Preferences, market structure, and welfare evaluations in the Argentinean FFP industry: a case in Buenos Aires Province

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Abstract

This paper analyzes the demand of frozen fried potatoes in an important city of Argentina, Mar del Plata, and the effect of changes in market structure on consumer welfare. We find that high income individuals are more concerned about health and nutrition, and that younger and lower-income consumers are more price sensitive. The results suggest that consumer surplus would decrease with a merger between the two smaller firms of the market, and would increase if the market turned into a single-product firms industry. The influence of these counterfactual changes would be greater for wealthier and older individuals. This article contributes to the analysis of a food market which is rapidly growing in developing countries and is starting to play a more relevant role in consumers' diet.

EconLit subject matter areas: [L11], [D12].

1. Introduction

The Argentinean frozen fried potato (FFP) industry is characterized by high concentration and high degree of horizontal and vertical differentiation. There are virtually no research on the characteristics, evolution, and development of the domestic market of FFP in Argentina. Few exceptions are studies committed to analyze contractual relationships and integration schemes between potato producers and agro-industry actors (Bruzone, 1998; Mateos, 2003), but there are not investigations concerned with understanding and identifying consumers' preferences for these products. This paper intends to fill this gap by analyzing the FFP market in an important city of Argentina, Mar del Plata.

The study of differentiated-product markets is a key topic of the recent literature in empirical industrial organization; in particular, the estimation of demand functions has introduced many challenges.[1] On the one hand, it is the computational complexity of estimating a large number of parameters. On the other hand, a difficulty associated with the possibility of modeling the heterogeneity in consumers' tastes with which to get more realistic estimations of substitution patterns and the level of product differentiation in the market. Since McFadden's logistic demand model (1973), the discrete choice literature has provided solutions to overcome such obstacles, especially the Random Coefficients Discrete Choice Model (Berry, 1994; Berry et al., 1995), henceforth RCDCM. This model has gained importance in the study of market power, new goods, and changes in market structure of differentiated-product markets. Berry, Levinsohn and Pakes (1999) evaluate the impact of the voluntary export restraint of Japanese vehicles exported to the United States that was set up in 1981. Nevo (2000a, 2001) examines collusive pricing behavior and evaluates actual and hypothetical mergers in the ready-to-eat cereal industry. Petrin (2002) quantifies the effect of the introduction of the minivan into the U.S. automobile market.[2] However, this approach has not been yet applied to analyze the FFP market, which is rapidly growing in developing countries.

[1] Since the Linear Expenditure System (Stone, 1954), econometric estimations of demand models, such as Rotterdam (Theil, 1965), Translog (Christersen et al., 1975), and AIDS (Deaton y Muellbauer, 1980), have faced the challenge of achieve flexible functional forms, consistent with economic theory.

[2] A lot of other studies can be mentioned. Mojduszka et al. (2001) investigate what affect consumer demand for prepared frozen meals in U.S., and evaluate price competition in the industry and the impact of a new mandatory labeling policy; Brambilla (2005) estimates the cost of the non-trade barriers in Argentina and Brazil bilateral trade of vehicles during 1996-1999, and assesses the impact of a counterfactual equilibrium in which the non-tariff barriers are removed and the common external tariff is adopted; Lopez & Lopez (2009) analyze consumer choices, demand elasticity, and price competition in a differentiated fluid milk market in Boston, MA; among others.

The objective of this paper is to explore consumers' preferences for FFP through the estimation of flexible elasticity coefficients and to measure the effect of hypothetical changes in FFP industry market structure on prices, sales, and consumers' surplus. To achieve this goal a RCDCM of household demand is estimated. The main data source is a monthly three-dimensional panel of quantities and sales for a five-year period provided by a local supermarket chain; socioeconomic information from the households' survey of the *Instituto Nacional de Estadísticas y Censos* (INDEC) of Argentina is the auxiliary data set. The individual-specific parameters of the utility function are estimated, as well as the own- and cross-price elasticities. Then, the marginal costs for the available products are obtained and counterfactual market structures are simulated. Finally we recover equilibrium prices after the proposed scenarios and calculate consumers' welfare changes.

The rest of the paper is organized as follows. A brief overview of FFP world market and some notes about the Argentinean case are presented in Section 2. Section 3 outlines the theoretical framework of discrete choice models. Data, estimation, and identifying assumptions are presented in Section 4. Results are reported in Section 5. Lastly, Section 6 concludes the paper.

2. The frozen fried potato industry

Potato is an extensive annual crop of relative high cost, whose productivity can be limited by agro-ecological conditions, water availability, technology, and use of fertilizers and other agrochemicals. These constraints are especially important when considering potatoes destined to processing, as FFP, due to the quality standards usually required. Straight-cut fries ("papas bastón" in Spanish) are the Argentinean FFP industry main product, even though there are others, like slices, noisettes, croquettes, etc.

FFP is an extensively consumed food in developed countries, mainly in North America. Although the FFP market has reached maturity in the United States, FFP consumption has rapidly grown in the developing countries, which is related to the higher women's labor force participation rates, the higher frequency of eating-out, and other changes in working patterns. All this has caused a rise in the demand for fast food, a market dominated by multinational chains that is the principal FFP supplier. The production of these goods is mainly concentrated in the United States, The Netherlands, Canada, and Belgium, which also are the top exporters. A few companies dominate this market in Mercosur: McCain supplies McDonald's, while Alimentos Modernos supplies Burger King and offers two own brands, FarmFrites and RapiPap. In Argentina, FFP production amounted to 215,000 tons in 2001 (last available figures), accounting for 80% of the potatoes destined to industrial processing (Mateos, 2003). Argentinean households' direct demand for FFP is primarily supplied by super and hypermarkets, even though restricted because of the high prices if compared with fresh potatoes.

3. Discrete-choice logit models

Product differentiation as a research topic of agricultural economics dates back to the decade of the 1920s, when Waugh (1928) published his seminal work devoted to analyze the relationship between price and characteristics of vegetables in the United States. Later, Houthakker (1951-52) and Thail (1951-52) incorporated the product characteristics in their utility maximization models, while Lancaster (1966) postulated that it is the properties or characteristics of the good from which utility is derived. The Simple Logit Model (McFadden, 1973) makes use of this conceptual framework and solves some challenges that arise when estimating demand functions for differentiated products. Specifically, it overcomes the dimensionality problem by projecting the products onto a characteristics space. However, in this model all individuals are assumed to be identical except for the error term, which entails strong restrictions on elasticity coefficients. On the one hand, the own-price elasticities are almost perfectly proportional to prices when the market share of the outside good is close to one (McFadden, 1981). On the other hand, the cross-sensitivity of demand is the same regardless the good whose price changes, and therefore consumers substitute towards other products in proportion to market shares, without considering the similarity of their characteristics. More flexible substitution patterns are achieved with the Nested Logit Model, whose estimation requires a priori clustering of products; the cross-price elasticity coefficients are different between groups but equal within them. Finally, the RCDCM (full model) allows for flexible own-price elasticities driven by the different price sensitivity of different consumers, and for cross-price substitution patterns driven by product characteristics and not constrained by arbitrary segmentation of the market. Table 1 synthesizes the advantages and limitations of the discrete-choice logit models.

[Table 1. Discrete-choice logit models]

The rest of the section presents the RCDCM of demand, the assumed supply behavior, and a measure of welfare change. In general terms, the idea is to estimate the structural parameters that govern demand and supply and to use them to analyze the effects on welfare of counterfactual changes of FFP market structure.

3.1 Demand

Suppose t = 1,…, T markets (as defined below) are observed, each with i = 1,…, I consumers. The conditional indirect utility of consumer i from product j (j = 1,…, J) at market t is

(1) $$u_{ijt} = x_j \beta_i^* - \alpha_i^* p_{jt} + \xi_j + \Delta\xi_{jt} + \varepsilon_{ijt}$$

where x_j is a K-dimensional (row) vector of observable product characteristics, p_{jt} is the price of product j in market t, ξ_j is the mean valuation of the unobserved product characteristics, $\Delta\xi_{jt}$ is a market specific deviation from this mean, and ε_{ijt} is a mean-zero stochastic term distributed i.i.d. with Type I extreme-value distribution. Finally, $(\alpha_i^* \; \beta_i^*)$ are K + 1 individual-specific coefficients, defined following the approach of Nevo (2001) as:

$$\begin{pmatrix}\alpha_i^* \\ \beta_i^*\end{pmatrix} = \begin{pmatrix}\alpha \\ \beta\end{pmatrix} + \Pi D_i + \Sigma v_i \tag{2}$$

$$v_i \sim N(0, I_{K+1})$$

where $(\alpha \; \beta)$ are the mean parameters of the utility function, D_i is a $d \times 1$ vector of observed demographic variables, v_i is a vector of normal random shocks in tastes,[3] Π is a (K + 1) × d matrix of coefficients that measure how the taste coefficients vary with demographics, and Σ is a scaling matrix.

The consumers may decide not to purchase any of the products, in which case they choose the "outside good". Without this allowance a homogeneous price increase of all products does not change quantities purchased. The indirect utility from this outside option is

$$u_{i0t} = \xi_0 + \pi_0 D_i + \sigma_0 v_{i0} + \varepsilon_{i0t}$$

The mean utility of the outside good, ξ_0, is not identified, so it is normalized to zero.

Let $\theta = (\theta_1, \theta_2)$ be a vector containing all parameters of the model. The vector $\theta_1 = (\alpha, \beta)$ contains the linear parameters and the vector $\theta_2 = (\Pi, \Sigma)$, the nonlinear parameters.[4] Combining equations (1) and (2):

$$u_{ijt} = \delta_{jt}\big(x_j, p_{jt}, \xi_j, \Delta\xi_{jt}; \theta_1\big) + \mu_{ijt}\big(x_j, p_{jt}, v_i, D_i; \theta_2\big) + \varepsilon_{ijt} \tag{3}$$

$$\delta_{jt} = x_j\beta - \alpha p_{jt} + \xi_j + \Delta\xi_{jt}; \; \mu_{ijt} = \left[p_{jt}, x_j\right]' * (\Pi D_i + \Sigma v_i)$$

[3] The vector v_i represents the unobserved individual characteristics (i.e., not available in the auxiliary dataset) that affect preferences.

[4] The reason for distinguishing between linear and nonlinear parameters has to do with how they enter the model and the estimator, as will be shown below.

where δ_{jt} represents the mean utility, which is common to all consumers, and $\mu_{ijt} + \varepsilon_{ijt}$ is a mean-zero heteroskedastic deviation from that mean that captures the effects of the random coefficients.

It is assumed that consumers purchase one unit of the good that gives the highest utility.[5] This implicitly defines the set of individual-specific variables that lead to the choice of good *j*:

$$A_{jt}(x, p_{.t}, \delta_{.t}; \theta_2) = \{(D_i, \upsilon_i, \varepsilon_{it}) | u_{ijt} \geq u_{ilt} \; \forall l = 0,1, \ldots, J\}$$

Assuming ties occur with zero probability, the market share of the *j*th product as a function of the mean utility levels of all the *J* + 1 goods, given the parameters, is

$$s_{jt}(x, p_{.t}, \delta_{.t}; \theta_2) = \int_{A_{jt}} dP^*(D, \upsilon, \varepsilon) = \int_{A_{jt}} dP_D^*(D) dP_\upsilon^*(\upsilon) dP_\varepsilon^*(\varepsilon) \quad (4)$$

where $P^*(\cdot)$ denotes population distribution functions. The second equality is a consequence of an assumption of independence of D, υ, and ε. Unlike the Simple Logit Model, in the full model the market share equations do not have an analytic closed form, therefore the integral given in equation (4) has to be computed numerically, as will be shown below.

Since the main data source includes aggregate sales data, heterogeneity can be modeled either by assuming a parametric distribution of $P^*(\cdot)$ (Berry, 1994; Berry et al., 1995) or as a function of the empirical nonparametric distribution of demographics (Nevo, 2001). We implement the second option in this paper, which allows us to assess the joint distribution of the demographic variables in D.

3.2 Supply

Suppose there are *F* firms, each of which produces some subset, $\mathcal{F}_f$, of the *j* = 1,…, *J* different products. The profits for a firm *f* are

[5] This is a reasonable assumption since most people consume only one kind of FFP at a time.

(5) $$\Pi_f = \sum_{j\in\mathcal{F}_f} (p_j - mc_j) M s_j(p) - C_f$$

where $s_j(p)$ is the market share of product j, which is a function of the prices of all products, M is the size of the market,[6] mc_j is the constant marginal cost of production, and C_f is the fixed cost of production. Assuming the existence of a pure-strategy Bertrand-Nash equilibrium in prices, and that the prices that support it are strictly positive, the price p_j of any product *j* produced by firm *f* must satisfy the first-order condition

(6) $$s_j(p) + \sum_{r\in\mathcal{F}_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0$$

In vector notation, the first-order conditions become

(7) $$s(p) + (\Omega .* \Delta)(p - mc) = 0$$

where Ω is the ownership matrix, whose element Ω_{jr} equals one if j and r are produced for the same firm, and zero otherwise. Δ is the derivative matrix, where $\Delta_{jr} = \partial s_r(p)/\partial p_j$, which is obtained when estimating the demand model. This implies a system of equations to compute the marginal costs, which are not observed:

(8) $$mc = p + (\Omega .* \Delta)^{-1} s(p)$$

Equation (7) also provides an equation to predict counterfactual equilibrium prices, p^*:

(9) $$p^* = \widehat{mc} - (\Omega^* .* \Delta)^{-1} s(p^*)$$

where $\widehat{mc}$ are the estimated marginal costs, and Ω^* is the ownership matrix that represents the hypothetical market structure of the counterfactual scenario. When computing post-change equilibrium prices and market shares we make two important assumptions. First, we assume

[6] The market size defined in this model includes the share of the outside good, which allows keeping the market size fixed while still allowing the total quantity of products sold to increase. Therefore, the analysis of a hypothetical change in market structure is less sensitive to the exact definition of market size.

that the cost structure stays the same before and after the changes. Second, the derivative of shares with respect to prices, matrix Δ, also remains unchanged.

3.3 Consumer welfare

The measure we use to evaluate the changes in consumer welfare as a result of hypothetical scenarios is the compensating variation. Unlike the Simple Logit Model, this measure does not have an analytical solution for the full model when α_i^* in equation (1) is a function of income. In this case, the compensating variation of individual i, CV_i, has to be computed iteratively, and is equal to $-\Delta y_i$, where Δy_i solves

$$u_i(y_i, p) = u_i(y_i + \Delta y_i, p^*)$$

where y_i is the income of individual i and p is the vector of prices in the initial situation. The mean compensating variation in the population is given by

$$CV = N \int CV_i \, dP_D^*(D) dP_v^*(v) \tag{10}$$

where N is the total number of consumers.

Two assumptions have to be made when computing these changes in consumer surplus. First, as with the observed characteristics, there is no change in the unobserved components, ξ_{jt}. Second, there are no changes in the utility from the outside good.

4. Data, estimation, and identifying assumptions

4.1 Data

The data required to consistently estimate the model previously described consist of the following variables: market shares and prices in each market (as defined below), product attributes, and demographic characteristics of individuals. Since we do not possess information about individual purchases, we match scanner data with an auxiliary database, which provides the distribution of demographic variables across population in each market, in order to identify the variable part of the coefficients.

The scanner database was provided by a traditional supermarket chain in Mar del Plata, Supermercados Toledo S. A., and consists of the value of monthly sales and the quantity sold for each product and each of the 23 branches of the supermarket, from July 2005 to December 2009. The city of Mar del Plata is located on the Atlantic Ocean cost, 400 kilometers (249 miles) south of Buenos Aires City, the capital city of Argentina. It is one of the major fishing ports, an important industrial area, and the biggest seaside beach resort in the country. With a population of roughly 600,000 inhabitants, Mar del Plata is the second largest city of Buenos Aires Province and the seventh largest Argentinean city, and is the main urban center of the major potato production area of the country, which is located in the southeast Province of Buenos Aires. Figure 1 shows the geographical distribution of the supermarket branches, confirming their widespread allocation in the city.

The sales data cover 18 FFP products supplied by three firms (McCain, Alimentos Modernos, and Granja del Sol) through four brands (McCain, FarmFrites, Granja del Sol, and RapiPap), and are classified in six segments or varieties (bastón, golden longs, noisette, rondelles, smiles, and croquettes) and offered in several container sizes. Nutritional information about calories, saturated fat, fiber, and sodium was collected by visual inspection of the products' nutrition facts labels. Unit value per serving was calculated as a proxy for price, by dividing the value of sales by the quantity of servings sold, which was computed as the package size divided by the serving size[7] and multiplied by the quantity of units sold.

[Figure 1. Allocation of Supermercados Toledo branches in Mar del Plata, Argentina]

Information on the distribution of demographics was obtained by sampling individuals from the *Encuesta Permanente de Hogares* (EPH), which is carried out by the *Instituto Nacional*

[7] According to the Argentine Food Code, the size of a serving of FFP is 85 grams (2.99 oz).

de Estadísticas y Censos (INDEC) in several cities of the country; in this paper we use the information about households of Mar del Plata. The socioeconomic variables of interest are per capita income and average age of the household members, which is related with both household size and presence of children.

In order to match both data sets it is necessary to define the criterion for aggregating sales data and sampling simulated individuals, i.e. to define a market. Since the EPH does not provide the geographical location of surveyed households, it is not possible to define a market as a combination of a geographical area and a unit of time, as in most previous work, which in our case would be a branch-month combination. Therefore, a market was defined as an income-month combination, and the data were prepared following three steps. First, the per capita average income of each Mar del Plata census tract was calculated using data from a household survey.[8] Second, the potential customers of each supermarket branch were identified according to the population of the census tract in which the branch is located. Finally, the branches were classified by the income level of their potential buyers (high, upper-middle, middle, lower-middle, and low)[9], and sales data of branches with the same income level were aggregated by month and product. Thus, the data were structured in 270 markets (5 income levels by 54 months) and 2,145 observations (considering different products sold in each market). The demographic characterization of each market was

[8] This data come from a probabilistic 500-household survey about potato consumption conducted in Mar del Plata in June 2009 by the Grupo de Economía Agraria of the Facultad de Ciencias Económicas y Sociales, Universidad Nacional de Mar del Plata, Argentina (Rodríguez et al., 2010).

[9] These income categories were defined according to the average quintile income of the households surveyed by the EPH in the second quarter of 2009, period in which the potato consumption survey was carried out.

accomplished by randomly drawing simulated individuals from the corresponding period and quintile of the EPH.[10]

Lastly, to calculate the market shares it is necessary to assess the market size, i.e. the total potential demand for FFP of the supermarket chain. This was obtained as the 35%[11] of the total potential demand of the city, which in turn was calculated by imputing the FFP consumption frequency of "real consumers"[12] to the entire city population. This was done for each of the branches regarding their potential customers, and then the market size for each income-month combination was calculated. The market share for each product in each market was determined by dividing the quantity of servings sold by the market size.

Table 2 presents the characteristics of the FFP products covered by our scanner database. We assign them an identification number (ID) which we will refer to in the results section. Bastón is the most popular variety followed by noisette, despite its relatively high price. On the other hand, croquettes and rondelles are the segments with the least market shares. It can be seen that Toledo customers can take advantage of economies of scale in these products, since price per serving decrease as container size increases, at equal value of the other characteristics.

Table 3 reports FFP average prices by segment and income level. For all varieties, prices increase with income; golden longs, rondelles and bastón are the least expensive products in all income levels, and croquettes are the most expensive. The last column shows the percentage difference between average prices in high- and low-income-level markets. Consumers of high income-level face higher prices than consumers of low income-level for

[10] Since the EPH is a quarterly survey, three random samples had to be drawn for each quarter and quintile. The sample size (ns) is of 180 individuals by market.

[11] This is the Supermercados Toledo share of total supermarket sales in Mar del Plata, according to the opinion of key actors in the supermarket industry.

[12] This refers to the FFP consumption frequency of those polled in the potato consumption survey who declared they consume FFP.

any product variety, which suggests the presence of a price discrimination strategy implemented by sellers. Golden longs and smiles are the segments in which the highest surcharges are imposed, while bastón and noisette present the lowest surcharges.

[Table 2. Product characteristics, market shares, and prices]

[Table 3. FFP average prices by segment and income level]

Lastly, Table 4 shows average prices by brand and income level. Such as in the previous table, prices increase with income regardless the brand. Granja del Sol offers the most expensive products on average, while RapiPap FFP are the least expensive options.

[Table 4. FFP average prices by brand and income level]

4.2 Estimation

The key point of the estimation is to exploit a population moment condition that is a product of instrumental variables and a structural error term to form a nonlinear GMM estimator. The main technical difficulties to deal with are related to the computation of the integral in equation (4), and to matching theoretical to observed market shares. Formally, let $Z = [z_1, \dots, z_M]$ be a set of instruments such that $E[Z' \cdot \omega(\theta^*)] = 0$, where ω, a function of the model parameters, is an error term defined below and θ^* denote the true value of this parameters. The GMM estimate is

(11) $$\hat{\theta} = \arg\min_{\theta} \omega(\theta)' Z A^{-1} Z' \omega(\theta)$$

where A is a consistent estimate of $E[Z'\omega\omega' Z]$. Because of the inclusion of product-specific dummy variables as product characteristics (as explained below), the error term is defined as the market specific deviation from the mean valuation of the unobserved product characteristics, $\Delta\xi_{jt}$[13]. This error term is computed by solving for the mean utility levels, $\delta_{.t}$, that solve the implicit system of equations

(12) $$s_{.t}(x, p_{.t}, \delta_{.t}; \theta_2) = S_{.t}$$

where $s_{.t}(\cdot)$ is the market share function defined by equation (4) and $S_{.t}$ are the observed market shares. For the Simple Logit Model the solution is equal to $n(S_{jt}) - ln\ (S_{0t})$, while for the full model this inversion is done numerically. Once this inversion has been done, the error term is defined as $\omega_{jt} = \delta_{jt}(x, p_{.t}, S_{.t}; \theta_2) - (x_j\beta - \alpha p_{jt})$. The reason for distinguishing between θ_1 and θ_2 becomes clear now: θ_1 enters this error term, and therefore the objective function, in a linear fashion, while θ_2 enters nonlinearly.

The estimation algorithm implemented to compute the estimates requires the following steps (Nevo, 1998):

(0) Prepare the data[14]. Define a vector of market shares and two matrices of attributes, X_1 and X_2. X_1 contains the variables that enter the linear part of the estimation, common to all individuals (δ_{jt} in equation (3)). X_2 contains the variables that will have a random coefficient, and therefore will enter the nonlinear part (μ_{ijt} in equation (3)). Draw individuals from the auxiliary database in order to obtain values for the variables in D, and draw values for the random shocks to tastes (υ) and to utility (ε).

[13] A straightforward approach to the estimation of this model is to define the error term as the difference between the observed and predicted market shares. In this work, we define a structural error term following the estimation method proposed by Berry (1994), which allows one to deal with correlation between the error term and prices. The advantage of working with a structural error is that the link to economic theory is tighter, allowing us to think of economic theories that would justify various instrumental variables (Nevo, 2000b).

[14] The actual organization of the data depends on the code used to compute the estimation. We adapted a code developed by Nevo (2000b).

(1) For a given value of θ_2 and δ, compute the market shares implied by equation (4). Assuming a Type I extreme-value distribution for ε, market shares are approximated by

$$s_{jt}(p_{.t}, x_{.t}, \delta_{.t}, P_{ns}; \theta_2) = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijt} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{exp\left(\delta_{jt} + \sum_{k=1}^{K} x_{jt}^{k}\left(\sigma_k v_i^k + \pi_1^k D_{1i} + \cdots + \pi_d^k D_{di}\right)\right)}{1 + \sum_{m=1}^{J} exp\left(\delta_{mt} + x_{mt}^{k}(\sigma_k v_i^k + \pi_1^k D_{1i} + \cdots + \pi_d^k D_{di}\right)\right)}$$

where s_{ijt} is the probability of individual *i* purchasing the product *j* in market *t*.

(2) For a given θ_2, compute the vector δ that equates the market shares computed in step (1) to the observed shares, by solving the system of equations in (12). It can be solved numerically by using a contraction mapping suggested by Berry et al. (1995).

(3) Determine θ_1 according to the mean valuation computed in step (2), and compute the error term $\omega = \delta - X_1\theta_1$. Interact ω with the instruments and calculate the value of the objective function $\omega(\theta)'ZA^{-1}Z'\omega(\theta)$.

(4) Search for the value of θ_2 updating starting values until minimizing the objective function.

4.3 Instruments and product-specific dummy variables

As pointed out, once product dummy variables are included in the regression, the error term is the unobserved (to the researcher) income-month specific deviation from the overall mean valuation of the product. Since we assume that players in the industry observe and account for this deviation (i.e., firms take it into account when setting prices, and it affects consumers' utility and willingness to pay), it will be correlated with prices, and therefore least-squares estimate of price sensitivity, α, will be biased and inconsistent.

Much of the previous work treats this endogeneity problem by using observed characteristics of other products to form instrumental variables (IV's). Characteristics of other products will be correlated with price since the markup of each product will depend on the distance from the nearest neighbor, and if characteristics are assumed exogenous they are valid IV's.

However, this is not feasible in this study because there is no variation in each product's characteristics over time and across income levels. Furthermore, this strategy assumes the location of products in the characteristics space is exogenous, which implies treating the characteristics as predetermined, ruling out the possibility of firms to change the product design in response to demand shocks.

Our identifying strategy follows that of Nevo (2001), which in turn use an approach similar to that used by Hausman (1994). Exploiting the panel structure of the data, the identifying assumption is that, controlling for product-specific means and demographics, income-level-specific valuations are independent across income levels (but are allowed to be correlated within an income level). Given this assumption, the prices of the product in other income levels and months (and in other cities) are valid IV's. Since prices are a function of marginal costs, and assuming marginal costs have a common component to all income levels and months, prices of product j in two markets will be correlated (relevance condition). On the other hand, due to the independence assumption they will be uncorrelated with the market-specific valuation of other income levels and months (exclusion condition). According to all this, we use prices in other income levels and months as instruments. Additionally, the data source provides sales data of branches located in other cities (Azul, Balcarce, Miramar, Necochea, Olavarría, and Tandil), so we use the monthly average price of the product in those branches as an IV too.

Regarding the inclusion of product-specific dummy variables as product characteristics, one reason to introduce them is that they improve the fit of the model since we cannot be sure that the observed characteristics capture the entire set of factors that determine utility. But a major motivation is to prevent the mean valuation of the unobserved product characteristics, ξ_j, from being part of the error term. These dummies capture all attributes that do not vary by market, and therefore the correlation between prices and the unobserved quality is fully accounted for and does not require an instrument. Because observable characteristics (except price) do not vary by market either, the taste parameters have to be retrieved by using a minimum distance procedure (as in Chamberlain, 1982). Let d denote the $J \times 1$ vector of product dummy coefficients, X be the $J \times K$ ($K < J$) matrix of product characteristics, and ξ be the $J \times 1$ vector of unobserved product qualities. Then from equation (1)

$$d = X\beta + \xi$$

If we assume that $E(\xi|X) = 0$,[15] the estimates of β and ξ are

$$\hat{\beta} = (X'V_d^{-1}X)^{-1}X'V_d^{-1}\hat{d}\ , \quad \hat{\xi} = \hat{d} - X\hat{\beta}$$

where $\hat{d}$ is the vector of coefficients estimated from the procedure described in Section 4.2, and V_d is the variance-covariance matrix of these estimates.

Finally, time dummy variables are included in the estimation in order to identify the pure effect of product characteristics on consumer's utility once the time effect is controlled for. This is especially relevant for price parameter estimates because significant inflation rates were verified over the analyzed period.

5. Results

5.1 Demand

This section presents the results[16] from the estimation of the utility parameters and price elasticities. Although this paper focuses on the RCDCM, we also estimate the Simple Logit Model for the sake of comparison and because, due to its computational simplicity, it is a useful tool to examine the importance of the inclusion of product-specific dummy variables, and of instrumenting for price. Table 5 displays the results from three specifications of the

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[15] This is the assumption required to justify the use of observed characteristics as IV's. Here this assumption is used only to recover the taste parameters and does not impact the estimates of price sensitivity.

[16] The software used to obtain the results in Section 5 are Stata 11.2 and MATLAB 7.0.

Simple Logit Model. In column (i) and (ii) we report ordinary least squares (OLS) regressions. The regression in column (i) includes observed product characteristics, but not product fixed effects, and therefore the error term includes the unobserved product characteristic, ξ_j. Column (ii) incorporates product dummy variables, fully controlling for ξ_j. Finally, column (iii) presents the results from an IV estimation using the instruments mentioned in Section 4.3 and including product fixed effects.

[Table 5. Results from the Simple Logit Model]

The attributes content and calories have statistically significant coefficients in the three specifications. The content coefficient changes sign from positive to negative as the unobserved valuation is accounted for, which gives a more intuitive result since small container sizes are more practical to manipulate and therefore are expected to increase utility. The calories estimates are positive in the three specifications, but their magnitude decreases as the strategies to solve the endogeneity problem (product fixed effects and instruments) are implemented. They also make the coefficients of McCain, fat, fiber, sodium, bastón, and noisette become significant. On the other hand, smiles variable is always nonsignificant. The estimates of the price coefficients are of the expected sign in the three columns, but the one from the IV regression is higher than the estimated by OLS, as in most previous work. It can be concluded that the effects of including product-specific dummy variables and of using instrumental variables are significant both statistically and economically.

However, as pointed out in Section 3, the Simple Logit Model yield restrictive and unrealistic substitution patterns, and therefore is inadequate for analyzing changes in market structure. To overcome these restrictions, we estimate a RCDCM of demand, whose results are shown in Table 6. The constant term, content, brand, and bastón and noisette segments enter the model linearly; price, nutritional variables, and smiles have random coefficients. While nutritional parameters are assumed to be affected by income, the coefficient of smiles variety is interacted with age. As for price, its coefficient is supposed to depend on both consumer income and age.

The estimates of the mean parameters of the utility function indicate that, on average, consumers' utility increases as the FFP content of fiber and calories increase, and as the content of fat decreases. McCain products were revealed as the least valued FFP. The most popular varieties, bastón and noisette, are valued very differently by the average consumer if compared with the base group (golden longs, rondelles, and croquettes): the valuation of bastón is negative, and the valuation of noisette is positive. The sign of the mean price coefficient is negative as expected, and is higher than those presented in Table 5; this result might be driven by the proper control for demographics and heterogeneity achieved by the full model, which guarantees the validity of the IV's. Finally, content, sodium, and smiles coefficient are statistically insignificant (though of the expected sign). As pointed out in Section 4.3, most of these mean parameters (except the mean price parameter) are estimated by the minimum-distance procedure described above. The ability of the observed characteristics to fit the coefficients of the product dummy variables is measured by using a chi-squared test provided by Chamberlain, which is presented at the bottom of Table 6. This test evaluates a restricted model that sets ξ to zero, and therefore the rejection of this model emphasizes the importance of product fixed effects to control for unobserved characteristics that affect utility.

Estimates of heterogeneity around these means are presented in the next few columns. The results suggest that the marginal valuation of nutritional attributes is accentuated by increasing income; in other words, individuals are more sensitive to the negative effect of fat and sodium as are wealthier consumers, and are also more sensitive to the positive effect of fiber. These results are in line with the literature, according to which high income individuals are more concerned about health and nutrition than low income individuals. Coefficients on the interaction of price with demographics are statistically significant, and indicate that younger and lower-income consumers tend to be more price sensitive. A more elastic demand of younger households might be associated with a low participation of FFP in their diet. Given that household average age decreases with the presence of children, and according to the literature, it could by driven by parents' concerns about their children's health, if FFP are perceived as an unhealthy food. This argument is reinforced by the statistical insignificance of the mean parameter of smiles and its interaction with age, since smiles is a kid-oriented variety.

[Table 6. Results from the full model]

Finally, the effect of random shocks to tastes on price and fat coefficients is nonsignificant, suggesting that the heterogeneity in the coefficients is mostly explained by the included demographics. On the contrary, calories, fiber, sodium, and smiles present statistically significant coefficients, implying that part of the parameter variability (all of it in the cases of calories and smiles) is captured by unobserved individual characteristics. This is especially interesting for sodium and smiles, since the average effect of these variables on utility is not statistically different from zero, but even so our results indicate there is heterogeneity in preferences for these attributes, driven by unobserved (smiles) or by both observed and unobserved (sodium) demographic characteristics.

Based on the results from the full model, we estimate flexible own- and cross-price elasticity coefficients, which are obtained with the following formulas

$$\eta_{jkt} = \frac{p_{kt}}{s_{jt}} \frac{\partial s_{jt}}{\partial p_{kt}} = \begin{cases} \dfrac{p_{kt}}{s_{jt}} \displaystyle\int \alpha_{it} s_{ijt} (1 - s_{ijt}) dP_D^*(D) dP_\upsilon^*(\upsilon), & \text{if } j = k \\ -\dfrac{p_{kt}}{s_{jt}} \displaystyle\int \alpha_{it} s_{ijt} s_{ikt} dP_D^*(D) dP_\upsilon^*(\upsilon), & \text{if } j \neq k \end{cases}$$

The estimates are shown in Table 7; each entry (*i*, *j*), where *i* indexes row and *j* column, gives the elasticity of product *i* with respect to a change in the price of *j*. Since the model does not imply a constant elasticity, this matrix will be different depending on what values of the variables are used to evaluate it; we report the average of each entry over the 270 markets in the sample. All own-price elasticities, shown in the main diagonal, are negative and greater than one in absolute value. Smiles and croquettes, the most specialized products, present the higher coefficients, while the noisette segment has the least elastic demand. As for cross-price elasticities they are all positive, as expected since the products are substitute goods. In general, pairs of products that belong to the same segment show greater coefficients, because they are closer substitutes.

[Table 7. Own- and cross-price elasticities]

Bastón of McCain and FarmFrites have the most elastic demand with respect to changes in the price of other FFP. On the other hand, golden longs and FarmFrites noisette have the least cross-price elasticities. The products whose prices affect other FFP demand the most are bastón of Granja del Sol and McCain; in fact, bastón Granja del Sol prices greatly influence all bastón FFP. On the other hand, the products whose prices are less influential in other FFP purchases are rondelles and FarmFrites noisette. Note that while McCain bastón in small package (ID 1110) is both one of the most influenced and one of the most influential products, FarmFrites noisette in small package (ID 2310) presents the opposite situation, i.e. it has one of the less sensitive demand and its price changes have little effect on other FFP demand. A similar pattern is observed, to a greater or lesser extent, for all the products. Figure 2 shows the relationship between the average of the cross-price elasticities of a product with respect to other FFP prices (sensitivity), and the average of the cross-price elasticities of other FFP with respect to the price of the product (influence).

[Figure 2. Cross-price elasticities: relationship between influence and sensitivity]

Table 8 displays the average of the own-price elasticities by income level. Middle-income households demand for FFP is less elastic than both high- and low-income households demand. This could be related to a higher participation of FFP in middle-income consumers' diet. On the one hand, due to concerns about healthy feeding, high income individuals might discard FFP from their diet. On the other hand, low income consumers could find them very expensive. Correct price discrimination should therefore charge higher prices in branches located in middle-income neighborhoods. This is partially supported by our data since, although in general higher prices are set for higher income neighborhoods, as noted in Section 4.1, FarmFrites and RapiPap FFP are more expensive for lower-middle income consumers, and the most popular segments (bastón and noisette) are as expensive for them as for high income individuals.

[Table 8. Own-price elasticities by income]

5.2 Counterfactual changes in FFP market structure

In this section, we simulate hypothetical changes in the industry structure and evaluate their effect on prices, market shares, and consumer surplus, given the demand parameters estimated in the previous section. We propose two hypothetical scenarios. The first one (Scn 1) is the merger between Alimentos Modernos and Granja del Sol, which is interesting because of McCain strong leadership in the market. On the other hand, considering the high concentration of the market, we propose an industry of single-product firms, i.e. each product is produced by a different firm (Scn 2).

First of all we recover marginal costs per serving using equation (8); then, we configure the ownership matrix that represents the hypothetical market structure, Ω^*, in order to estimate the post-change equilibrium prices and market shares (equation (9)). Both costs and counterfactual equilibrium values are computed for a specific market: high income level in December 2009. Table 9 presents the recovered marginal costs and actual prices, market shares, price-cost margins, and sales in the analyzed market.

[Table 9. Initial equilibrium values in high income – Dec 2009 market]

Croquettes are the FFP with the highest marginal cost among the available products in the market, and the most expensive too, which makes sense since it is the most specialized product. McCain presents higher costs and prices than FarmFrites and RapiPap, but FarmFrites is the firm that charges the highest margins. In spite of being the second most expensive product, McCain noisettes have by far the greatest market share, and therefore McCain is the firm with the highest sales in this market.

In Table 10 we present the counterfactual simulation results on prices, market shares, and sales for the proposed industry structures.

[Table 10. Counterfactual changes in prices, market shares, and sales]

After the merger between the two smaller firms the prices of all products would increase, especially those from the merged companies. The increase of firms' market power leads to higher markups, which explain the higher prices in this scenario. This would cause a drop in the demand (and therefore an increase in the market share of the outside good), which is more pronounced for McCain FFP. Moreover, the sales of all firms would decrease, a result that is consistent with the relatively elastic demand for FFP found in Section 5.1. On the other hand, if the FFP market turned into a single-product firms industry, all prices would decrease. The reduction in prices encourages some consumers who did not buy before to start buying (the market share of the outside good decreases), and hence there would be an increase in the market shares of all products and sales. The lower prices in this scenario have to do with the lack of a portfolio effect: if two products are perceived as imperfect substitutes, a firm producing both would charge a higher price than two separate manufacturers.

To assess how important these changes really are, we evaluate their influence on consumer welfare. Compensating variation, CV_i, was computed for each sampled individual in the analyzed market, as described in Section 3.3. Then we averaged the compensating variation across the sample and multiplied by the number of consumers to get total change in consumer surplus (equation (10)). Total number of consumers was assumed to be 600,000 (the population of Mar del Plata). Table 11 shows the monthly change in consumer welfare implied by each hypothetical scenario; both average individual surplus and welfare change for the entire population of the city are reported. The merger between Alimentos Modernos and Granja del Sol would cause a decrease in the welfare of the consumers of Mar del Plata of $13,277 a month. If the market turned into a single-product firms industry, the monthly improvement in consumer surplus would rise to $67,558.

[Table 11. Monthly change in consumer welfare due to hypothetical market structures]

Figure 3 shows the relationship between individual compensating variation and demographic variables. In general, the wealthier and older the individual, the greater the influence of hypothetical changes in market structure on his welfare; the relationship is more evident in the case of the age. These results might be driven by the heterogeneity in price sensitivity. Since younger and lower-income consumers tend to be more price sensitive, they in general stay out of the market by choosing the outside good; therefore it is reasonable to expect that they are less affected by changes in the FFP market structure.

[Figure 3. Welfare change and demographic variables]

6. Conclusions

This paper makes a contribution to the empirical literature of Random Coefficients Discrete Choice Model of demand, which has been scarcely applied in Argentina, mainly regarding food industries. Besides, the paper contributes to the analysis of a food market which is rapidly growing in developing countries and is starting to play a more relevant role in consumers' diet. The article examines the frozen fried potato (FFP) industry in an important city of Argentina, Mar del Plata. We study the heterogeneity in consumer preferences for FFP attributes and evaluate the effect of changes in market structure on consumer welfare.

A discrete choice approach is used to analyze the demand for FFP. First, we estimate a Simple Logit Model, and we find that the effects of including product-specific dummy variables and of using instrumental variables are significant both statistically and economically. Then we estimate a Random Coefficients Discrete Choice Model of demand; the results suggest that high income individuals are more concerned about health and nutrition than low income individuals, and that younger and lower-income consumers tend to be more price sensitive. The flexible elasticity coefficients achieved with this method indicate that middle-income households demand for FFP is less elastic than both high- and low-income households demand, which could be related to a higher participation of FFP in middle-income consumers' diet.

Lastly, we simulate hypothetical changes in the FFP industry structure and evaluate their effect on prices, market shares, and consumer surplus. It also serves to identify the effect of different sources of price-cost margins. On the one hand, a merger between the two smaller firms of the market (Alimentos Modernos and Granja del Sol) would cause an increase in prices and therefore a decrease in consumer welfare. On the other hand, if the market turned into a single-product firms industry, the prices would drop and hence the consumer surplus would increase. Regarding the relationship between individual compensating variation and demographic variables, the influence of the counterfactual changes in market structure would be greater the higher the consumer income and age.

7. References

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Tables and figures

Table 1. Discrete-choice logit models

	Simple	*Nested*	*Random Coefficients*
Utility space	Characteristics space		
Taste heterogeneity	Not incorporated		Incorporated
Own-price elasticity	Proportional to price		Driven by the different price sensitivity of different consumers
Cross-price elasticity	Equal for all goods	Different between nests, but equal within them	Different for each pair of goods

Source: Own elaboration based on literature review.

Figure 1. Allocation of Supermercados Toledo branches in Mar del Plata, Argentina

Source: Google Maps ©2011 at www.supertoledo.com.

Table 2. Product characteristics, market shares, and prices

ID	*Brand*	*Segment*	*Cont size (g)*	*Calories (kcal)*	*Fat (g)*	*Fiber (g)*	*Sodium (mg)*	*Avg price*	*Avg mkt sh*
1110	McCain	Bastón	720	106	0.3	4	66	0.71	0.0026
1111	McCain	Bastón	720	106	0.3	4	66	0.40	0.0008
1120	McCain	Bastón	1000	106	0.3	4	66	0.48	0.0021
1130	McCain	Bastón	1500	106	0.3	4	66	0.42	0.0007
1210	McCain	Golden Longs	1000	127	0.4	0.6	54	0.44	0.0014
1310	McCain	Noisette	500	228	0.4	1.7	336	1.45	0.0012
1320	McCain	Noisette	1000	228	0.4	1.7	336	0.99	0.0013
1410	McCain	Rondelles	1000	127	0.4	0.6	54	0.53	0.0005
1510	McCain	Smiles	600	177	0.6	1.9	383	1.04	0.0008
2110	Farm Frites	Bastón	400	91	0.1	1.7	15	1.06	0.0009
2120	Farm Frites	Bastón	700	91	0.1	1.7	15	0.65	0.0021
2130	Farm Frites	Bastón	1000	91	0.1	1.7	15	0.61	0.0019
2310	Farm Frites	Noisette	450	121	2	3	374	1.20	0.0008
2320	Farm Frites	Noisette	1000	121	2	3	374	1.04	0.0013
3110	Granja del Sol	Bastón	500	99	0.5	2.8	34	0.51	0.0021
3120	Granja del Sol	Bastón	800	99	0.5	2.8	34	0.50	0.0014
3610	Granja del Sol	Croquettes	300	174	0.9	2.4	444	1.93	0.0005
4110	RapiPap	Bastón	700	99	1.1	2.8	20	0.66	0.0030

Note: 1 g = 0.0353 oz. Nutritional information refers to a serving of the product. Prices are expressed in Argentine Pesos ($1 = U$S 3.19, on average, during the period of analysis). Products 1110 and 1111 differ in package design. The average market size of the outside good is 0.98714.
Source: Own elaboration based on Supermercados Toledo scanner data and products' nutrition facts labels.

Table 3. FFP average prices by segment and income level

Segment \ Income	*High*	*Upper-middle*	*Middle*	*Lower-middle*	*Low*	*High/low surcharge*
Bastón	0.613	0.611	0.604	0.612	0.607	0.99%
Noisette	1.125	1.119	1.092	1.124	1.103	1.99%
Golden Longs	0.446	0.441	0.439	0.423	0.421	5.94%
Rondelles	0.539	0.534	0.529	0.519	0.518	4.05%
Smiles	1.069	1.059	1.033	1.028	1.021	4.70%
Croquettes	1.956	1.964	1.907	1.921	1.885	3.77%

Note: Prices are expressed in Argentine Pesos.
Source: Own elaboration based on Supermercados Toledo scanner data.

Table 4. FFP average prices by brand and income level

Segment \ Income	*High*	*Upper-middle*	*Middle*	*Lower-middle*	*Low*	*High/low surcharge*
McCain	0.752	0.740	0.728	0.728	0.722	4.16%
FarmFrites	0.875	0.885	0.870	0.895	0.875	0.00%
Granja del Sol	1.235	1.240	1.210	1.210	1.195	3.35%
RapiPap	0.66	0.660	0.650	0.670	0.660	0.00%

Note: Prices are expressed in Argentine Pesos.
Source: Own elaboration based on Supermercados Toledo scanner data.

Table 5. Results from the Simple Logit Model

	OLS		IV
Variable	(i)	(ii)	(iii)
Constant	-9.246 ***	-8.699 ***	-8.673 ***
	(0.672)	(0.569)	(0.548)
Price	-0.654 **	-0.338	-0.784 **
	(0.271)	(0.280)	(0.336)
Content	0.390 **	-0.660 ***	-0.644 ***
	(0.162)	(0.139)	(0.146)
McCain	-0.393	1.135 ***	1.238 ***
	(0.453)	(0.325)	(0.335)
Calories	1.546 ***	1.061 ***	0.937 ***
	(0.240)	(0.269)	(0.259)
Fat	0.270	1.185 ***	1.194 ***
	(0.310)	(0.237)	(0.237)
Fiber	0.266	-0.747 ***	-0.864 ***
	(0.275)	(0.199)	(0.196)
Sodium	-0.517 **	0.176	0.290 *
	(0.211)	(0.152)	(0.150)
Bastón	-0.035	2.746 ***	3.118 ***
	(0.970)	(0.702)	(0.692)
Noisette	-0.412	-0.595 **	-0.527 *
	(0.340)	(0.285)	(0.292)
Smiles	0.232	-0.225	-0.330
	(0.414)	(0.289)	(0.295)
R^2	0.135	0.227	0.477
Joint significance	6.29	9.84	109.38
	(0.000)	(0.000)	(0.002)

Note: Standard errors are given in parentheses. *** indicates significance at a 1% level, ** 5%, * 10%. All regressions include time dummy variables. F-test for the OLS regressions and Wald χ^2 for the IV regression are the joint significance tests reported (p-values in parentheses). The units of measurement of content and nutritional variables were adjusted to scale these variables similarly.

Table 6. Results from the full model

Variable	Mean parameters (α, β)		Interactions with demographic variables (∏)				Random shocks to tastes (Σ)	
			Income		Age			
Constant	-5.975		-		-		-	
	(3.953)							
Price	-6.677	**	0.030	**	1.500	*	2.033	
	(2.823)		(0.015)		(0.879)		(6.008)	
Content	-0.584		-		-		-	
	(0.608)							
McCain	-6.938	***	-		-		-	
	(2.483)							
Calories	5.581	***	0.006		-		1.060	***
	(1.779)		(0.009)				(0.382)	
Fat	-1.763	***	-0.183	*	-		-2.159	
	(0.509)		(0.099)				(1.974)	
Fiber	5.229	**	0.220	*	-		0.813	***
	(2.491)		(0.120)				(0.313)	
Sodium	-4.243		-0.003	**	-		-1.126	**
	(2.847)		(0.001)				(0.488)	
Bastón	-15.97	*	-		-		-	
	(9.845)							
Noisettes	0.891	*	-		-		-	
	(0.477)							
Smiles	0.715		-		0.128		2.495	**
	7.334				(0.090)		(1.257)	
R^2			0.647					
GMM Objective			4.36					
Minimum distance χ^2			13,369.93					
% of price coefficients > 0			0.067					

Note: Standard errors are given in parentheses. *** indicates significance at a 1% level, ** 5%, * 10%. The regression includes time dummy variables. The units of measurement of content, nutritional characteristics, and demographic variables were adjusted to scale these variables similarly.

Table 7. Own- and cross-price elasticities

	1110	1111	1120	1130	1210	1310	1320	1410	1510	2110	2120	2130	2310	2320	3110	3120	3610	4110
1110	**-1.872**	0.033	0.075	0.037	0.010	0.025	0.026	0.006	0.031	0.039	0.057	0.043	0.001	0.001	0.110	0.067	0.018	0.089
1111	0.055	**-1.557**	0.074	0.056	0.009	0.037	0.014	0.005	0.010	0.077	0.011	0.012	0.001	0.001	0.106	0.064	0.000	0.014
1120	0.054	0.031	**-1.616**	0.045	0.010	0.039	0.016	0.005	0.018	0.073	0.028	0.029	0.001	0.001	0.098	0.065	0.000	0.036
1130	0.052	0.035	0.078	**-1.710**	0.009	0.028	0.015	0.006	0.013	0.005	0.013	0.019	0.004	0.001	0.111	0.067	0.001	0.045
1210	0.012	0.006	0.014	0.006	**-1.548**	0.028	0.003	0.004	0.007	0.006	0.004	0.004	0.001	0.001	0.022	0.012	0.000	0.007
1310	0.051	0.037	0.010	0.025	0.026	**-2.069**	0.023	0.004	0.037	0.011	0.029	0.026	0.002	0.005	0.056	0.027	0.019	0.053
1320	0.032	0.005	0.013	0.005	0.004	0.030	**-1.686**	0.002	0.017	0.009	0.021	0.017	0.001	0.001	0.019	0.015	0.019	0.043
1410	0.013	0.006	0.017	0.007	0.008	0.053	0.009	**-1.740**	0.010	0.007	0.009	0.006	0.007	0.043	0.024	0.013	0.000	0.016
1510	0.061	0.009	0.037	0.015	0.008	0.037	0.027	0.005	**-2.099**	0.019	0.032	0.024	0.001	0.000	0.030	0.019	0.016	0.053
2110	0.070	0.040	0.024	0.056	0.027	0.039	0.009	0.007	0.020	**-1.973**	0.050	0.024	0.002	0.001	0.001	0.001	0.006	0.042
2120	0.074	0.017	0.059	0.018	0.010	0.028	0.021	0.006	0.029	0.022	**-1.701**	0.052	0.001	0.001	0.060	0.046	0.013	0.077
2130	0.077	0.016	0.063	0.018	0.011	0.028	0.021	0.006	0.028	0.029	0.063	**-1.557**	0.000	0.001	0.056	0.046	0.012	0.073
2310	0.001	0.001	0.001	0.018	0.004	0.002	0.001	0.000	0.001	0.001	0.001	0.002	**-1.270**	0.046	0.056	0.027	0.019	0.005
2320	0.001	0.004	0.001	0.001	0.022	0.004	0.001	0.001	0.002	0.001	0.001	0.001	0.027	**1.142**	0.018	0.010	0.003	0.006
3110	0.042	0.023	0.078	0.025	0.010	0.036	0.013	0.006	0.022	0.001	0.023	0.019	0.024	0.036	**-1.725**	0.038	0.001	0.037
3120	0.040	0.024	0.056	0.027	0.010	0.034	0.013	0.006	0.019	0.001	0.008	0.013	0.059	0.018	0.110	**-1.763**	0.000	0.004
3610	0.034	0.001	0.001	0.005	0.001	0.026	0.026	0.000	0.017	0.005	0.019	0.017	0.002	0.001	0.002	0.002	**-2.185**	0.053
4110	0.079	0.007	0.043	0.014	0.008	0.028	0.025	0.004	0.024	0.022	0.049	0.044	0.001	0.001	0.018	0.004	0.036	**1.712**

Figure 2. Cross-price elasticities: relationship between influence and sensitivity

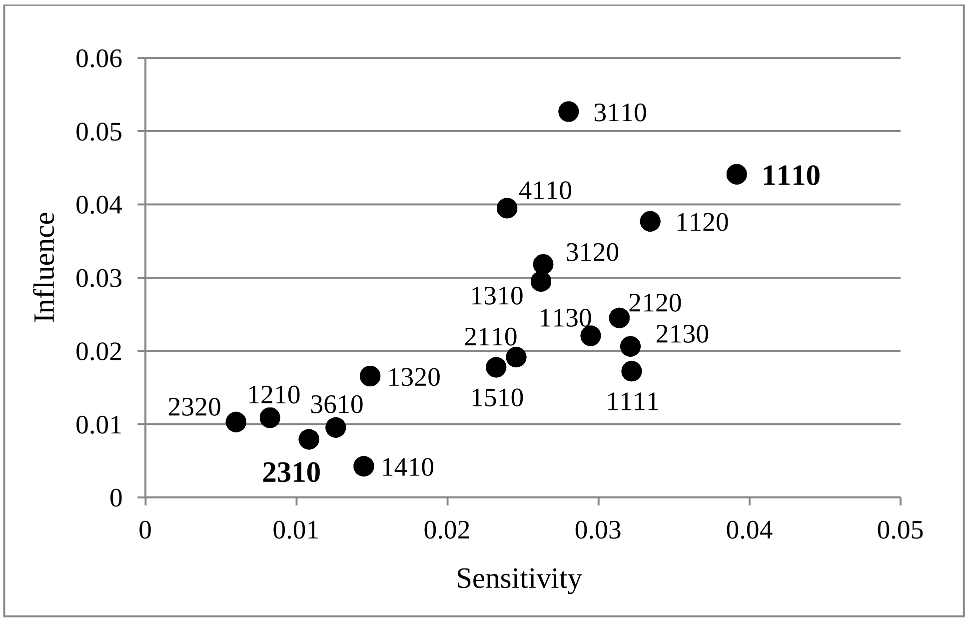

Table 8. Own-price elasticities by income

Product	Average	High income	Middle income	Low income
1110	-1.872	-1.649	-1.615	-2.939
1111	-1.557	-1.468	-1.422	-2.080
1120	-1.616	-1.559	-1.412	-2.354
1130	-1.710	-1.757	-1.445	-2.849
1210	-1.548	-1.707	-1.325	-2.145
1310	-2.069	-3.163	-1.630	-3.365
1320	-1.686	-2.300	-1.472	-2.480
1410	-1.740	-1.777	-1.365	-2.046
1510	-2.099	-2.408	-1.689	-3.004
2110	-1.973	-2.498	-1.508	-3.157
2120	-1.701	-2.035	-1.403	-2.441
2130	-1.557	-1.939	-1.375	-2.359
2310	-1.270	-1.450	-0.942	-2.100
2320	-1.142	-1.198	-0.890	-1.855
3110	-1.725	-1.749	-1.556	-2.260
3120	-1.763	-1.862	-1.439	-2.817
3610	-2.185	-3.392	-1.393	-3.913
4110	-1.712	-1.881	-1.452	-2.339

Table 9. Initial equilibrium values in high income – Dec 2009 market

Product		Marginal cost	Price	Margin	Market share	Sales
1310	McCain noisette 500g	1.363	1.595	14.56%	0.0048	0.0077
1510	McCain smiles 600g	1.206	1.305	7.57%	0.0013	0.0017
2120	FarmFrites bastón 700g	0.808	0.960	15.88%	0.0007	0.0006
2130	FarmFrites bastón 1000g	0.637	0.839	24.11%	0.0013	0.0011
2310	FarmFrites noisette 450g	0.813	1.446	43.76%	0.0013	0.0019
2320	FarmFrites noisette 1000g	0.854	1.189	28.16%	0.0013	0.0015
4110	RapiPap bastón 700g	0.801	0.940	14.81%	0.0007	0.0007
3610	Granja del Sol croquettes 300g	2.706	2.743	1.36%	0.0003	0.0008
Outside good					0.9883	

Note: Marginal costs are expressed in Argentine Pesos. Margins are defined as (*p*-*mc*)/*p*.

Table 10. Counterfactual changes in prices, market shares, and sales

Prod.	Scn 1: Merger						Scn 2: Single-product firms					
	Price	Share	Sales	Δp	Δs	Δsls	Price	Share	Sales	Δp	Δs	Δsls
1310	1.600	0.0043	0.0069	0.3%	-10.8%	-10.5%	1.594	0.0049	0.0077	-0.1%	1.1%	1.0%
1510	1.312	0.0012	0.0016	0.6%	-6.2%	-5.7%	1.298	0.0014	0.0019	-0.5%	8.4%	7.8%
2120	0.968	0.0007	0.0006	0.8%	-1.0%	-0.1%	0.950	0.0007	0.0006	-1.1%	2.8%	1.7%
2130	0.856	0.0012	0.0010	1.9%	-4.7%	-2.9%	0.838	0.0013	0.0011	-0.2%	0.3%	0.1%
2310	1.469	0.0013	0.0019	1.6%	-2.0%	-0.4%	1.423	0.0013	0.0019	-1.6%	1.7%	0.1%
2320	1.298	0.0012	0.0015	9.2%	-8.8%	-0.4%	1.176	0.0013	0.0015	-1.1%	2.1%	0.9%
4110	0.945	0.0007	0.0007	0.5%	-3.2%	-2.7%	0.937	0.0007	0.0007	-0.4%	0.6%	0.2%
3610	2.754	0.0003	0.0008	0.4%	-0.2%	0.3%	2.738	0.0003	0.0009	-0.2%	2.9%	2.7%
Out.		0.9891			0.1%			0.9880			0.0%	

Note: Prices are expressed in Argentine Pesos. Δp = price variation, Δs = variation in market share; Δsls = variation in sales.

Table 11. Monthly change in consumer welfare due to hypothetical market structures

Counterfactual scenario	Average CV_i	Total CV
Scn 1: Merger between Alimentos Modernos and Granja del Sol	-0.00013	-13,277
Scn 2: Industry of single-product firms	0.00064	67,558

Note: Welfare changes are expressed in Argentine Pesos.

Figure 3. Welfare change and demographic variables