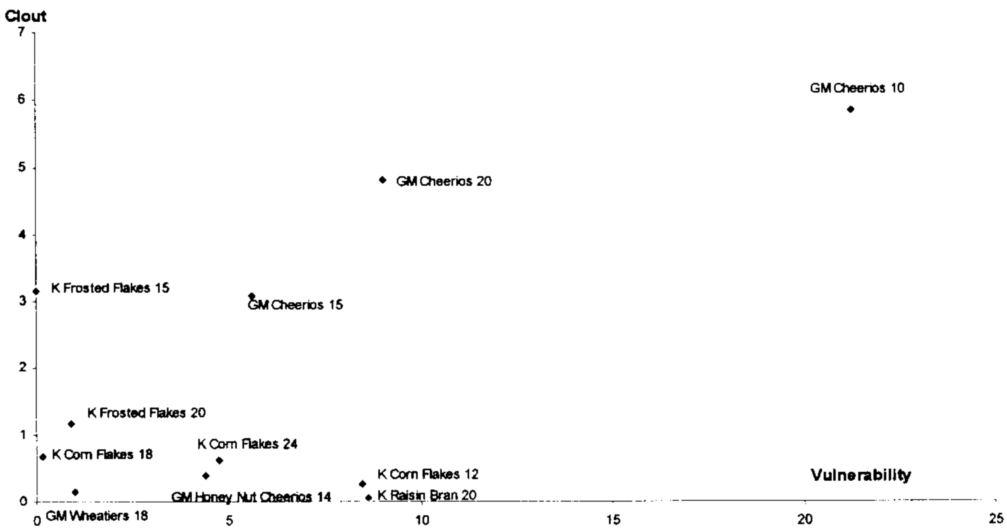
In addition to the product position map, the proposed model produces valuable byproducts, measures of vulnerability and clout. ⟨Figure 2⟩ displays the products in the vulnerability-clout dimension. High vulnerability of a product corresponds to high susceptibility of the product to the change in the prices of other products while high clout is related to the ability to influence the demands for other products. So products with high clout and low vulnerability are likely to be strong players in the market. However, note that these measures are not ratio-scaled nor theoretically derived. The only the relative comparison of these measures would be meaningful.

Kellogg Frosted Flakes 15oz appears to be a strong product while Kellogg's Raisin Bran 20oz and Corn Flakes 12oz look vulnerable to competing products price changes. The strong appearance of Kellogg Frosted Flakes 15oz in the vulnerability-clout map, combined with its close positioning to other Kellogg products as seen in ⟨Figure 1⟩, seems to be the major factor leading to the large intra-Kellogg substitution pattern in ⟨Table 4⟩, or cannibalization. One of the noticeable results is that the strength of product varies over same Corn Flakes products. Corn Flakes 18oz appears quite strong while 12oz looks very vulnerable. And Corn Flakes 24oz seems to lie in-between. Another noteworthy observation is that the two manufacturers have different sets of product portfolio in terms of vulnerable products and very strong products. General Mills products are less diverse in terms of product strength than Kellogg's.

Combining ⟨Figure 1⟩ and ⟨Figure 2⟩, I can conclude that Kellogg Frosted Flakes 20oz is an effective competitive product since it has positioned near to the competitor's products and has a strong stance. As seen in ⟨Table 4⟩, it is very effective in affecting the demand for General Mills Wheaties 19oz. However, 15oz size Frosted Flakes seems not as successful in position as 20oz. It is located close to Kellogg Corn Flakes products, leading to possible cannibalization. Although Kellogg's Raisin Barn 20oz seems to avoid cannibalization, it seems not to work as an effective competitive weapon because this product has too a small clout parameter to compete effectively.



〈Figure 1〉 Product Positioning Map



〈Figure 2〉 Vulnerability and Clout of Products

Ⅳ. Conclusion and Direction for Future Research

This study develops a simple procedure for obtaining brand positions from aggregate sales data by imposing some restrictions on cross price elasticity matrix. The restrictions are useful not only in identifying the brand positions but also in assuring the signs of the estimated cross elasticities are consistent with economic theory. The proposed procedure provides useful information on vulnerability and clout of the products in a market. The information provided by the proposed model is obtained only from the cross price elasticity matrix. So the input requirement for implementing the proposed model is relatively minimal since the cross price elasticity information is easily obtainable owing to the increasing availability of standard store level or market level scanner data.

This study can be extended along a few dimensions. First, current study does not utilize the information contained in brand intercepts and own price elasticities. It is possible to obtain more accurate and meaningful results by further exploiting information contained in the brand intercepts and own price elasticities. Second, I do not model the supply side behaviors although the endogeneity issue has been accounted for by the use of instrumental variables. By explicitly modeling competitive pricing reactions as functions of brand locations, one may get interesting insights on firm behaviors as well as demand structure. Finally, experimenting with various functional forms for $\eta(a,b,z)$ would also be an interesting venue for future research.

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