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Product differentiation and brand competition in the Italian breakfast cereal market: a distance metric approach.

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Paper prepared for presentation at the 1st AIEAA Conference
'Towards a Sustainable Bio-economy: Economic Issues and Policy Challenges'

4-5 June, 2012
Trento, Italy

Summary

This article employs a nation-wide sample of supermarket scanner data to study product and brand competition in the Italian breakfast cereal market. An Almost Ideal Demand System (AIDS) modelled to include Distance Metrics (DMs) and consistent with the methodology proposed by Pinske, Slade and Brett (2002), is estimated to study demand responses, substitution patterns, own-price and cross-price elasticities.

Estimation results indicate a certain level of brand loyalty and opposite attitudes towards product type. Elasticities point out the presence of patterns of substitution within products sharing the same brand and similar nutritional characteristics.

Keywords: distance metric, almost ideal demand system, breakfast cereals, differentiated products, competition

JEL Classification codes: Q11, D12, L11

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1. INTRODUCTION

Although it's not as developed as in the United States and in the rest of Europe, the market of breakfast cereals has been expanding over the last ten years also in Italy, showing an upward trend in market penetration, volume and value sales. In particular, the years 2004 to 2007 shown a sharp increase in households expenditure in breakfast cereals even though this positive trend has flattened in late 2008-2009, probably because of the ongoing economic crisis, and begun to fall late 2009-2010.

The market for breakfast cereals is characterized by a relevant concentration: the concentration ratio (CR4) is almost 80% and the first two players hold 75% of the market shares. Overall, in 2007 Kellogg's accounted for a share of 49.9% in volume sales considering the entire market, followed by Nestle which accounted for 25%. Because of its presence in the muesli business only, Cameo had a relatively low market share (4%) when considered within the overall market. The same applies also to Barilla: the Italian brand accounted for the 1.4% on the entire market, since it is present only in the segments of simple and fortified cereals.

The situation in terms of volume sales across different market segments saw Kellogg's dominating the market with a 45% share in muesli cereals, 46% in fortified cereals and 54% in simple cereals. The following player was Nestlé, accounting for 38% of volume sales in fortified cereals and 20% in simple cereals. Cameo was the second player in the muesli business after Kellogg's with a volume sales share of 32% after being the segment-leader for years. Although it was the second player in the muesli business, Cameo did not play any significant role in any other business. After launching its new product line "Gran Cereale", in 2006 Barilla had just re-engaged the competition in fortified and simple cereals after the withdrawal of "Mulino Bianco Armonie di Cereali", thus its shares was still below 2% in both businesses but increasing over time. Faced with such a competition, manufacturers wishing to set up new businesses in this market incur in high entry barriers when trying to build their (new) reputation and when trying to set up new brands; the result is that consumers can choose among a certain range of products supplied by a limited number of firms.

Although the Italian market is still lagging behind the European and American markets in terms of per capita consumption, and despite strong competition, most operators argue that outlooks are encouraging (even for new manufacturers) thanks to the likely evolution of demand in terms of new target consumers (mainly women and children). In fact, innovation plays a strategic role, since a relevant number of new products is systematically launched on the market every year by the two biggest players.

In this context of extreme concentration and relevant product-innovation, we aim to study this market from two points of view, the role that brand loyalty plays on consumers' choices as well as consumers' behavior when faced with (new) different products. Consistent with the methodology proposed by Pinske, Slade and Brett (2004) and Bonanno (2010), our aim of investigating consumers' attitude towards different

breakfast cereals is carried out through an Almost Ideal Demand System (AIDS) structured in a way that it accounts for discrete and continue products' qualitative attributes. These sets of continue and discrete characteristics are employed to compute Distance Metrics, which are included in the model as interaction terms among cross-product prices.

The DM approach was first developed to address the challenges of differentiated products in demand applications. It was first proposed by Pinkse, Slade and Brett (2002) which developed the DM technique to overcome the dimensionality limitation of neoclassical demand models. Recent examples of studies based on DM are Pinkse and Slade (2004), Rojas and Peterson (2008), Pofahl and Richards (2009) and Bonanno (2011).

The insight of this approach is that each product in a category can be viewed as a unique combination of characteristics and that substitution patterns among these products might be the result of the proximity between these characteristics. In line with the Lancaster's approach to demand theory (Lancaster, 1966), such characteristics can be thought as spatial attributes where different products can be positioned along, according to their own peculiarities; this means that any differentiated product can be considered as a combination of characteristics in a multidimensional space and substitution patterns are spatially determined. The products attributes can be both continuous and discrete; continuous metrics also incorporate the concepts of spatial (local and global) competition within a single modeling framework (Hotelling 1929).

In demand estimation, the DM method applies by defining cross-price coefficients as functions of different distance measures between products.

Besides accounting for spatial distance in products' characteristics, this methodology also allows us to address one of the AIDS. model weaknesses, namely the large amount of cross-price coefficients to be estimated when the model accounts for a sizable number of products.

2. THE MODEL

The demand for breakfast cereals in Italy is modeled following the Linear Approximated–Almost Ideal Demand System developed by Deaton and Muellbauer (1980):

$$(1) \quad W_{jrt} = a_{jrt} + \sum_{k=1}^J b_{jkrt} \log p_{krt} + \beta_{jrt} \log (X_{rt}/P_{rt}) + \epsilon_{jrt}$$

The subscript r denotes the regional markets we're dealing with ($r = \text{region} = 1, \dots, R$) while t denotes the time period ($t = \text{time} = 1, \dots, T$). The system is made up of J equations (where $j=1, \dots, J$ is the number of products in each market r , and in each time period t); these equations are linked each other by the expenditure term X_{rt} and by the properties of the demand functions.

The total level of expenditure for the J products in market r at time t is X_{rt} , defined as $\sum_j p_{jrt} * q_{jrt}$.

The product j 's sales share (the share of expenditure allocated to product j) in market r , at time t is W_{jt} , defined as $(p_{jrt} * q_{jrt})/X_{rt}$.

P_{rt} is a log-linear analogue of the Laspeyeres price index in market r at time t defined as $\sum_j \log p_{jrt} * w_{jrt}$ where W_{jrt} are fixed budget shares, and it is employed to normalize the total expenditure X_{rt} .

In principle, J-1 equation and J(J-1)/2 cross price coefficients can be estimated by imposing the properties of the demand functions to the entire system¹. For large J, it might become impractical to estimate a large system of equations. The adoption of the Distance Metrics approach will reduce the number of cross-price parameters b_{jkrt} to be estimated through the definition of a new subset of metrics related to cross price coefficients.

In this application of the Distance Metrics method (which will be referred to as DM-LA/AIDS), let Z_j^c and Z_j^D be product j's attributes, measured in continuous (calories, fat content, etc...), and in discrete space (brand, flavour, etc...), respectively. Let δ_{jk}^c and δ_{jk}^D be measures of closeness between products j and k, function of continuous and discrete attributes, respectively.

The continuous measure of closeness, namely the continuous Distance Metrics (δ_{jk}^c), is defined adopting the inverse measure of the Euclidean distance in product space between j and k. Euclidean distance indicates how far apart two products are, given their characteristics, in the attribute space: if two products were different, the magnitude of this indicator would get larger. Mathematically, this distance between j and k is the square root of the sum of the squared differences between continuous attributes Z_j^c belonging to product j and k.

$$ED_{jk} = \sqrt{\sum_l (Z_{jl}^c - Z_{kl}^c)^2}$$

The continuous DM (δ_{jk}^c) is then specified as the reciprocal of the Euclidean distance:

$$\delta_{jk}^c = \frac{1}{1 + 2 * ED_{jk}}$$

This measure varies between 0 and 1: the larger the value, the closer the location of products along the continuum. This provides a continuously defined indicator of the proximity of two products within the defined attribute space.

Discrete Distance Metrics do measure the competitive effect of attributes that are not measurable through continuous characteristics. Visually, discrete DMs are comparable to dummy variables whose value is 1 whenever product j and k share the same qualitative status or level for a discrete attributes D:

$$\delta_{jk}^D = \begin{cases} 1 & \text{if } |z_{jl}^D - z_{kl}^D| = 0 \\ 0 & \text{if } |z_{jl}^D - z_{kl}^D| \neq 0 \end{cases}$$

For food products, examples of discrete attributed might be: brand, presence of a given attribute (i.e. functional vs. nonfunctional,...)²

¹ The properties of the demand function refers to: (1) Adding-up: $\sum_{j=1}^J a_{jrt} = 1$; $\sum_{j=1}^J b_{jkrt} = 0$; $\sum_{j=1}^J \beta_{jrt} = 0$; (2) Homogeneity of degree 0: $\sum_{k=1}^J b_{jkrt} = 0$; (3) Symmetry: $b_{jkrt} = b_{kjrt}$; \forall_{jk}

² Taking D1 = brand, a value of $\delta_{jk}^{D1} = 0$ implies that the two products belong to different manufacturers.

Given the closeness measures δ_{jk}^c and δ_{jk}^D , the cross-price parameter portion of the LA/AIDS is reformulated as follows:

$$(2) \quad \sum_{k=1}^J b_{jkrt} \log p_{krt} = b_{jrt} \log p_{jrt} + \lambda_j \sum_{k \neq j}^J \delta_{jk}^c \log p_{krt} + \sum_d \varphi_j^D \sum_{k \neq j}^J \delta_{jk}^D \log p_{krt}$$

Replacing the cross price parameter (2) in the LA/AIDS equation (1) we obtain:

$$(3) \quad W_{jrt} = a_{jrt} + b_{jrt} \log p_{jrt} + \lambda_j \sum_{k \neq j}^J \delta_{jk}^c \log p_{krt} + \sum_d \varphi_j^D \sum_{k \neq j}^J \delta_{jk}^D \log p_{krt} + \beta_{jrt} \log (X_{rt}/P_{rt}) + \varepsilon_{jt}$$

Which gives $b_{j1} = \lambda_j \delta_{j1}^c + \sum_d \varphi_j^D \delta_{j1}^D, \dots, b_{jm} = \lambda_j \delta_{jm}^c + \sum_d \varphi_j^D \delta_{jm}^D$, where φ_j^D and λ_j are parameters to be estimated.

Since $(Z_{jl} - Z_{kl})^2 = (Z_{kl} - Z_{jl})^2$ then $\delta_{jk}^c = \delta_{kj}^c$ and symmetry can be imposed to the (λ) parameters across equations (i.e., for each product j). Furthermore, symmetry can also be imposed for φ^D because there is no difference between δ_{jk}^D and δ_{kj}^D (if D =brand and $\delta_{jk}^D = 1$, then also $\delta_{kj}^D = 1$). Therefore this implies that $b_{jk} = b_{kj}$ across the j equations.

Given the symmetry for (λ) and (φ) parameters, in principle $J-1$ equations can be estimated for obtaining 2 cross price parameters. To further reduce the dimensionality of the estimation one may assume own-price and expenditure coefficients to be constant across equations thereby reducing the estimation to a single equation. Because of the restrictiveness of this assumption, in this work we assume these coefficients, together with the intercept, to be functions of subsets of each product's characteristics.

$$a_{jrt} = a_0 + \sum_m a_m z_{jm}^a$$

$$b_{jrt} = b_0 + \sum_s \gamma_s z_{js}^b$$

$$\beta_{jrt} = \beta_0 + \sum_h \beta_h z_{jh}^b$$

Where z_j^a, z_j^b, z_j^b are subsets of product j 's attributes. The specification of the LA/AIDS model then becomes:

$$(4) \quad W_{jrt} = a_0 + \sum_m a_m z_{jm}^a + \log p_{jrt} \left(\gamma_0 + \sum_s \gamma_s z_{js}^b \right) + \lambda \sum_{k \neq j}^J \delta_{jk}^c \log p_{krt} + \sum_d \varphi_j^D \sum_{k \neq j}^J \delta_{jk}^D \log p_{krt} + \left(\beta_0 + \sum_h \beta_h z_{jh}^b \right) \log (X_{rt}/P_{rt}) + \varepsilon_{jrt}$$

3. DATA

The database employed for estimating the model has been obtained starting from a raw SymphonyIRI census® scanner dataset including forty-eight monthly observations of breakfast cereals sales for the period January 2004 – December 2007. Sales are recorded in Hyper- and Supermarkets located in seventeen Italian IRI regions covering most of the national territory. Each of the forty-eight monthly observations recorded product-specific data for: volume sales; value sales; unit sales; % of store selling (indicating the share of stores where at least one unit of a particular product was sold); weighted distribution (indicating the share of annual sales represented by the stores where at least one unit of a particular product was sold); average number of items per store (for a given product in a particular geography, this measure indicates the average of barcodes available for that product per store selling the product; namely, it is a measure of the depth of the product's distribution); units sold any merchandising; value sold any merchandising; volume sold any merchandising.

The products chosen for this analysis belonged to firms operating nationally with a value of expenditure share in the national market of at least 0.5%. Since the database accounted for some small producers typically bound to regional markets, data were reduced by filtering for these producers, in order to obtain a nationally representative market of Italy with 8160 observation: 10 product combination identified by vendor (Barilla, Cameo, Kellogg's, Nestle and Private Label) and segment (Muesli, Fortified and Simple) observed across 48 months (from January 2004 to December 2007) and 17 regions³ (Liguria, Lombardia, Trentino Alto Adige, Friuli Venezia Giulia, Veneto, Emilia Romagna, Toscana, Lazio, Umbria, Sardegna, Marche, Puglia, Campania, Sicilia, Valle d'Aosta+Piemonte, Abruzzo+Molise, Basilicata+Calabria). These 8160 observations built up the database from which the share values W_{jt} were calculated.

Continuous Distance metrics were computed from hand collected information about: calories (Kcal/100g); proteins (g/100g); carbohydrates: total and simple (g/100g); fats: total and saturated (g/100g); fiber (g/100g); calcium (mg/100g); sodium (g/100g); iron (mg/100g). From raw measures of continuous attributes, Euclidean Distances were calculated and Distance Metrics were afterwards computed and imported in the database. Together with continue DMs, the raw information on continuous attributes and the previously computed discrete DMs were imported as well.

Prices for each of the ten products were computed dividing Value Sales measures by the corresponding Volume Sales measure.

Table 1 presents descriptive statistics of the data for the 10 products included in our analysis; products' characteristics are included together with average prices, expenditure shares and the promotion rate per item. Muesli products are the fattest and most caloric ones while Private labels are the cheapest products on the market. Despite their high price, Kellogg's fortified products are the ones showing the second largest expenditure share after Kellogg's simple, that are also the most merchandised ones. Overall Kellogg's holds more than 50% of expenditure in breakfast cereals, followed by Nestlé and Private Labels.

³ IRI regions are defined consistently with the political boundaries of the Italian regions except for "Piedmont and Val d'Aosta", "Basilicata and Calabria" and "Abruzzo and Molise".

Table 1. Descriptive statistics of the ten products analyzed in the sample (N=8160).

Brand	Type	Calories (Kcal/100g)	Proteins (g/100g)	Total Carbohydrates (g/100g)	Simple Sugars (g/100g)	Total fats (g/100g)	Saturated fats (g/100g)	Fiber (g/100g)	Price (€/Kg)	Promotion Share	Exp. Share (W _{ijt})
Barilla	Fortified	405.00	9.50	70.40	22.00	8.00	5.10	6.50	7.03	8.03%	0.58%
Cameo	Muesli	396.00	8.85	59.90	23.20	12.65	3.80	8.50	6.34	18.80%	4.32%
Kellogg's	Fortified	388.17	9.33	79.33	30.17	3.00	1.42	3.08	8.30	19.40%	26.77%
Kellogg's	Muesli	482.00	8.00	60.00	19.00	22.00	11.00	6.00	7.67	9.17%	3.09%
Kellogg's	Simple	379.00	8.35	83.22	17.73	1.15	0.28	2.13	6.48	22.86%	28.02%
Nestlé	Fortified	382.80	7.56	76.52	31.04	4.32	1.92	5.56	7.15	16.72%	17.51%
Nestlé	Simple	367.00	7.60	77.10	23.30	1.85	0.85	5.70	6.65	17.70%	10.86%
Private Label	Fortified	385.50	8.15	77.61	26.04	3.94	2.34	4.70	4.77	14.33%	2.90%
Private Label	Muesli	428.50	7.63	62.32	24.70	15.00	6.93	6.82	4.61	8.25%	1.21%
Private Label	Simple	374.64	8.18	81.45	10.89	1.05	0.29	4.29	4.15	20.03%	4.42%

4. MODEL SPECIFICATION

In estimating the LA/AIDS model we need to account for the issue of endogeneity, since the model may not account for factors affecting consumer's behavior (W_{jt}) which are related to suppliers/retailers' price setting choices. Considering that we're actually dealing with differentiated products, retail prices may not be considered fully exogenous. In fact, in an oligopolistic market, prices are likely to be determined by strategic pricing rules of firms, incorporating both supply and demand characteristics of those products. Whenever these pricing rules involve some unobserved demand characteristics, assuming prices as exogenous would lead to biased and inconsistent parameter estimates. The same problem arises with the expenditure variable. Instruments are therefore employed to deal with endogeneity of prices and expenditure variable. Instrumental variable estimations were obtained following Dhar and Chavas (2003): ten first-stage regressions for price were specified as:

$$(5) P_{irt} = \theta_{i0} + \theta_{i1}US_{irt} + \theta_{i2}MRCH_{irt} + \theta_{i3}PRD_{irt} + \theta_{i4}ITPS_{irt}$$

$$i = j + \sum_{k \neq j, \dots, J} k$$

While the expenditure first stage regression was specified as:

$$(6) X_{rt} = \eta TTR_{rt} + \sum_{r=1}^R D_{rt} + \phi_1 INC_{rt} + \phi_2 INC_{rt}^2$$

Fitted values for prices and expenditure obtained by estimating (5) and (6) were used to replace the corresponding actual values in model (4).

With regard to model (4) one should adopt different intercept, own-price and expenditure shifters in order to minimize the risk of multicollinearity, which would arise from using the same product characteristics across shifters. Nevertheless brand and type discrete shifters must be adopted both on the own-price side (z_{js}^b) and the expenditure side (z_{jh}^b); in order to derive proper elasticity measures. In fact z_{js}^b and z_{jh}^b identify different products through 2 sets of dummy variables: the former identifies the brand⁴ (namely: Barilla, Cameo, Nestlé, Kellogg's and Private Label), the latter identifies the type⁵ (namely: Fortified, Muesli and Simple). Own-price specification is also shifted by a continuous attribute: average calories (\overline{Kcal}). This particular products' characteristic was adopted because of its property to describe multiple nutritional peculiarities of the products we study (Sugar content, Fats and Fiber). This avoided the risk of multicollinearity that would have arisen if we had adopted other multiple attributes in the model. Thus the price and expenditure shifters in (4) are defined as:

$$\sum_s \gamma_s z_{js}^b = \sum_n \gamma_n Brand_{jn}^b + \sum_p \gamma_p Type_{jp}^b + \gamma_l \overline{Kcal}$$

⁴ Since there are 5 brands, two sets of 4 dummy variables are included in the specification, one for the own-price and one for the expenditure (Brand1=Barilla, Brand2=Cameo, Brand3=Kellogg's, Brand4=Nestlé);

⁵ Since there are 3 types, two sets of 2 dummy variables are included in the specification (Type1=Fortified, Type2=Muesli).

$$\sum_h \beta_n z_{jh}^\beta = \sum_n \beta_n Brand_{jn}^\beta + \sum_p \beta_p Type_{jp}^\beta$$

The intercept term is shifted by a set of discrete variables z_{jm}^a : one to account for seasonal patterns of consumption during the year and a second one to account for regional differences in food consumption habits. This means that z_{jm}^a translates to 2 sets of dummy variables applying on the intercept: 16 regional dummies, since we have 17 regions in our database, and 11 monthly dummies.⁶ Thus:

$$\sum_m a_m z_{jm}^a = \sum_g a_g Region_{jg}^a + \sum_m a_m Month_{jm}^a$$

Model (4) then becomes:

$$(5) \quad W_{jrt} = a_0 + \sum_g a_g Region_{jg}^a + \sum_m a_m Month_{jm}^a + \log \hat{p}_{jrt} (\gamma_0 + \sum_n \gamma_n Brand_{jn}^b + \sum_p \gamma_p Type_{jp}^b + \gamma_l \overline{Kcal}) + \lambda \sum_{k \neq j}^J \delta_{jk}^c \log \hat{p}_{krt} + \sum_d \varphi^D \sum_{k \neq j}^J \delta_{jk}^D \log \hat{p}_{krt} + (\beta_0 + \sum_n \beta_n Brand_{jn}^\beta + \sum_p \beta_p Type_{jp}^\beta) \log (\hat{X}_{rt}/P_{rt}) + \varepsilon_{jrt}$$

In this model, $\sum_d \varphi^D$ can be considered as indicators of loyalty. In fact, assuming $D = Brand$, $\varphi^{D=Br}$ would be a measure for the cross-price effect of j with respect to other products sharing the same brand with j (if j and k share the same brand, $\delta_{jk}^D = 1$ and $\sum_{k \neq j}^J \delta_{jk}^D \log \hat{p}_{krt}$ will account only for those products k whose $\delta_{jk}^D = 1$). This is, if $\varphi^{D=Br} > 0$ then consumers are likely to respond to an increase in price of the products sharing the same brand with j by switching to an alternative produced by the same manufacturer (thus: W_{jrt} increases as well and consumers are brand loyal). On the other hand, if $\varphi^{D=Br} < 0$ consumers are likely to respond to an increase in price of the products sharing the same brand with j by switching to an alternative manufacturer (thus: W_{jrt} decreases and consumers are not brand loyal).

Assumed that δ_{jk}^c represents a measure of how distant 2 products j and k are in the attribute space, two products with similar characteristics will show a higher value for δ_{jk}^c as compared to couples showing different attribute sets. Thus, any term $\delta_{jk}^c * \log \hat{p}_{krt}$ will influence more the demand response if j and k are close to each other. This means that $\sum_{k \neq j}^J \delta_{jk}^c \log \hat{p}_{krt}$ can be interpreted as an average of cross-prices, weighted by their distance from j , with δ_{jk}^c being the weights. In this context the continue closeness measure, λ , is a measure of the impact of all products similar to j on its expenditure share: for $\lambda > 0$ consumers tend to respond to any increase in similar products' prices by switching to references with similar nutritional

⁶ This second set of dummy variables is also an important tool for correcting a problem of biasness related to the method utilized for collecting the raw data: some months are made up of 5 weeks and others of 4 weeks. This inflates total expenditure in the 5-week months and the monthly dummies control for this effect.

profiles, while for $\lambda < 0$ consumers tend to respond to any increase in similar products' prices by switching to references with different nutritional profiles.

5. ESTIMATION AND EMPIRICAL RESULTS

Parameters estimates of the first-stage regressions for prices and expenditure are omitted for brevity⁷. Estimation of model (5) was carried out through least squares estimation in TSP 5.0. Parameters estimates are reported in table 2. In term of explanatory power, the model shows a very good R-squared (0.95), which is a remarkable result for a model of this type.

Table 2. Least squares estimated parameters.

Variables	Parameter	Parameter estimate	p-value
Intercept Basilicata+Calabria/Month12	a0	0.19685	0.000
Intercept Liguria	a31	-1.21E-03	0.420
Intercept Lombardia	a32	0.012615	0.000
Intercept Trentino Alto Adige	a33	-4.39E-03	0.012
Intercept Friuli Venezia-Giulia	a34	-1.37E-03	0.359
Intercept Veneto	a35	7.40E-03	0.000
Intercept Emilia Romagna	a36	6.95E-03	0.000
Intercept Toscana	a37	6.46E-03	0.000
Intercept Lazio	a38	9.11E-03	0.000
Intercept Umbria	a39	-5.76E-03	0.001
Intercept Sardegna	a310	-3.97E-03	0.011
Intercept Marche	a311	-1.52E-03	0.295
Intercept Puglia	a312	8.00E-04	0.580
Intercept Campania	a313	4.39E-03	0.006
Intercept Sicilia	a314	4.75E-03	0.003
Intercept Valle d'Aosta+Piemonte	a315	6.04E-03	0.001
Intercept Abruzzo+Molise	a316	-1.19E-03	0.413
Intercept Month1	a41	-3.44E-04	0.774
Intercept Month2	a42	-1.05E-03	0.384
Intercept Month3	a43	-1.29E-03	0.281
Intercept Month4	a44	8.85E-06	0.994
Intercept Month5	a45	2.32E-04	0.850
Intercept Month6	a46	8.48E-05	0.945
Intercept Month7	a47	-1.53E-03	0.208
Intercept Month8	a48	-8.31E-04	0.501
Intercept Month9	a49	-9.01E-05	0.943
Intercept Month10	a410	1.31E-03	0.283
Intercept Month11	a411	1.21E-03	0.311
Own-Price Simple Cereals/Private Label	γ_0	0.495257	0.000
Own-Price Fortified Cereals	γ_{11}	0.129336	0.000
Own-Price Muesli Cereals	γ_{12}	0.240051	0.000
Own-Price Barilla	γ_{21}	0.264439	0.000
Own-Price Cameo	γ_{22}	0.101563	0.000
Own-Price Kellogg's	γ_{23}	0.122802	0.000

⁷ Such results are available from the authors upon request.

Own-Price Nestlé	γ_{24}	0.237512	0.000
Own-Price*Caloric content	γ_{34}	-2.19E-03	0.000
Closeness Continue Attributes	λ	0.398916	0.000
Cloeness Brand	φ^{br}	0.064706	0.000
Closeness Type	φ^t	-0.037504	0.000
Expenditure Simple Cereals/Private Label	β_0	3.71E-03	0.004
Expenditure Fortified	β_{11}	-0.01626	0.000
Expenditure Muesli	β_{12}	-8.37E-03	0.000
Expenditure Barilla	β_{21}	3.51E-03	0.002
Expenditure Cameo	β_{22}	-6.94E-03	0.000
Expenditure Kellogg's	β_{23}	5.71E-03	0.000
Expenditure Nestlé	β_{24}	-0.014753	0.000

Source: own elaboration

5.1 Estimated coefficients

The coefficients of the intercept α are not statistically significant for the 12-month shifters (α_{11} to α_{411}) thus we're not able to capture any significant seasonality for breakfast cereal consumption. On the contrary, differences in regional food habits do exist: α_0 identifies Basilicata+Calabria (Region 17) which does not statistically differ from Liguria (α_{31}), Friuli Venezia-Giulia (α_{34}), Marche (α_{311}), Puglia (α_{312}), Abruzzo+Molise (α_{316}). Different patterns appear in other regions, consistently with estimated parameters for the corresponding regional dummies.

Coefficients γ associated with interactions of own-price with “type” (γ_0 = Simple, γ_{11} = Fortified, γ_{12} = Muesli), “brand” (γ_0 = Private Label, γ_{21} = Barilla, γ_{22} = Cameo, γ_{23} = Kellogg's, γ_{24} = Nestle) and Kcal content (γ_{34}) are statistically significant at the 1% level and positive, except for that associated with the interaction of log-price with the Kcal content shifter.

Any positive sign of the own-price coefficient would reduce the negative impact of the own-price on the corresponding quantity, making the demand function more inelastic and consumers less price sensitive⁸. Therefore, given the significance and the positive sign of all γ s in our estimation, the consumers' price sensitiveness for brands like Barilla, Cameo, Kellogg's and Nestlé and for types like muesli and fortified is lower than for Private Labels and simple cereal products (note that γ_0 is the own-price coefficient for Private Label simple cereals).

Nevertheless this effect is mitigated by the caloric content of the product, which increases the price sensitivity due to its negative sign (-.218572 E-02).

The positive sign of φ^{br} (.064706) suggests that any increase in price for a products k s sharing the same brand with j induces consumers in switching to products of the same manufacturer. The market is therefore characterized by a certain level of brand loyalty.

The argument for φ^t (-.037504) is different because of its negative sign (-.037504). “Type” discrete attribute appears to be a determinant of substitution patterns across cereals: consumers are likely to switch to other types of cereals as the prices of those sharing the same type with j increase.

⁸ This is consistent with the structure of the Slutsky term for estimating price responses in the AIDS model (Moro, 2004):

$$s_{jj} = \frac{\lambda_{jt}}{(\beta_{jt})^2} \left[(\gamma_0 + \sum_s \gamma_s z_{js}^b) + (W_{jt})^2 - W_{jt} + \left(\beta_0 + \sum_n \beta_n z_{jn}^\beta \right)^2 (\ln X_{jt} - \ln P_{jt}) \right] \text{ if } j=k$$

$$s_{jk} = \frac{\lambda_{jt}}{\beta_{jt} \beta_{kt}} \left[(\lambda + \sum_d \varphi^d) + W_{jt} W_{kt} + \left(\beta_0 + \sum_n \beta_n z_{jn}^\beta \right) \left(\beta_0 + \sum_n \beta_n z_{kn}^\beta \right) (\ln X_{jt} - \ln P_{jt}) \right] \text{ if } j \neq k$$

The last set of parameters to be discussed includes those accounting for interactions between expenditure allocated to breakfast cereals (Xrt) and both “brand” (β_{21} = Barilla, β_{22} = Cameo, β_{23} = Kellogg’s, β_{24} = Nestle) and “Type” (β_{11} = Fortified, β_{12} = Muesli) discrete shifters. In particular, negative and significant coefficients for the interaction between expenditure and “type” discrete attributes indicate that an increase in the total purchases of breakfast cereals leads to a smaller share of Fortified and Muesli cereals. Differently, an increase in expenditure for breakfast cereals leads to a larger share for simple cereals. The same intuition applies also for “brand” discrete shifter: results show that an increase in expenditure for cereals leads to larger (smaller) shares allocated to Barilla, Kellogg and Private Label (Cameo and Nestle).

5.2 Own-price and cross-price elasticities

Estimated Marshallian own-price and cross-price elasticities are obtained using the estimated parameters and applying the following formulas:

$$\eta_{jk} = \begin{cases} \frac{\gamma_0 + \sum_n \gamma_n z_{jn}^b + \sum_p \gamma_p z_{jp}^b + \gamma_l z_{jl}^b}{\overline{w_{jrt}}} - \left(\beta_0 + \sum_n \beta_n z_{jn}^\beta + \sum_p \beta_p z_{jp}^\beta \right) - 1 & \text{if } j = k \\ \frac{\lambda \delta_{jk}^c + \sum_d \varphi^d \delta_{jk}^d}{\overline{w_{jrt}}} - \left(\beta_0 + \sum_n \beta_n z_{jn}^\beta + \sum_p \beta_p z_{jp}^\beta \right) \frac{\overline{w_{krt}}}{\overline{w_{jrt}}} & \text{if } j \neq k \end{cases}$$

where $\overline{w_{jrt}}$ ($\overline{w_{krt}}$) is the average of product j’s (k’s) expenditure share.

Own-price and cross-price elasticities are reported in table 3.

Own-price elasticities are negative as expected and their magnitude is the largest in products whose price sensitivity is expected to be higher (Private Labels). Furthermore, muesli products appear to have larger own-price elasticities with the exception of Cameo’s. Note that the absolute size of these own-price elasticities is in line with those estimated with the DM approach by Pofhal and Richards (2009) and Bonanno (2011) on similar databases. Despite this consistency with the literature, the high value of Kellogg’s Muesli own-price elasticity remains difficult to explain.

Different patterns of positive and negative cross-price elasticities arise and some rationales can be provided to support these findings.

First, cross-price elasticities for products belonging to the same brand but showing different type attributes are positive, thus showing a substitution relationship.

There are two possible rationales for this: Kellogg’s Fortified (Muesli/Simple) cereals may not be perceived enough different from Kellogg’s Muesli (Fortified/Simple) for justifying negative cross-price elasticities (complementarity).

The same reasoning applies also to Nestlé: Nestlé Fortified cereals are unlikely to be perceived enough dissimilar from Nestlé simple for justifying negative cross-price elasticities. This applies to Private Labels as well: PL Fortified may not be perceived enough different from PL Muesli for justifying negative cross-price elasticities; the same reasoning applies for other PL products.

Another possible rationale is linked to our findings concerning brand/type loyalty: the positive value for φ^{B^r} suggests a certain level of brand loyalty while φ^T points out the opposite attitude towards type, therefore any change in prices for Kellogg’s Muesli or Simple products might translate to their substitution with Kellogg’s Fortified quantities. The same reasoning applies also other Kellogg’s products, but also the corresponding Nestlé’s and Private Labels’ products.

Table 3. Marshallian elasticities estimated at the mean point of the sample.

	Barilla Fortified	Cameo Muesli	Kellogg's Fortified	Kellogg's Muesli	Kellogg's Simple	Nestlé Fortified	Nestlé Simple	PL Fortified	PL Muesli	PL Simple
Barilla Fortified	-0.36019	2.21199	-4.32574	0.45976	1.47347	-4.65864	0.98907	-4.67954	1.25746	0.9872
Cameo Muesli	0.30275	-1.65275	0.25466	-0.67808	0.21628	0.23265	0.15706	0.20522	-0.72747	0.14147
Kellogg's Fortified	-0.10641	0.030449	-1.36953	0.24933	0.29288	-0.03595	0.034914	-0.0197	0.016208	0.031701
Kellogg's Muesli	0.08022	-1.13401	2.13603	-7.28406	2.12999	0.055933	0.050215	0.062594	-1.08962	0.055367
Kellogg's Simple	0.022397	0.020078	0.26312	0.23504	-1.75565	0.03657	-0.09122	0.052575	0.012009	-0.05658
Nestlé Fortified	-0.16922	0.052521	-0.02011	0.015843	0.1123	-0.82746	0.44904	-0.03181	0.02458	0.056202
Nestlé Simple	0.046548	0.055035	0.10645	0.018545	-0.19812	0.71204	-1.62623	0.097288	0.029224	-0.22411
PL Fortified	-0.97745	0.31066	-0.07269	0.081176	0.63876	-0.20562	0.39902	-8.46216	2.36699	2.58201
PL Muesli	0.6259	-2.60488	0.45876	-2.80396	0.39993	0.39799	0.29564	5.73738	-17.7267	5.66631
PL Simple	0.12517	0.12247	0.16256	0.037274	-0.37375	0.1798	-0.57041	1.68306	1.53136	-8.30076

The magnitudes of these cross-price elasticities are higher for Private labels and Kellogg's muesli, while are lower for Nestlé; thus, their incidence on purchasing behavior is more significant in the first case.

Second, cross-price elasticities for products sharing the same type but different brand attributes are negative, thus showing a complementarity relationship. However, their magnitudes are rather low, except for muesli cereals.

A possible rationale for this might be the following: given their loyalty to the brand rather than to a specific type, consumers tend to react switching to a products of the same manufacturer. For instance, changes in Private labels or Nestlé fortified prices would lead to a switch towards Private labels or Nestlé muesli or simple products, rather than moving towards Kellogg's fortified. The same intuition applies also to muesli and simple type

Consistently with the value of λ , this within-brand substitution is likely to be oriented towards products with similar nutritional characteristics. Thus, consumers will tend to switch from fortified to simple (and vice versa) rather than to muesli.

However, motivating these findings for those brands with just one product type (Cameo, Barilla) is not straightforward. The pattern in this case is unclear, as it is unclear the magnitude of some Barilla fortified cross-price elasticities (one explanation may be related the small value of its expenditure share, that makes demand very sensitive to small changes in prices).

6. CONCLUDING REMARKS

In our analysis of the Italian market for breakfast cereals, the AIDS model adapted to the Distance Metrics' approach, has proven to be a good method for estimating demand effects of differentiated products. Besides reducing the number of cross-price parameters from 45 ($J(J-1)/2$) to 2, thus increasing the number of degrees of freedom and reducing the burden of estimating a large number of parameters, the model allow us to obtain excellent results in terms of significance of the relevant parameters.

Cross-price parameters, own price parameters and expenditure parameters are all significant at the 1% level and the R-squared of the model is 0.95 indicating the large explanatory power of the variables employed in defining the expenditure shares. Price elasticities are also significant, and most of the times they are consistent with the other results obtained from the model estimation.

Our findings indicate that globally, consumers tend to be more brand loyal than they are to the type of product and respond to fluctuations in similar products' prices by switching among references with similar nutritional profiles. Furthermore, Private Labels are confirmed to be the most price-sensitive products, while the products supplied by the biggest players on the market are the less-price sensitive ones. Although being the produce with the smaller market share, Barilla Grancereale shows the lowest own-price elasticity which probably indicates that it is perceived as a niche product.

Despite the relatively large range of products resulting from innovation proposed by market leaders, given a supply side managed by a very restrictive number of firms, it is unlikely for consumers to take any advantage from competition among National Brands (NB). This intuition is supported by our findings: the price sensitiveness for NB cereals products is low. In this context, Private labels represent an alternative and offer an increasing range of cheap products; on the other hand, their reliance on low prices makes Private labels demand extremely price sensitive.

Besides the strong implications these findings have on the demand side, the supply side deserves to be taken into account as well. As we previously mentioned, the biggest players on the market (namely Kellogg's and Nestlé) show an important product innovation rate: new products are yearly launched on the

market, and some of them do not last for long time. Consistently with our findings concerning the absence of consumers' loyalty to the product type and their tendency to switch to products with similar nutritional attributes, it would be interesting to carry out a cost-benefit analysis for innovating manufacturers. Product innovation in a broad sense will undoubtedly help to keep consumers loyal to the brand; however one should propose new lines in line with this consumer profile. For example, a consumer may be happier to switch from simple cereals to fortified cereals rather than to more caloric ones (muesli).

The model is however far from being without problems. Choosing shifters for the DM specification is a rather complicated task and the issue of multicollinearity is very likely to arise. Further difficulties could arise when dealing with spatial attributes other than the nutritional ones; in such case defining a unique unit of measure and choosing the correct dimensionality could represent a significant hurdle. Finally, the adoption of the DM approach makes the imposition of the standard demand theory restrictions rather complicated. This is clearly a strong limitation, that should be overcome with an appropriate reformulation of the model.

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