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Texto para Discussão

Série Economia

TD-E 04 / 2011

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A Simplified Mixed Logit Demand Model with an Application to the Simulation of Entry

Sergio Aquino DeSouza*

The key contribution of this paper is to show how to incorporate more information into the empirical strategy in order to avoid the need of valid instruments, which are difficult to find in many instances. I use information on price elasticity to propose a methodology that is able to determine the parameters of a simplified Mixed Logit Model. I also apply this methodology to the ready-to-eat cereal industry and simulate the competitive and welfare effects of the introduction of new products.

Keywords: Discrete-Choice, Demand Models, Competition
JEL Codes: L11, D12

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I-INTRODUCTION

Demand estimation in product-differentiated industries has been the central object in many studies in the industrial organization field. Indeed, after pinning down the preference parameters it is possible to analyze issues related to innovation, antitrust (mergers and divestitures), calculation of quality adjusted price-indices and prediction of the competitive effect of entry and exit of products. However, uncovering demand parameters from aggregate data on product-differentiated markets imposes several challenges: (1) number of parameters to be determined; (2) incorporation of consumer heterogeneity and (3) price endogeneity.

There are basically two categories of demand models that are taken to data: representative consumer and discrete-choice demand models. Models in the former category are based on a representative consumer who has preference over a set of differentiated products and in equilibrium may purchase simultaneously more than one variety. However, for markets characterized by the presence of many brands the representative consumer models may be too restrictive. Indeed, with many brands such models imply a demand system with many equations (the number of brands is equal to the number of demand equations), which results in an over parameterized system. Furthermore, by construction, representative consumer models can not naturally deal with the presence of consumer heterogeneity. The second set of demand models is based on the theory of discrete-choice, in which it is assumed that the consumer chooses only one variety (i.e., simultaneous consumption of different varieties is not allowed in this setup). Further, the product choice is made indirectly as the consumer has preferences over attributes and picks the product that offers the best combination of such attributes. Using the literature jargon, the choice is made on the attribute space rather than on the product space as assumed in representative consumer models. This projection onto the attribute space makes the discrete-choice model a very attractive option of modeling product differentiation for empirical purposes. Indeed, the number of parameters depends on the number of attributes rather than the number of products. This can substantially reduce the size of the parameter set. In addition, consumer heterogeneity can be incorporated into the model in a natural way.

However, discrete-choice models do not avoid all the problems associated with the estimation of demand. As in representative consumer models, the endogeneity problem emerges as prices are expected to be correlated with unobserved determinants of demand (e.g., omitted attributes, unobserved quality). Then, as predicted by standard econometric theory, the researcher is likely to face inference problems regarding the estimation of the price coefficient.

The common solution to this problem is to find instruments that are correlated with the endogenous variable (prices) but not with the unobserved determinants of demand (regression error term). Berry, Levinsohn, and Pakes (1995) - BLP henceforth- propose a GMM method based on three sets of instruments. These instruments are based on the product attributes, which are assumed to be exogenous. The first set is formed by the attributes (excluding potentially endogenous ones). The second is composed the sum of the values of the same attribute across own-firm products. Finally, the third set of instruments is calculated by the sum of the values of the same attribute across rival firm products. An alternative to the BLP instruments was first introduced by Hausman et al. (1994) who exploit the panel structure of the data (geographically separated markets are observed through time) and the assumption that, given the cost structure and after controlling for some fixed effects (observed and unobserved), the price of a brand *j* in market *r* is a valid instrument for the price of the same brand *j* in another market *r'*.

The types of instruments proposed by BLP and Hausman et al. (1994) are far from being a consensus among researchers in the IO field. Indeed, there are instances in which those instruments may fail. For instance, (Nevo, 1998) reports that in the ready-to-eat cereal industry the BLP instruments do not work, as they show little variation through space, time, or cross-section. In turn, the instruments proposed by Hausman et al. (1994) require rich data sets (which are not usually available), as they require the observation of prices of the same brand in other geographical markets. Further, even if such detailed data set is available, the validity of prices in other markets as instruments may be questioned since there is always some common demand effect across markets that is not captured by usual controls (Bresnahan, 1996). Therefore, as described above, there are situations in which the researcher does not have applicable instruments. Thus, either he or she abandons the research or proceed with typically upward biased estimates (in numerical, not absolute, value) of the price coefficient, which usually leads to implausible inelastic demands (see BLP) or, possibly, unreasonable positive own-price elasticities.

In this paper I propose a novel methodology to uncover the demand parameters that offers an alternative to this uncomfortable dichotomous decision the researcher may face (abandon the research or proceed with biased estimates). By augmenting the researcher's information set I demonstrate that one can retrieve the demand parameters of a particular class of mixed logit demand models without resorting to instrumental variables. The strategy can be summarized as follows: (i) use this external information to deterministically uncover (calibrate) the coefficient on the endogenous variable (price) and (ii) then project the residual (part of market shares that are not explained by prices) in the space of non-price attributes to econometrically estimate the remaining parameters.

This paper is organized as follows. In Section II, the theoretical mixed logit demand model is presented. Section III presents the proposed methodology to uncover the parameters of this model. In section IV, the methodology is applied to uncover the Mixed Logit demand parameters and simulation of new entry is performed, using data on the U.S ready-to-eat cereal industry. And, finally, Section V presents final remarks.

II - MODEL

In this section, I shall describe a mixed logit demand model with one random coefficient – henceforth MLOGIT[1]. Consumers rank products according to their characteristics and prices. There are *N+1* choices in the market, *N* inside goods and one reference good (or outside good).

Consumer *i* chooses brand *j*, given price p_j, a K-dimensional row vector of observed characteristics (x_j), an unobserved characteristic (denoted by the scalar ξ_j), and unobserved idiosyncratic preferences ε_{ij}, according to the following indirect utility function:

(1) $$u_{ij} = g(\alpha, v_i) p_j + x_j \beta + \xi_j + \varepsilon_{ij}$$

where $g(\alpha, v_i)$ is a random coefficient that represents consumer *i*'s marginal utility (or disutility) of price, which is a function of the parameter α and

[1] It will be made clear why the restriction on the number of random coefficients is necessary in the methodology developed in this paper. The limitations arising from using a mixed logit model with only one random coefficient rather than its more general version with more than one random coefficient deserves further attention. However, it is important to stress that this restricted mixed logit model is superior to logit and nested logit models, which impose severe restrictions on price elasticities (see Nevo, YEAR). Song (2007) uses a mixed logit with one random coefficient as a basis of comparison with pure characteristics models.

an unobserved (by the researcher) consumer-specific term v_i. The K-dimensional column vector β , whose typical element β_k represents the marginal utility of characteristic k, assumed invariant across consumers.

Alternatively, Equation (1) can be rewritten as

(2) $$u_{ij} = g(\alpha, v_i) p_j + \delta_j + \varepsilon_{ij}$$

where $\delta_j = x_j \beta + \xi_j$ and represents the mean utility o product j derived from characteristics other than prices. The utility derived form the consumption of the outside good can be normalized to zero u_{i0}=0. Assuming that ε_{ij} has a Type I Extreme Value distribution, the probability of individual i choosing good j (s_{ij}) takes the familiar logit form

(3) $$s_{ij}(\alpha, p, \delta(\beta, X, \xi), v_i) = \frac{\exp(g(\alpha, v_i) p_j + \delta_j)}{1 + \sum_{m=1}^{N} \exp(g(\alpha, v_i) p_m + \delta_m)}$$

The scalar s_{ij} is the conditional market share of product j, i.e. the market share that would prevail if all individuals had the same v_i. In the MLOGIT model this is not true therefore, some aggregation argument has to be invoked.

Indeed, taking the expected value with respect to the distribution of v_i's yields the market share of product j implied by the model(s_j).

(4) $$s_j(\alpha, p, \delta(\beta, X, \xi)) = E_v[s_{ji}(\alpha, p, \delta(\beta, X, \xi), v_i)]$$

The theoretical market share of product j depends on the parameter α, and *N+1*-dimensional vectors *p* and *δ*, that collect all p_j*'s* and δ_j*'s* respectively. Notice that, by definition, *δ* is an implicit function of *β* and *X* (a matrix containing all observed characteristics of all products in the market).

III- AUGMENTING THE INFORMATION SET TO UNCOVER DEMAND PARAMETERS

The basic idea of empirical strategies commonly adopted in structural models is to search for parameters that are able to match the shares predicted by the theoretical model $s_j(\alpha, p, \delta(\beta, X, \xi))$ to the observed shares ($\bar{s}_j$). Thus, we try to find the set of parameters that better explain the following relation

(5) $$\bar{s}_j = s_j(\alpha, p, \delta(\beta, X, \xi)) \ ; \qquad j=1,\dots N$$

Although traditional econometric techniques do not apply to the equation above, due to the non-linearity in the error term ξ, the main idea behind identification is standard. BLP develop an algorithm to uncover numerically the error term as function of the parameters. These error terms are combined with variables (instruments) to form moment conditions of the type $E[\xi_j \mid Z_j] = 0$, where Z_j is *L*-dimensional vector (*L* is the number of instruments). BLP propose a GMM method based on three sets of instruments. These instruments are based on the product attributes, which are assumed to be exogenous. The first set is formed by the so-called trivial instruments: the attributes themselves (excluding potentially endogenous ones, such as prices). The second is composed the sum of the values of the same attribute across own-firm products. Finally, the third set of instruments is calculated by the sum of the values of the same attribute across rival firm products. The non-trivial instruments (those included in the second and third set of BLP instruments) are functions of the trivial ones and therefore may in many instances prove to be weakly correlated with the endogenous variable (price), leading to inference problems regarding the estimation of the coefficient on price (see Nevo, 1998).

The key contribution of this paper is to show how to incorporate more external information into the empirical strategy in order to avoid the use of non-trivial instruments. Although this is rarely noticed, the researcher already brings many objects to the empirical strategy based on some belief. Indeed, structural IO models have many assumptions regarding consumer and producer behavior. Typical studies in this field assume a discrete-choice demand side and Bertrand behavior on the supply side. These assumptions constrain the data to accommodate a parametric family of functions. The data set plays an important role, as the empirical strategy picks the parameters that better explain the observed data. However, there is one parameter of the model that is not left for the data to explain: the market size M. Virtually all papers in this literature assume a particular value for this parameter.

For instance, in BLP study of the U.S automobile industry, *M* is assumed to be the number of families. This assumption is based on the researcher's belief that each family is a potential consumer for an automobile in each year. A similar assumption is made by Petrin (2002) and Nevo (2001).

What I propose in this work is to go a little further and augment the set of information that is not left for the data to explain. One variable that economists and industry experts are used to dealing with is elasticity. Although any own- or cross price elasticities between any tow goods could be used in the framework to be developed below, I use extrenal information on price elasticity of the inside good l , defined as η_{ll} . The reason for this choice is that it represents a very intuitive economic magnitude: the attractiveness of the inside good *l*. This information could come from different sources. The researcher could use his own experience and knowledge of the industry or, alternatively, he or she could draw on industry experts as information sources. This latter type of source has been utilized in another automobile study undertaken by Berry, Levinsohn, and Pakes (2004). They report that "*based on their experience, the staff at the General Motors Corporation suggested that the aggregate price elasticity in the market for new vehicles was near one*".

For the MLOGIT demand model presented in section II the implied price elasticity of the inside goods *l* is given by

$$(6) \qquad \eta_{ll}(\alpha, p, \delta) = \frac{p_l}{s_l} E_v[g(\alpha, v_i).s_{il}(\alpha, p, \delta, v_i)(1 - s_{il}(\alpha, p, \delta, v_i)]$$

Methodology to uncover the demand parameters

The methodology can be divided into two stages. In the first stage we uncover the parameter of marginal utility of price α. Then, in the second stage, I show how to uncover the characteristics marginal utilities (β).

The first stage

I begin by setting up the following system of equations:

$$(7) \qquad \bar{s}_j = s_j(\alpha, p, \delta); \text{ j=1,....N}$$

$$(8) \qquad \bar{\eta}_{ll} = \eta_{ll}(\alpha, p, \delta)$$

The first equation in this system is simply the reproduction of equation Equation (5), while the second equation is a consequence of the new information brought to the empirical method. In addition to matching the observed market shares, the parameters of the theoretical model are also asked to match the elasticity of the inside good *l*. Notice that, the system of equations above has *N+1* equations and, since *p* represents data (prices), there are *N+1* unknowns (*N*-dimensional vector

δ plus the scalar α)[2]. Therefore, we can solve for the *N+1*- dimensional vector (δ, α). One possible method to find the solution of the system is to employ commonly applied algorithms that search for the solution directly in the (δ, α) space. However, this would be computationally inefficient. If we had 40 brands, for example, the algorithm would be searching directly in a space with dimension 41.

Instead, we can take advantage of an important result derived in BLP. Given the parameter α and p the mapping defined pointwise by

$$T(s, \alpha, p)[\delta_j] = \delta_j + \ln(\bar{s}_j) - \ln(s_j(\alpha, p, \delta))$$

is a contraction mapping with modulus less than one. Therefore, we can improve computational efficiency by concentrating the search. Shortly, the algorithm goes as follows. First, we initiate the outer loop with a initial value of α', and then solve for the implied $\delta'(\alpha')$ by applying the contraction mapping algorithm (inner loop) to the sub-system formed by the *N* equations in (7). Then we calculate the implied elasticity of one of the inside goods $\eta_{ll}(\alpha', p, \delta')$ and check whether equation (8) is satisfied. In this last step we verify how large is the distance between the external information on the elasticity $\bar{\eta}_{ll}$ and the implied $\eta_{ll}(\alpha', p, \delta')$. If this α' does not imply a close enough distance, measured by $|\bar{\eta}_{ll} - \eta_{ll}(\alpha', p, \delta')|$, we repeat this process, by reinitiating the outer loop, until convergence has been attained.

[2] If α is vector of dimension greater than one, and not a scalar as assumed here, or if we had more than one random coefficient, the system would certainly be under identified. For this reason we have to posit a mixed logit model with only one random coefficient with only one parameter. Whether this is a plausible model is largely an empirical question. Notice also that α is deterministic and therefore it does not have a standard error.

The second stage

Once we have δ^*, obtained from the first part of the methodology, we are able to project this vector onto the space of product characteristics (except price) and estimate the parameters of the corresponding regression equation, which is given by

(9) $$\delta_j = x_j \beta + \xi_j$$

This equation can be estimated by OLS since characteristics are assumed to be exogenous, an assumption that, to the best of my knowledge, is shared by all papers in this literature. Notice also that we do no need to search for non-trivial instruments, i.e. instruments other than non-price characteristics (the trivial instruments), avoiding the problems associated with BLP instruments, that are likely to be weak in many instances, and Hausman price instruments, that places greater demands on the data set[3] and may be invalid in some situations.

The Simple Logit

In this subsection I present the simplest discrete-choice model: the Logit. This exposition serves the purpose of highlighting the contribution of bringing more external information (price elasticity) to the model without having to deal with the lack of analytical formulas and the consequent numerical and computational issues. However, this is done for expositional purposes only. As well documented in the discrete-choice literature (see BLP), the Logit demand model places very restrictive

[3] we need to observe at least one cross-section of markets

limitations on own and cross price elasticities, which constitute critical parameters in the economic evaluation of innovation, mergers and entry of new products.

In the Logit case, we can assume without loss of generality that $g(\alpha, v_i) = -\alpha$. Then shares are given by $s_j(\alpha, p, \delta) = \dfrac{\exp(-\alpha p_j + \delta_j)}{1 + \sum_{m=1}^{N} \exp(-\alpha p_m + \delta_m)}$

Log-linearizing this equation we have $\ln s_j - \ln s_0 = -\alpha p_j + \delta_j$. The Logit also implies an analytical formula for the own proce elasticity of a given good l.

Indeed, $\eta_{jj}(\alpha, p, \delta) = -\alpha p_l (1 - s_l(\alpha, p, \delta))$. The system of equation - Equations (7) and (8) - simplifies to the following system of linear equations[4]:

(10) $\ln \bar{s}_j - \ln \bar{s}_0 = -\alpha p_j + \delta_j$; $j=1,\ldots N$

(11) $\bar{\eta}_{jj}(\alpha, p, \delta) = -\alpha p_l (1 - s_l)$

This system is much simpler than its version for the more general ORDC model. We can directly solve for α from Equation (11), giving $\alpha = -\dfrac{\bar{\eta}_{ll}}{p_l(1 - s_l)}$.

Once α is determined, we can find the corresponding δ_j's ($\delta_j = \ln \bar{s}_j - \ln \bar{s}_0 + \alpha p_j$) from Equation (10). The second part of the methodology is the same as in the MLOGIT. With the δ_j's we are able to run the regression $\delta_j = x_j \beta + \xi_j$ using OLS. The logit version of the model bears a resemblance with the so-called Antitrust Logit Model, a methodology developed by Werden and Froeb (1994). Indeed, these authors use an equivalent set of equations to determine α and the δ_j's.

[4] The system is linear in the unknowns (δ, α)

It is important to notice that the MLOGIT model presented in this paper provides a generalization of their idea as it accommodates consumer heterogeneity, a crucial element if we want to generate reasonable patterns for the elasticities between any two products.

IV - AN EMPIRICAL EXAMPLE

In order to illustrate the methodology, I use data on the ready-to-eat cereal industry. However, it should be noticed that the objective of this section is to illustrate the methodology proposed in this paper rather than providing a detailed study of the ready-to-eat cereal industry. Nonetheless, an application of this methodology that takes into consideration all or most of the idiosyncrasies of this industry would be an interesting extension of this work.

The reason for the choice of this industry is mainly methodological. Indeed, the BLP instruments, constructed from typical data sets available for this industry, are likely to be weak. Indeed, unlike the automobile industry, there is not much variation in these instruments over time, and even less so between geographic markets (Nevo, 1998). Therefore, unless we are willing to exploit the panel structure and use the prices in other geographic markets as instruments, we are stuck with a cross-section and the weak BLP instruments. This is the scenario for which the methodology presented in this paper is most appealing. The data set is a cross-section of the fifty top selling brands in the U.S in 1992. The summary statistics are presented below[5]. The data set reports information on shares, prices, fat, sugar, advertising exposure and two dummies: DKIDS assumes the value 1 if the brand

[5] This data was collected by Matt Shum and is publicly available in his personal webpage.(Acessed December 2007).http://www.econ.jhu.edu/people/shum.

belongs to the kids segment and DKG, which takes on the value 1 if the brand belongs to Kelloggs (the market leader). To construct the shares it is assumed that *M* is the total cereal purchases observed in the dataset. Thus, this implies that the outside good is representative of all other brands not included in the top fifty best selling list[6].

Table I

Summary statistics for Ready-To-Eat Cereal Industry in the U.S – 1992

	Mean	*Std Dev*	*Variance*	*Min*	*Max*
Share	0.0152	0.0102	0.0001	0.0067	0.0567
Price ($/lb)	2.9830	0.4916	0.2416	1.7700	3.9600
Fat(cal)	1.6080	1.6884	2.8505	0	8.0000
Sugar(g)	10.1080	5.4177	29.3514	0	20.000
Advert. ($millions)	2.8643	1.9049	3.6287	0	7.8670
DKIDS	0.24	0.4314	0.1861	0	1.000
DKG	0.34	0.4785	0.229	0	1.000

Source: Descriptive statistics for variables available in the data set mentioned above.

[6] This implies that not purchasing the product is not an option, which may constitute a restrictive assumption in many setups. However, according to Schum's data, for the cereal industry this is could be a good approximation since, in 1992, 97.1% of American households purchased some cereal during the year. Furthermore, notice that the methodology developed in this paper can accommodate any other value for *M*, and therefore any other value of the market size could have been used to illustrate the methodology.

I follow Berry, Levinsohn, and Pakes (1999) and parameterize the consumer marginal utility for price according to the functional form given by $g(\alpha, v_i) = -\frac{\alpha}{v_i}$, where the consumer-specific term v_i represents household income, whose distribution is obtained from the 1992 Current Population Survey (CPS). In order to simplify the computation of the ORDC model, I made a few simplifications regarding this distribution. I have divided the income space into intervals of the same size (2500 USD) and computed the frequencies of each interval. Then, I discretize the distribution assuming that the average income in each interval is representative of all individuals included in this interval. In the end, we have 21 income levels and thus 21 consumer types. The discretization avoids the need for numerical integration (e.g. quadrature methods) or simulation methods (as employed by BLP) to compute the markets shares in Equation (4). This is done to reduce the computational burden. Notice that if the researcher is not willing to make these simplifications, the methodology model outlined in section III can certainly accommodate different distributional assumptions for income such that quadrature or simulation methods can be used.

In the first stage of the methodology, I pick the brand AppleCinn. Cheerios from General Mills and assume its elasticity to be $\overline{\eta}_{ll} = $-3 and, as mentioned before, *M* is the total cereal purchases observed in the dataset[7]. Then we are able to uncover *N+1*-dimensional vector (δ, α). I find that α is 36482.18, from which we can derive the distribution of the price coefficients (in absolute values) across consumers. This

[7] These values compose the information set the researcher brings to the empirical strategy. I could have used other values for the price elasticity and market size to perform robustness checks. This is left for future developments of this work.

distribution is given by the distribution of the ratio $\frac{\alpha}{v_i}$. We can also construct descriptive statistics for the δ_j's. These results are summarized in Table II below.

Table II

Summary statistics of stage 1 results (ORDC model)

	Mean	Median	Max	Min
Price coefficient	1.739	0.694	14.593	0.347
Mean utilities (δ_j's)	3.223	3.258	4.647	1.051

The distribution of the price coefficient has mean 1.739 and median 0.694, implying that the distribution is not symmetric around its mean. The mean utilities dos not exhibit much variation across brands and the distribution is approximately symmetric around the mean since the mean and the median are approximately equal.

In the second stage of the MLOGIT model, we are able to estimate the characteristics coefficients using OLS. The results for the MLOGIT model can be found in Table III below. All coefficients are statistically significant at the 10% confidence level. However, only the coefficients on fat, sugar and advertising are significant at the 5% confidence level.

Table III

Stage 2 results (MLOGIT model)

	Coef. (β)	Stand. error	t-value	Prob>|t|
Fat	0.223	0.108	2.069	0.044
Sugar	0.080	0.029	2.726	0.009
Advert.	0.463	0.072	6.426	0.000
DKIDS	0.764	0.411	1.859	0.070
DKG	0.698	0.363	1.923	0.061

Counterfactual experiment

An advantage of structural estimation is that, once the parameters of interest are determined, one can simulate the effect of different market environments using the usual welfare metrics. The framework for counterfactual simulations laid out in this section is standard in discrete-choice demand models. The distinctive difference is that the entries on the welfare metric are obtained by the method described in section III that shows how to incorporate external information to uncover the demand parameters without the need to search for instruments. The counterfactual experiment goes as follows. Determine the demand parameters. Next, simulate the entry of a new good with a given price (p_*), a k-dimensional row vector of characteristics (x_*) and a value for quality that is not captured by these characteristics (ξ_*). Then, calculate the market penetration o the new good and consumer surplus variation.

For the MLOGIT model described in section II, McFadden (1981) shows that surplus variation (ΔCS) of consumer i is given by

(12)

$$\Delta CS_i = \frac{1}{|g(\alpha, v_i)|} \ln \left\{ \frac{1 + \left(\sum_{m=1}^{N} \exp[g(\alpha, v_i) p_m + x_m \beta + \xi_m] \right) + \exp[g(\alpha, v_i) p^* + x_* \beta + \xi_*}{1 + \sum_{m=1}^{N} \exp(g(\alpha, v_i) p_m + \delta_m)} \right\}$$

In order to obtain the average of consumer welfare variation we have to integrate out the consumer specific term v_i. This measure is given by

(13)

$$\Delta CS = E_v \left\{ \frac{1}{|g(\alpha, v_i)|} \ln \left\{ \frac{1 + \left(\sum_{m=1}^{N} \exp[g(\alpha, v_i) p_m + x_m \beta + \xi_m] \right) + \exp[g(\alpha, v_i) p^* + x_* \beta + \xi_*}{1 + \sum_{m=1}^{N} \exp(g(\alpha, v_i) p_m + \delta_m)} \right\} \right\}$$

Tables IV and V show the results from different simulations. The first columns describe the characteristics of the new good (indexed in the first column). The last 2 columns present the simulation results in terms of market shares the new product is able to gain and average per consumer surplus in 1992 USD. Each row of this table defines the characteristics of the new good that is introduced. For instance, in the experiment indexed by 1, I simulate the introduction of a product with the following characteristics. It is the destination of 2.86 million USD spent on advertising and contains zero fat and 20 g of sugar. Also, it does not belong to the kids segment and is not produced by Kelloggs (the market leader). From table IV below we verify that this new product gains a market share of 1.24% and implies a positive per consumer surplus variation of 3.94 USD. In the other entries of this table I reduce the sugar content and verify that market shares and consumer gains decrease. In each experiment I simulate the introduction of a different good. This process is non-cumulative.

In addition, we conduct the same sequence of experiments but assume that the introduced product belongs to Kelloggs (see table V). The results are superior for market shares and consumer gains, due to the fact that Kelloggs' products are in average more attractive than non-kelloggs' products (see regression results in table III).

Table IV

First set of Simulation results

Experiment Index	Fat	Sugar	Adv	DKIDS	DKG	Mkt.Share (%)	ΔCS (1992 USD)
1	0	20	2.86	0	0	1.248	3.941
2	0	15	2.86	0	0	0.842	2.645
3	0	10	2.86	0	0	0.567	1.774
4	0	5	2.86	0	0	0.381	1.191

Note: Only sugar content varies across experiments

Table V

Second set of Simulation results

Experiment Index	Fat	Sugar	Adv	DKIDS	DKG	Mkt.Share (%)	ΔCS (1992 USD)
5	0	20	2.86	0	1	2.467	7.920
6	0	15	2.86	0	1	1.673	5.314
7	0	10	2.86	0	1	1.131	3.566
8	0	5	2.86	0	1	0.762	2.393

Note: Only sugar content varies across experiments

V. FINAL REMARKS

Demand estimation in product-differentiated industries has been the central object in many studies in the industrial organization field. Indeed, after pinning down the preference parameters it is possible to analyze issues related to innovation, antitrust (mergers and divestitures), calculation of quality adjusted price-indices and prediction of the competitive effect of entry and exit of products. However uncovering consumers' preferences using aggregate data on product-differentiated markets imposes a serious challenge: find instruments do deal with price endogeneity. Berry, Levinsohn, and Pakes (1995) propose a GMM method based on instruments that are functions of the regressors (except price) to estimate general Random Coefficients Discrete-Choice models. Therefore these instruments in many instances may prove to be weakly correlated with the endogenous variable (price), leading to inference problems regarding the estimation of the coefficient on price. The key contribution of this paper is to show how to incorporate more information into the empirical strategy in order to avoid the need for such instruments. What I propose in this work is to augment the researchers' set of information. I use external information on price elasticity to propose a methodology to determine the parameters of a particular class of Random Coefficients Discrete-Choice models. I show that, provided that the external information is valid, we can determine the demand parameters using only the exogenous regressores (characteristics other than prices) as instruments, avoiding then the need to use potentially weak instruments. Finally, for illustrative purposes, I apply this methodology to the ready-to-eat cereal industry and simulate the entry of new products.

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