Identifying changes in behavior in a multiproduct oligopoly: Incumbents' reaction to tariffs dismantling*

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This version: November 2004

Preliminary and incomplete

Abstract

The Spanish automobile market of the nineties experienced a perfectly foreseeable tariff dismantling, complicated by a strong demand downturn, with the observed result of an apparently sharpened producer competition, both in products and prices. This paper is aimed at testing whether or not there really was a change in pricing behavior, using a structural model of competition among oligopolistic multiproduct firms. We understand by behavior the particular strategies, in a set of well defined, market-specific equilibrium concepts, which are sustained at a given moment. To answer that question, we specify and estimate a pricing equation with panel data for 164 models belonging to 31 firms which competed in the market during this period. The specification includes several equilibria as alternative (overlapping) estimating models, considering prominently tacit coalitions by which a group of firms sets prices, taking into account the cross effects on their demands. The statistical test selects as the best model given the data a switch from collusion to competition of domestic and European producers at the beginning of the nineties.

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*We are grateful to Simon Anderson and Steve Berry for comments on previous drafts of this paper. We also wish to acknowledge useful comments by Tim Bresnahan, Neil Gandal, Marc Ivaldi, Tor Klette, Pedro Marín, Lars-Hendrik Röller and the audience at the Third CEPR Conference on Applied IO (Bergen). All remaining errors are ours. This research has been supported by grant SEC2000-0268.

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1. Introduction

At the beginning of the nineties, the Spanish automobile market completed a tariff dismantling planned since the Adhesion to the EEC. This fact, perfectly foreseeable since years before, complicated with a strong demand downturn (see Figure 1), lead to an apparently sharpened producer competition, both in products and prices. Domestic producers (installed multinational firms) and foreign producers (European and non-European) introduced new models and increased model turnover, engaged in network investment and high advertising expenditures, at the same time that several signs of price competition appeared. This paper is aimed at testing whether or not there really was a change in pricing behavior, using a structural model of oligopolistic multiproduct firms which compete in a product differentiated market.

We understand by behavior the particular strategies, in a set of well defined market-specific equilibrium concepts, which are sustained at a given moment. Clearly all producers, multiproduct firms with a rough average of more than three car models on the market at any given moment, must be assumed internalizing optimally the cross effects of their model pricing. Moreover, it is natural to assume that firms continuously adjusted model prices to their environment (sales evolution, entry and changes in characteristics of rival models), independently of the type of pricing equilibrium. The addressed question is whether, in addition, the environmental changes induced a change in firms' pricing strategies, modifying their degree of rivalry.

To try an answer to this question, we develop the pricing equation implications of a series of equilibria in the form of alternative (overlapping) estimating models. Among these equilibria we consider prominently tacit coalitions, by which a group of firms sets prices taking into account the cross effects on their demands, and the change of these coalitions. We then relatively assess the models by testing which one best fits the data.

We specify and estimate the pricing equation with (monthly) panel data on quantity, prices and characteristics for 164 car models belonging to the 31 firms which competed in the Spanish market during the period 1990-96. A key question is how demand side information is used along the pricing equation. In our preliminary work, the statistical test selects as the best model a switch from collusion of domestic and European producers, at the beginning of the nineties, to a whole competition.

The type of exercise that we perform can have some general interest. We try to uncover whether a policy change combined with a demand downturn triggered a behavioral change. A similar issue becomes relevant when any exogenous market event may trigger a change in behavior: e.g. demand changes, approval of a merger or regulatory change, irruption of an innovation...As they now stand, quantitative methods of analysis of market competition have largely avoided the question of changes in behavior, with and without government intervention. It seems useful the development of techniques to assess the impact of these changes.

Let us briefly comment on the relevant literature. Some of the pioneering works in the "new empirical industrial organization" were motivated by and focussed on the analysis of behavior changes (Porter,1983; Bresnahan, 1987[1]). More generally, this set out the question of the precise identification of firms' behavior[2]. A detailed specification of a set of market equilibrium behavioral alternative (static) outcomes in a product differentiated market, and the test among them given the data, was carried by Gasmi, Laffont and Vuong (1992). Only a few works have focussed on this type of testing (see for a recent application Jaumandreu and Lorences, 2002), but many discuss the potential effects of different behaviors or use, at some point, alternative behavioral assumptions.

Exercises of market modelling, concerned with assessing market power and describe its sources, e.g. product differentiation versus price coordination, discuss the likelihood of different behaviors. Nevo 2001, for example, compares the markups implied by his estimated elasticities, under the alternative behavioral assumptions of Bertrand-Nash competition and collusion, with the real industry markups, to conclude that pricing is non-collusive and markups come from product differentiation. Pinkse and Slade 2003 use the estimated elas-

[1] See also Bresnahan 1981, which develops the model and assess the inpact of imports.

[2] As something different from the use and empirical measurement of "conjectural variations" (on this use see Bresnahan's 1989 survey).

ticities to evaluate the effects of real and potential mergers, using the Bertrand equilibrium after concluding that is not rejected by the data.

On the other hand, two examples of the use of alternative behavioral specifications just come from examples on the automobile market. Berry, Levinsohn and Pakes 1999 estimate their oligopoly model for the American automobile industry under the alternative assumptions (to Betrand equilibrium) that firms play Cournot, that there is a "mixed" equilibrium in which Japanese firms set quantities, and that Japanese firms play Bertrand as do the rest, but colluding among them. Goldberg and Verboven, 2001[3], in their automobile model for five European countries, also estimate the model under the alternative assumption that firms in the UK collude. The conclusion of these exercises seems at first glance somewhat disappointing. The first paper concludes that estimated parameters are quite similar and that differences seem really do not matter for policy conclusions. The second finds the models indistinguishable in terms of fit. However, all estimates of the pricing equations are carried out constraining markups to have the value determined by the demand estimated elasticities, either simultaneously (first paper) or even sequentially (second paper) to the demand parameters estimation. As Berry, Levinsohn and Pakes 1999 point out, using "the estimated elasticities to investigate the cost side of the model...would be more flexible and impose less structure..".

More generally, a rich methodology for the specification and estimation of demand in industries with product differentiation has been developed since the papers by Berry,1994, and by Berry, Levinsohn and Pakes,1995. Berry, Levinsohn and Pakes 2004 show in particular how this methodology may be precise in estimating the patterns of substitution. But the rich modelling of the demand side has often come at the cost of constraining behavior. Here, we explore the explore the extension of ideas and techniques of the recent advances to a framework which addresses the identification of firms' behavior through pricing equations.

The methodology consists of specifying and estimate pricing equations which nest the unobservable marginal cost and the margins established by firms. Margins can be shown to be in general a function of demand price effects, firms' market shares and behavior. By

[3] See also Goldberg 1995.

specifying alternative behaviors, one ends with a series of models which predict different margins which depend on different ways on observed shares. Equations may be developed by using methods which range from non-parametric specifications of the price effects to the use of parametric demand models. Then, the alternative models can be estimated and the model that best fits the data selected by means of the suitable test. In the present version of this paper we develop an example which uses price effects parametrized according to an specific discrete choice model, and employ a selection test for non-nested models to choose among price equations. We are currently developing complementary estimates using a full set of elasticities previously estimated by simulation in the demand side.

The rest of this paper is organized as follows. Section 2 explains in detail the competition changes that took place in the Spanish market and descriptively explores the price data. Section 3 discusses the way to specify and test for behavior. Section 4 is devoted to detail the specification and estimation techniques that we apply to the pricing equations, and Section 5 to explain the empirical results. Section 6 concludes. An Appendix develops a series of technical details on price effects under discrete choice demand models which we use at different points of our exercise.

2. Competition changes

At the start of the nineties, the Spanish automobile market[4] was served by three types of car producers: domestic producers, European foreign producers and non-European foreign producers, just then beginning to enter the market. The domestic producers were the multinationals with plants installed in Spain during the seventies and the eighties, aimed at exporting an important part of production, manufacturing in them some of the car models they sold[5]. The European foreign producers were the multinational European producers

[4] The Spanish market was at the time about 1 million cars sold a year, a non-negligible size from the European perspective.

[5] In 1990, they sold in the domestic market 39% of the domestic production. Production capacity grew faster than the market in the following years and, by 1996, the proportion of production going to domestic sales was only 25%. Notice that Spain was at the time the 3rd European and the 5th World car producer.

without manufacturing in Spanish territory, and the non-European foreign producers were firstly exclusively Asian producers, sometimes possessing an incipient production in European territory. Tables 1 and 2 report some basic facts about the structure and evolution of the market.

Domestic producers accounted for seven brands belonging to five groups (Citroen-Peugeot, Ford, Opel, Renault and Seat-VW), which coincided with the most important non-Japanese world producers with the absence of Fiat and Chrysler (recall that Opel is a GM subsidiary). They had dominated the Spanish market during the eighties, and they started the nineties with a joint market share of 82% (see Table 1). At this time the European foreign producers' supply consisted of 14 brands[6], with a joint share of only 16%, but with an important presence in the upper segments (e.g., more than half of the cars of the highest segment). And non-European producers accounted initially for 5 Asian brands, representing all together just a market share of 2%. This number grew up to 9 brands in the following years[7], and the American Chrysler entered the market in 1992.

Tariff and non-tariff protection made it unprofitable to import cars from abroad during the early eighties, dampening even the import of the models from domestic producers not produced in Spain. All imported cars in 1985 amounted to only 13% of sales. But this year the Spanish Adhesion Treaty to the EEC, setting the transition framework to full integration in the single market of 1992, firmly established a different perspective. Tariffs on cars imported from the EEC had to be decreased as stipulated from the then-current value of 36,7% to zero by the beginning of 1993. And tariffs on cars imported from third countries had to be reduced from the then-current value of 48,9% to the common EEC tariff of 10%.

This perspective immediately started a new competition preparing the coming open market, stimulated by a very dynamic demand (see Figure 1). Domestic producers enlarged

[6] Audi, Alfa-Romeo, BMW, Fiat, Jaguar, Lada, Lancia, Mercedes, Porshe, Rover, Saab, Skoda, Volvo and Yugo.

[7] Honda, Hyundai, Mazda, Nissan, and Toyota were in the market at the start of the 90´s, Mitsubishi and Suzuki entered in 1990, Subaru in 1991 and Daewo in 1995.

the range of models distributed in the market with models imported from their production in plants abroad, while foreign producers entered new models. Imports had risen to 32% of sales by 1990 (recall that only 18% are imports by foreign producers) and product variety was already quite high (79 marketed models, see Table 2). But, the beginning of the nineties, when tariffs reached the minimum and at a moment in which demand transitorily experienced a stagnation and then a sharp downturn (see Table 1 and Figure 1), triggered a new competition intensity.

Competition during the nineties adopted several dimensions: product behavior resulted in a high rate of model introduction and turnover, producers heavily invested in construction and enlargement of sales networks, engaged in a sharp increase of advertising and started an unprecedented price competition which consumers perceived through promotional advertising.

The entry of car models, both replacing old models and introducing in the Spanish market models absent until this time, was particularly important. In the years following 1990, 104 models entered the market and 59 exited, which implies 123 marketed models by the end of 1996 (see Table 2). Entry was important from the beginning, but notice that exit increases after the first years (seeTable 1), a sign of more acute product competition[8]. Asian cars accounted for a disproportionate share of this entry, but entry by the European foreign producers and even domestic producers is also important. The role of replacement can be seen by noting that 90% of exits are separated from a model entry by the same brand by less than 48 months. Advertising expenditures suddenly jump in 1993, with the expenditure by unit sold during the period 1993-96 being 170% of the amount during 1990-92. Competition in prices is apparent in the advertising developed by the brands and commented by sector analysts during the period.

Among all these competition changes, the focus of this paper is on pricing. In particular,

[8] We take as an exit the fact that monthly sales persistently go under some minimun threshold. This can be obviously determined either because consumers stop buying this particular model or the brand decides retire it from sales or some mix of both aspects. Increased exits can be taken in both cases as a sign of increased product competition.

did the dismantling of tariffs, perhaps complicated with the demand downturn, change firms' price behavior? Foreign firms found themselves able to sell at significantly lower prices for the same received prices. Domestic producers experienced the same change for the models which were introduced from abroad and, at the same time, they expected increased competition for all their models, including enlarged substitutes and lower rivals' prices. All producers are multiproduct firms, with several car models on the market at a given moment, which implies that they must be assumed to optimally internalize the cross effects of their models pricing. Moreover, firms are continuously adjusting each model price to the changing environment (sales level, entry and changes in characteristics), independently of the game they play. The central question is whether, in addition to all this, the environment induced any change in firms' pricing strategies, modifying their degree of rivalry, in the sense explained in the next section.

To acquire an impression of possible pricing behavior changes in our sample period, the cost changes induced by quality changes must be disentangled. With this aim, we will use the hedonic coefficients resulting from regressing prices on car characteristics. Let us define the price corrected by quality changes as

$$\widetilde{p}_{jt} = p_{jt} - (x_{jt} - x_{j0})\widehat{\beta} \tag{1}$$

where x_{jt} is the vector of characteristics of model j at moment t, x_{j0} stands for this vector when the model enters the sample, and $\widehat{\beta}$ represents the cost per unit of characteristic estimated in the hedonic regression[9] . Averages of these quality-corrected prices will change with the entry and exit of models, which embody idiosyncratic qualities that shift the mean. To correct for these effects, let us define quality change and entry-corrected prices as

$$\widetilde{p}_t = \frac{1}{N} \sum_j (\widetilde{p}_{jt} - (x_{j0} - \overline{x})\widehat{\beta}) \tag{2}$$

where $\overline{x}$ is the sample mean of attributes and N is the number of models at date t. Entry

[9] We employ the coefficients corresponding to our preferred model (see Section 5), but the exercise produces very similar results using alternative estimates.

and quality change-corrected prices, depicted as indices, give the change in prices which may be attributed to reasons other than quality-induced cost variations. Of course, they can show cost changes attributable to other reasons, but they are likely to clearly reflect changes in pricing.

Figures 2, 3 and 4 summarize the results of descriptively exploring price changes. Figure 2 represents simple average monthly prices for the three producer types, deflated by the consumer price index, and the average received prices; that is, the price received by producers after deducting the relevant tariffs[10]. The figure highlights an apparent parallel evolution of European and domestic received prices during the period, at a different level determined by the diverse sales composition, and a sharp decrease of the Asian received prices. Figure 3 represents the evolution of received prices differencing out the quality-induced cost variations (normalized to unity the first year), and Figure 4 represents the evolution differencing out the quality composition effects of entry and exit. The hedonic corrections work very well, and in particular denote that quality increments of marketed cars are introduced at a similar pace for all producers, particularly after 1992, and that Asian entry mainly consists of models directed to compete in the lowest segments as time goes by. Notice how the sequential corrections notably reduce the range of variation of what remains of prices variation.

Figure 4 highlights several points. Firstly, all prices tend to show a fall during the first three years (1990-92) and some recovery at some point of the following subperiod. This suggests partly procyclical pricing, matching the demand evolution reported above, which does not contradict the possible change in pricing. Secondly, Asian car prices show a sharp new decrease by the year 1993. Asian producers seem to price more aggressively when the transitory tariff period reaches its end. Thirdly, domestic producers' pricing seems to recover less steadily than the European producers' pricing, slightly changing the relative level of their prices. These sensible changes in relative pricing (notice that the biggest difference is

[10]Tariffs during the years 1990, 1991 and 1992 are estimated as 12.37,8.25 and 4.125% for European cars, and 23.6,18.7,13.8% for non-European cars. Since the beginning of 1993, only remains the 10% tariff for the non-European.

on average less than 15%) suggests that, since 1993 onwards, the market may be working on a different equilibrium. In particular, theoretical models of price competition in product differentiated markets indicate that the equilibrium relative prices of all competitors will be clearly different from Bertrand prices if part of the competitors price together (establish "price coalitions"). For example, when there is such an implicit coincidence, outsiders tend to price less aggressively. Figure 4 may be suggesting a change to a more competitive equilibrium.

3. A framework to test for behavior.

This section presents the framework to specify and test for behavior by means of price equations. Firms are assumed to be multiproduct, competing in a product-differentiated industry given products and their characteristics. Behavior consists of the particular strategies, among a set of well-defined equilibrium concepts, sustained by firms. A wide range of behaviors may be covered, although here we confine ourselves to price games equilibria. The equations stem from the market equilibrium relationships between prices and output, represented by shares, in a broad class of price games. Firms' shares are hence endogenous variables, given by the relevant (in principle unspecified) demand system. Testing behavior consists of assessing which equilibrium best fits the data.

We firstly describe the basic setting and show that "nonparametric" specifications of behavior amount to include the own and the behavior-specific relevant rivals' shares as right-hand variables of the pricing equations. In this context, testing behavior can be done by means of testing exclusion restrictions. But we also show that non-parametric specifications impose strong data requirements when the number of products is not very small and, hence, the method becomes impracticable. Then we discuss how the use of discrete choice demand models for the price effects increases feasibility and efficiency. In particular, it is shown how some demand parameters can be estimated through the pricing equations, although the most complete models need the use of separate demand estimates. On the other hand, pricing models become non-nested and testing behavior needs the use of non-nested selection tests.

3.1 Basic setting.

Let us assume a product-differentiated industry consisting of F multiproduct firms, indexed $f = 1, ..., F$. Each firm produces J_f products and there are in total $J = \sum_f J_f$ products. When we generically refer to a product j, it is implicitly assumed to be one of the products of the set $j = 1, ..., J_f$ produced by firm f. Demand for each product j is a function of the $J \times 1$ vector of prices p and the vectors of products characteristics. Write demand, for convenience, in the shares simplified form $q_j = s_j(p)M$, where M is market size[11] (usually the number of potential consumers.) Share $s_0(p)$ stands for the fraction of consumers buying nothing. Let s be the $J \times 1$ vector of shares and define the $J \times J$ price effects matrix $D = \{\frac{\partial s_k}{\partial p_j}\}$, where row j collects the own and cross-demand effects of price j. Product j constant marginal cost, which is assumed here to be known to simplify notation, is c_j[12].

3.2 Behavior.

We assume that prices are strategic complements (reaction curves are upward-sloping)[13]. Therefore, any price increase on a product generates a positive externality on the other product profits, including rival firms' product profits. We also assume that in any case firms care about internalizing the cross-price effects of their own profits (they are not "myopic"). That is, firm f sets prices by maximizing $\sum_{k \in J_f} (p_k - c_k) q_k$. But firms can also set prices which internalize the positive cross-price effects among a group of rivals. That is, they can form price coalitions (Deneckere and Davidson, 1985), by maximizing $\sum_{k \in J_h} (p_k - c_k) q_k$,

[11] Dependence on characteristics is omitted to simplify notation. The model can be equally applied to demands in the form $q_j = q_j(p)$.

[12] The model can be extended to allow for non-constant marginal costs by specifying relevant marginal cost as $c_j(1 + k)$, where k is the elasticity of cost with respect to output.

[13] With goods being economic substitutes this is the usual case, although it is not the unique possibility. The model, however, can be extended to any other situation.

where summation is extended to the $J_h = \sum_{f \in h} J_f$ products of the firms which take part in the coalition[14]. Let H be the number of coalitions. Belonging to a coalition implies setting prices to maximize over a set of products which contain the own products as a subset. Hence, from now on, we will speak exclusively about the grouping of products at the level of coalition without loss of generality (firms can simply be thought of as one-member coalitions).

Prices maximize profits of the relevant set of products given the other prices, and we will write this as $p_j = \arg\max\{\sum_k \delta_{jk}(p_k - c_k)q_k|\delta_j\}$, where δ_j is a $1 \times J$ vector of ones and zeroes, with element δ_{jk} being the indicator of inclusion of product k in the relevant profits sum (i.e., $\delta_{jk} = 1$ if $k \in J_h$ and $\delta_{jk} = 0$ otherwise).

Notice that we are simply specifying the "one-period" price interactions, not the full conditions for each equilibrium. This does not constraint the set of behaviors to static equilibria. Any particular set of interactions may be the result of a Nash perfect equilibrium under strategies corresponding to repeated or dynamic games. In fact, price coalitions are usually understood as sustainable under repeated games (see, for example, Tirole 1989). On the other, partial specification may be seen as a loss of efficiency in order to test for behavior, because we leave aside binding conditions which could reinforce identification. But, at the same time, it has the important advantage that a full range of equilibria may be addressed without going into all the details.

3.3 The determination of prices.

Let us stack all vectors in a $J \times J$ matrix δ. With uniproduct Bertrand players or "myopic" multiproduct Bertrand players $\delta = I$. With multiproduct Bertrand players, each row j has ones in the entries corresponding to the rest of products produced by the firm that owns j. With price coalitions, the ones of a row expand to all the products of firms in the coalition. The set of FOC conditions which define a price equilibrium can be written in matrix form

[14] Here we assume that firms enter price coalitions with all their products. Other equilibria can be considered, but notably complicate the analysis and notation.

as

$$s + (\delta \circ D)(p - c) = 0$$

where $\circ$ represents Hadamard product (element by element product). Equilibrium prices are easily obtained as

$$p = c - (\delta \circ D)^{-1} s \tag{3}$$

This system consists of J equations in the form $p_j = c_j + m_j(B(\delta), s)$, where $B(\delta) = -(\delta \circ D)^{-1}$, and shows that margins corresponding to a particular equilibrium are a equlibrium-specific function of demand price effects and firm shares. These equations are structural equilibrium relationships, relating the endogenous variables p and s, with s determined additionally through an arbitrary system of demands. A useful property of equation (3) may be summarized in the following

Property. Product j margin can be written as a linear combination of the shares of the products included in the coalition, with weights which are a function of the coalition submatrix of demand price effects.

To see this property, let P_H be the permutation matrix which induces a re-ordering of firms (and hence products) according to the coalition they belong to. $P_H\ s + P_H(\delta \circ D)P'_H P_H(p - c) = 0$ is a system equivalent to (3), and hence $P_H p = P_H c - (P_H(\delta \circ D)P'_H)^{-1} P_H s$ gives the same prices. But, by definition of δ, $(P_H(\delta \circ D)P'_H)^{-1}$ is a block diagonal matrix of elements D_h^{-1}, $h = 1, ..., H$. A useful implication is that $\delta \circ B(\delta) = B(\delta)$.

3.4 Specifying and testing behavior.

Equation (4) suggests that behavior can be tested by comparing the fit of alternative pricing equations, with behavior imposed on each equation through the constraints on the price derivatives that each equilibrium implies. In addition, an important implication of the above proposition is that, if price effects can be considered stable, and hence estimable, econometric specifications of behavior may be obtained by simply including the relevant rivals' shares among the right-hand side variables. This constitutes an attractive non-parametric way of specifying the price effects. In what follows, we firstly detail this approach and its difficulties, then we discuss alternatives based on the discrete choice demand models.

Non-parametric specification. The estimating equation corresponding to a fully non-parametric alternative can be written as

$$p_j = c_j + \beta_j s_j + \sum_{k \neq j, k \in J_h} \beta_{jk} s_k + u_j, \qquad j \in J_h \tag{4}$$

where u represents a disturbance term with $E(u|z) = 0$ for a suitable set of instruments z. Parameters β estimate the elements of the $B(\delta)$ matrix and the J_h product shares in the coalition enter the J_h equations for j $(j = 1, ..., J_h)$ with specific coefficients. Equilibria as described by equation (4) imply the estimation of $\sum_h J_h^2 \leq J^2$ parameters.

Equations like (4) are attractive because: a) they do not impose any functional-form structure on the price effects, and b) different behaviors raise nested models. Consistent estimation will imply the use of IV, because shares are endogenous, but tests between equilibria may be easily carried out as tests of exclusion restrictions. The problems are that we need to estimate a number of parameters which can be very high, and that the number of parameters increases with the degree of collusion (up to the J^2 parameters of full collusion). This may be simply unfeasible in many contexts. Hence, equations like (4) can only be estimated for a very small number of products and enough repeated observations for each product j, either over time or across markets. Efficiency could in principle be improved by simultaneously estimating the price effects with demand data, but the highly non-linear form in which these effects enter the price equations makes this approach highly impractical.

The situation partially improves when similar price effects can be assumed for groups of analogous products or "nests." Let us suppose G nests, indexed $g = 1...G$, with N_g products each. It can be easily shown that the estimating equation becomes

$$p_j = c_j + \beta_{gh} s_{gh} + \sum_{m \neq g} \beta_{gmh} s_{mh} + u_j, \qquad j \in J_h, j \in N_g$$

where $s_{mh} = \sum_{k \in J_h, k \in N_m} s_k$ stands for the share of products of coalition h in nest m. The number of parameters to be estimated is now $\sum_h G_h^2 \leq G^2 H$, which will generally imply a dramatic fall[15].

Demand models for the price effects. Demand models are a potentially powerful tool for dealing with the dimensionality of the price effects. Theoretically-founded demand models, by specifying price effects as a function of a few parameters and observable variables, can reduce the number of parameters to be estimated[16]. Discrete-choice demand models have recently shown to be a successful tool to estimate sensible demand elasticities in markets with product differentiation, particularly when using a random coefficients specification which fully accounts for consumer heterogeneity (see the references in the introduction). And the generated demand systems have already been used to specify pricing equations. But the role of these equations has generally been constrained to help the identification of the demand system, mostly under tight constraints on behavior. In what follows, we address the problem of how the discrete choice specification of the demand system can help the estimation of behavior-unconstrained pricing equations.

To see the problems involved, let us start with an enough general discrete choice demand model: the BLP model. We assume that the relevant price effects for the firms' pricing problem are the market average partial effects, i.e. the expectation of the price derivatives across consumer heterogeneity. For the BLP model, calling $P(j)$ to the aggregated probabilities and using v to summarize the heterogeneity to integrate over, these expectations

[15] A further reduction of the number of parameters to a maximum of $\frac{G(G+1)}{2}H$ can be obtained by imposing (when reasonable) symmetry of the price effects. And, if coalitions are not very dissimilar in the number of products in each nest, the idiosyncratic parameters may be approximated by common estimates, i.e., $\beta_{gmh} \simeq \beta_{gm}$, with the result of only G^2 or $\frac{G(G+1)}{2}$ parameters to be estimated.

[16] For example, a previous modelling of the matrix D of price effects, using some specific market structure knowledge, has been used for obtaining a more tractable matrix B, which sometimes may even be the result of an analytical inversion.

can be written as (see the Appendix)

$$
\begin{aligned}
\frac{\partial P(j)}{\partial p_j} &\equiv E_v\left[\frac{\partial P(j|v)}{\partial p_j}\right] = -\alpha_j P(j)[1-P(j)](1+\omega_j) && \forall j=1,...,J \\
\frac{\partial P(k)}{\partial p_j} &\equiv E_v\left[\frac{\partial P(k|v)}{\partial p_j}\right] = \quad \alpha_j P(j)P(k)(1+\omega_{jk}) && \forall k \neq j
\end{aligned}
\tag{5}
$$

where α_j is average marginal utility of income for buyers of good j and the $\omega's$ reflect how buying probabilities covariate across consumer heterogeneity (in addition, the $\omega's$ fulfil the constraint $\omega_j = \sum_{k\neq j} \frac{P(k)}{1-P(j)}\omega_{jk}$). Notice that there are just the varying $\alpha's$ and the presence of the $\omega's$ what make the price effects different from the simple logit models. In matrix notation, this implies the D matrix

$$D = -\alpha P(I + diag(\omega)) + \alpha P(ee' + \omega)P$$

where α and P are $J \times J$ diagonal matrices which colect the product-specific $\alpha's$ and the J aggregated probabilities, e is a $J \times 1$ vector of ones and ω is a $J \times J$ matrix which collects the ω_{jk} elements.

Given some behavior represented by δ, $B(\delta) = -\left[\delta \circ (I + diag(\omega) - ee'P - \omega P)\right]^{-1} P^{-1}\alpha^{-1}$. Under the assumption that aggregated shares converge to aggregated probabilities, the relevant equation in terms of observables can be written as

$$p = c + \left[\delta \circ (I + diag(\omega) - ee'S - \omega S)\right]^{-1} \beta + u \tag{6}$$

where $\beta = \left[\frac{1}{\alpha_1}, \frac{1}{\alpha_2}, \frac{1}{\alpha_3}, ... \frac{1}{\alpha_J}\right]'$[17].

Models generated by expression (6) can be estimated by equations as

$$p_j = c_j + \beta_j \theta_j(s,\omega) + \sum_{k\neq j, k\in J_h} \beta_k \theta_k(s,\omega) + u_j, \qquad j \in J_h \tag{7}$$

where the $\theta's$ are variables constructed from the observable vector of shares s and some specification of matrix ω.

[17] Matrix $(I + diag(\omega) - ee'S - \omega S)$ cannot be inverted analytically for a completely general matrix ω, although matrix $\left[(I + diag(\omega))^{-1} + c_1 ee'S + c_2(I + ee'S)\omega(I + See'S)\right]$, where c_1 and c_2 are given constants, is likely to be a good approximation to the inverse.

Equations (6) and (7) show how the demand parameters of the discrete choice specification appear in the pricing equations (conditional on behavior). They make clear that different assumptions on the form of the demands can reduce drastically the number of parameters on which the margin depends on, and suggest that several demand parameters can be estimated through the pricing equations (namely the $\alpha's$). But they also show how this depends on the assumptions on the form of the demand model and hence how consistency in estimation relies on these assumptions. Think of the different possible constraints on the $\alpha's$ and on the form of ω. The simple logit assumes that $\alpha_j = \alpha$ and $\omega = 0$, and hence gives an equation in which, using an adequately constructed variable, only one parameter should be estimated. With a nested-type logit specification with α_g $(g = 1..G)$ parameters, and the $\omega's$ estimated according to a guess of parameter σ, only G parameters have to be estimated. But restrictions can easily impose non-realistic patterns of substitution among the goods and hence inconsistency in estimation. In general, equations (6)and (7) show that, if we knew ω, we could estimate any equilibrium without estimating more than J parameters α.

Finally notice that, in the non-parametric setting, coefficients were non-linear functions of the underlying price effects but shares enter linearly. In the demand-based specification of the price effects, coefficients directly estimate parameters of theoretical interest, but regressors are behavior-specific, non-linear functions of the observed shares. That is, alternative behaviors imply non-nested, partially-overlapped models.

4. Econometric specification.

In this section we discuss the specification and estimation techniques to be employed in the empirical exercise. We are going to estimate price equations using data on the car models sold on the Spanish market from 1990 to 1996 by the 31 firms with a presence in the marketplace. The data consist of unbalanced panel observations for a rather standard number of individuals (164 models[18]) but with the more unusual characteristic of monthly

[18]The total number of models are 182, but we must drop 18 in estimation due to the lack of enough lagged observations: the 16 entrant models of the last year and 2 models which stayed in the market less that 12 months.

data frequency (a maximum of 84 observations per individual). Using the price equilibrium relationships established in Section 3, the final objective of this empirical exercise is to obtain estimates under the assumption of different behaviors and to test their relative likelihood given the market data.

We must carry out the simultaneous estimation of a nested marginal cost function and the firms' markups. Section 3 has shown us that equilibrium prices are additively separable in two components, marginal costs and unit markups. To estimate marginal costs, we adopt the "hedonic" approach[19]: we take cost as a function of a set of product attributes. We specify marginal cost as independent of output (in fact we do not observe the relevant output for most of the involved producers), and we are going to allow for unobserved components of marginal cost.

Assuming the employment of a demand-constrained price-effects specification our estimating equation has the form

$$p_{jt}/(1+tariff_{jt}) = \beta_0 + \widetilde{x}_{jt}\beta + \sum_g \beta_g \theta_g(s,\omega) + \eta_j + u_{jt} \tag{8}$$

where the dependent variable is received prices; that is, model monthly prices deflated, when relevant, by the tariff. Variables $\widetilde{x}$ represent the attribute variables We approximate marginal cost around its mean using a quadratic polynomial with attributes entering in the form of deviations with respect to the sample mean and the squares of these deviations. The term η is an unobservable model-specific error, representing possible cost unobservable advantages or disadvantages, and u is a model and time specific disturbance which we assume uncorrelated across models and time These errors have zero mean conditional on the appropriate set of instruments z. In practice, to control for possible seasonality, we also include a set of monthly dummies.

The sum of terms in θ stands for the specification of behavior according to Section 3, for a given constraint of the $\alpha' s$ to be estimated. The sum of regressors θ is, given

[19] Cost estimates starting from regressions on product characteristics can be called "hedonic" because they use the methodology of the traditional hedonic price regressions (see Griliches,1961; Rosen, 1974, and the recent discussion in Pakes, 2003). We follow the approach by Berry, Levinsohn and Pakes (1995).

their theoretical specification, close to unity by construction (see below, for example, the regressors specification that we use in our present example). This implies a serious difficulty in separately identifying the average margin cost and the average level of margins, at least without more cost data and estimating the pricing equation in isolation. Some cost data allowing for identification of mean cost, and/or joint estimation with a demand equation, imposing cross constraints on the coefficients, would probably improve the identification conditions. But, for the moment, we will limit ourselves to identifying relative margin differences by constraining the behavioral coefficients to add up to zero. We expect his does not, in any case, affect the model capacity of discrimination among conducts.

The optimal pricing expressions developed in Section 3 starting from first order conditions are equilibrium relationships; that is, they relate the endogenous variables prices and shares (or functions of shares) in equations that also include the specification for products' marginal cost. They define only implicitly the "reduced-form" equations for equilibrium prices, in which prices would depend only -given behavior- on marginal costs, demand parameters, and product attributes appearing in the shares (demand) equations. Given the highly non-linear form in which shares depend on prices, explicit reduced-form equations cannot be obtained.

In this context, estimation of markups raises an endogeneity problem. Shares and functions of shares are likely to be correlated with η and u. We are assuming that costs are explained by observed attributes plus some additional unobserved cost components summarized in the individual, time invariant $\eta' s$ and the time and individual specific shocks u. But market shares are a function of prices and therefore of these costs. Hence, shares will be correlated with the cost side unobservable terms η and u. Moreover, on the demand side, shares can also be influenced by unobserved components of utility that are likely to be correlated with the cost unobserved components.

We have then an estimating expression that is linear in parameters but includes a set of endogenous variables. This implies the use of instrumental variables (IV) methods of estimation. We are going to employ GMM methods suitable to our particular unbalanced panel data context. Let ξ_j represent the $T_j \times 1$ vector of elements $\xi_j = \eta_j + u_{jt}$. We need to define the moments $E(Z_j'\xi_j) = 0$, where Z_j stands for the matrix of instruments, that we are going to exploit.

The most standard way to treat the setting explained above is to estimate the equation taking differences in order to difference out the individual component of disturbances, and to use lags of the endogenous variable in order to set valid moment restrictions (see, for example, Arellano and Honoré (2001)). In our case, this is an undesirable alternative because the time dimension of the data is short in relation to the pace of variation of attributes. Monthly data are likely to contain useful information about prices and shares, which change frequently, but much less about reactions to attributes, which change less frequently and whose change has mainly longer-term effects. The differentiation of the attributes would eliminate crucial information contained in the levels equation and would exacerbate the variance of the disturbances. Instead, we will use as instruments the differences of the shares with respect to their individual time means, $\widetilde{s}_{jt} = s_{jt} - (1/T_j)\sum_l s_{jl}$, lagged a number of periods. This uses as moments the covariance of shares with their past time variations, avoiding the use of their level variations across models, which are likely to be correlated with the errors η, and their current values, which are likely to be correlated with the u shocks. Instruments of this type were first proposed by Bhargava and Sargan (1983), and moment restrictions of this type have been studied in Arellano and Bover (1995). A recent discussion may be found in Blundell and Bond (1998). As additional instruments, we will employ the set of 31 brand dummies. To test the validity of the employed instruments, we employ the Sargan test statistic for the overidentifying restrictions.

We employ the estimator $\widehat{\beta} = (M_{zx}'AM_{zx})^{-1}M_{zx}'AM_{zx}$, where $M_{zx} = \sum_j Z_j'X_j$, with the consistent "one-step" choice $A = (\sum_j Z_j'Z_j)^{-1}$. To obtain inferences robust to serial correlation, we will use a robust estimate of the variance-covariance matrix (see Newey and West, 1987). All statistics are then computed using this "two-step" weighting matrix A_R in the formula $V(\beta) = (M_{zx}'AM_{zx})^{-1}M_{zx}'AA_RAM_{zx}(M_{zx}'AM_{zx})^{-1}$. To estimate a robust inverse of $E(Z_j'\xi_j\xi_j'Z_j)$, we assume that $E(\xi_j\xi_j') = \Omega_j$ are matrices corresponding to conditional homoskedastic errors, and we obtain $\widehat{\Omega}_j$ values using the Newey-West Bartlett-kernel computations for the autocovariances of individual j. We use 72 time observations as the maximum lag that we take into account in the Bartlett kernel.specification. Then we employ the estimate $A_R = (\sum_j Z_j' \, \widehat{\Omega}_j \, Z_j)^{-1}$. The Sargan statistic is computed as $S = \left[\sum_j \widetilde{\xi}_j' Z_j\right] A_R \left[\sum_j Z_j' \widetilde{\xi}_j\right]$, where $\widetilde{\xi} j$ are "second-step" residuals obtained from the corresponding "two-step" GMM estimator.

5. Empirical results.

Estimation of the pricing equation is carried out employing as attributes the power measure *ratio cubic centimeters to weight* (CC/Weight), the fuel efficiency ratio *km to liter* (Km/l), used in the particular form of the relative efficiency in city driving with respect to 90 Km/h driving, the measure of size and safety *length times width* (Size), the *maximum speed in km/h* (Maxspeed) and *air conditioning* (ac) as “luxury” indicators, and the materials use indicator *weight* (Weight). We try to be deliberately close to Berry, Levinsohn and Pakes' (1995) specification for the sake of comparisons. The use of other characteristics or a more complete list does not change the main results.

Let us develop an estimate using the price effects specification corresponding to a demand model with group-specific $\alpha's$ and the pattern of correlation among the groups corresponding to a "nested" logit specification. Price effects corresponding to (5) are hence taken to have the form $\frac{\partial P(j)}{\partial p_j} = -\alpha_g P(j)[\frac{1}{1-\sigma} - P(j)(1 + \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)})]$ for $\forall j = 1...J$, with $j \in J_g$, $\frac{\partial P(k)}{\partial p_j} = \alpha_g P(j)P(k)(1 + \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)})$ for $k \neq j$, with $k \in J_g$, and $\frac{\partial P(k)}{\partial p_j} = \alpha_g P(j)P(k)$ for $k \neq j$, with $k \in J_m$, where J_g and J_m index product groups. Correlation is therefore somewhat limited, but the corresponding matrix D is analytically invertible and regressors not difficult to compute. Equation (7) can be written in this case as

$$p_j = c_j + \frac{1}{\alpha_g} w_{gh}(1 + \frac{w_{gh}}{1-w_h} s_{gh}) + \sum_{m \neq g} \frac{1}{\alpha_m} \frac{w_{gh} w_{mh}}{1-w_h} s_{mh}, \quad j \in J_h, j \in N_g$$

where $w_{gh} = (1 + \frac{\sigma}{1-\sigma}(1 - \frac{\sigma s_{gh}}{s_g}))^{-1}$, $w_h = \sum_g w_{gh} s_{gh}$, and s_{gh} is the share of coalition h in products group g.

We group models into 5 categories that closely follow common industry and marketing classifications. The nests of cars considered are: small, compact, intermediate, and luxury.

We separately group minivans, which were at that moment a product beginning their market penetration. The number of models in each segment are, respectively, 33, 37, 56, 47 and 9.Variables of behavior are computed using a σ value of 0.8. This is a pretty standard value and also the value which is obtained in an independent demand estimation with the same data (see Table A1).

We are going to test for selection among non-nested models. To statistically compare the results, we then use a Vuong-type test of selection among non-nested or overlapping models. We compute it with the GMM analogous to the likelihood ratio. That is, for every two models, we compute the value

$$V = \frac{N(J_2 - J_1)}{\left[\sum (J_{j1} - J_{j2})^2 - N(J_1 - J_2)^2\right]^{1/2}}$$

where $J_1$and J_2 are the corresponding minimised values of the objective function, J_{j1} and J_{j2} are the individual observation values of the objective function evaluated at the minimum, and N the total number of observations. We expect this statistic to be distributed as a $N(0,1)$

Table 3 presents the results of estimating some key models. All attribute coefficients show the sign expected in a cost function and sensible values (cost increases in weight in all the sample values). Moreover, they do not change dramatically from estimate to estimate, although some changes are significant.

Estimates of Table 3 implement the three more straightforward specifications of behavior. The first equation assumes that behavior was Bertrand-Nash all the time and for all players, a common assumption in many models and estimates of this type. The second equation makes the unrealistic assumption that behavior was collusion of all players all the time. The third estimate makes the sensible assumption that domestic and European producers set prices, at the beginning of the period, internalizing the cross effects of their prices; i.e., they constituted a price coalition, but this coalition broke up at the end of 1991. Domestic and European producers are then supposed to switch to play Bertrand, while Asian producers are assumed to play Bertrand the entire period. The estimate of a model in which the breaking up of the coalition is assumed at the end of 1992 gives very similar results.

This third estimate is the best in economic and statistical terms. On the one hand, the coefficients of the variables' modelling behavior exactly follow the pattern expected according the theoretical specification, and they are roughly consistent with the coefficients and price elasticities of demand which have been obtained in a demand equation estimated separately. On the other, the Vuong-type test of selection among non-nested or overlapping models selects it as the best among the three models.

Given the central role of the year 1992, and to check that the conclusion is also robust to closer, less differentiated alternatives of behavior, two additional (a-priori), more or less likely sequences of behavior are estimated. One specifies that domestic producers left the domestic-European coalition at the end of 1991, i.e., began to play Bertrand, but that European producers continued to coordinate pricing. The other is that European producers were never involved in price coordination: there was a coalition exclusively formed by domestic producers which broke up at the end of 1991.

Table 4 identifies all the estimated behavior sequences by numbers and reports the results of the Vuong-type test. From inspection of the matrix of values, it becomes clear that model 3, the coalition of domestic and European producers which broke up at the end of 1991, is a model which clearly statistically dominates the others, i.e., best fits the data.

6. Conclusion.

This paper has addressed the question of whether the Spanish car market underwent a change in pricing behavior that coincided with the tariffs dismantling attained by 1992. The preliminary answer is yes, that it was tacit coordination in pricing maintained up to this moment by domestic and European producers, and that this coordination seems to have broken up by this time. The result is, of course, conditional on the modelling. This is simply the model which best explains the data among the behavior sequences proposed to match the data. And the model also does not inform us about the relative role played in this change of behavior by the tariffs dismantling and, for example, the demand downturn.

But the answer provides, at least, a first step for focussing on narrower hypotheses and more complex structural models. In addition, the estimates carried out will permit us to assess the weight of price coordination in the pre-change prices and the welfare effects of the change.

More generally, the exercise carried out shows that the estimation and test of suitably-specified price equations can be the basis for identifying behavior and behavior changes. In addition, these estimates provide a method for assessing the sources and the effects of market power, and even estimates of some demand parameters.

Appendix: Price effects in discrete-choice demand models with heterogeneous consumers.

Recent demand models stress the importance of modelling consumer heterogeneity for obtaining market demand sensible substitution patterns (see mainly Berry,1994, and Berry, Levinsohn and Pakes, BLP, 1995 and 2004). In empirical work it has become familiar the BLP model, with utility function which can be written as

$$u_{ij} = x_j \overline{\beta} - \alpha(y_i, p_j)p_j + \mu(x_j, z_i) + \xi_j + \varepsilon_{ij}$$

where subindex j stands for product and i for consumer, x and ξ represent the observed and unobserved components of product characteristics, $\mu(.)$ is made of interactions between product attributes and consumer characteristics z, with vector z typically containing unobserved components, and $\alpha(.)$ adopts in practice slightly different functional forms[20] The model embodies two types of consumer heterogeneity: "tastes" heterogeneity, by which different consumers obtain different utilities from the same characteristics of a good, and income heterogeneity, by which marginal utility of income changes with consumer's wealth. This appendix briefly examines how consumer heterogeneity influences price effects and some implications for model specification.

Consumer choice when income (and heterogeneous preferences) matter.

Let the consumer (contingent) utility derived from her choice in the market of interest be additively separable in the utility of the rest of consumption and the characteristics of the chosen good. Assume in addition that utility of the rest of consumption is given by a monotonically increasing differentiable (strictly) concave function $h(.)$. Then, the indirect (contingent) utility function can be written as

$$v(y - p_j, x_j) = h(y - p_j) + u(x_j, z) \tag{1}$$

[20] The fuction $\alpha(.)$ is specified, for example, as $-\ln(y_i - p_j)^{\alpha}/p_j$ in Berry et al., 1995; $-\ln(y_i)^{\alpha}/p_j + a/y_i$ in Berry et al., 1999, and $\exp(-y_i)$ in Berry et al., 2004.

where p_j stands for the price of the good j and y represents consumer income (consumer subindex is dropped for the ease of notation). Subfunction $u(.)$ is assumed to include all relevant product attributes and interactions with consumer characteristics, both observed and unobserved. Applying the mean value theorem, (1) can be written as

$$v(y - p_j, x_j) = h(y) - \alpha(y, p_j)p_j + u(x_j, z) \tag{2}$$

where $\alpha(.)$ is marginal utility of income, a continuous function with derivatives $\frac{\partial \alpha}{\partial y} < 0$ and $\frac{\partial \alpha}{\partial p} > 0$, the property that $\left|\frac{\partial \alpha}{\partial y}\right| > \frac{\partial \alpha}{\partial p}$ for all p such that $p < y$, and second derivatives which depend on the curvature properties of $h(.)$. Call the choice-relevant part of (2) the utility "contribution" of good j and write

$$u_j = -\alpha(y, p_j)p_j + u(x_j, z) \tag{3}$$

Expression (3) clearly establishes that, when consumers are heterogeneous in income, marginal utility of income must be considered non-constant across consumers and is likely to be a major source of heterogeneous choice. Model (3) with $z = 0$ was employed by Bresnahan (1981,1987), although presented in terms of different tastes (normalizing marginal utility), is discussed and reinterpreted in Tirole (1989), and can be called the "vertical differentiation model" (Berry and Pakes, 2002), i.e. consumers agree on the ranking of the goods given their physical attributes but perceive different utility "sacrifice" associated to its consumption.

A given consumer will chose variety j if and only if $-\alpha(y, p_j)p_j + u(x_j, z) > -\alpha(y, p_k)p_k + u(x_k, z)$. As in specifications with α constant, the consumer can strongly prefer the attributes of k (a high quality version), but be deterred from its consumption by the counterbalancing weight of its higher price. But now this effect may crucially change according to the income that characterizes the particular consumer, even if consumers share the same attributes valuation. Some consumers with higher income (lower $\alpha's$) will choose, at the same prices, more expensive varieties[21]. Assume that goods can be ranked by utility and price in a way that implies that, if $u(x_k) > u(x_j)$, then $u(x_k)/p_k < u(x_j)/p_j$ (the price of quality increases

[21] Notice that this effect does not depend on the price entering the $\alpha(.)$ function.

faster that its valuation). Figure 1 gives a useful illustration of the way in which choice among the different varieties depends on consumer's income.

Utility contributions of each good are depicted as a function of income, with slopes $\frac{\partial u_s}{\partial y} = -p_s \frac{\partial \alpha}{\partial y}$ which assume $\frac{\partial \alpha}{\partial y}$ constant for simplicity[22]. They show, for example, that the consumer will only decide to buy one of the product varieties when his income reaches y^j. At the income interval (y^j, y^k) he will buy variety j and, with income in the interval (y^k, y^l), he will choose the superior variety k. The model hence predicts a deterministic association between income levels and chosen goods (including the alternative of non buying).

Two modifications make the model flexible. First, the addition of consumer characteristics z softens the association between choices and income. In fact, any consumer characteristic z interacted with an attribute of the good raises exactly the same type of association between goods (now sorted by the particular attribute) and the level of the consumers characteristic (for example, consumers with a given age may tend typically to buy a given level of "safety," say). These associations could eventually even override the income relationship. The fact of considering the consumer characteristic unobservable, and having its distribution replaced by the realizations of a random effect, changes only that now the origin of the association remains unknown. Notice however that, as the attributes of the good are likely to be highly correlated with its price, and many consumer characteristics with income, misspecification of the income effect may raise doubts about the identification of genuine heterogeneity in preferences.

Second, the inclusion in (3) of an additive random term. Now model (3) becomes

$$u_j = -\alpha(y, p_j)p_j + u(x_j, z) + \varepsilon_j \tag{4}$$

This amounts to assume that an individual's behavior cannot be completely predicted by any of the usually alleged reasons (see Anderson, Palma and Thisse, 1992). If the random term for an individual is assumed i.i.d. across varieties and distributed as a type I extreme value, the probability of choosing good j for a consumer with with income y and characteristics z

[22] Notice that utility curves cross the y-axis at points that verify $\alpha(\overline{y}_s, p_s) = \frac{u_s}{p_s}$. On the one hand, slopes at these points increase with price. On the other, $\alpha(\overline{y}_k, p_k) \leq \alpha(\overline{y}_j, p_j)$ together with $\frac{\partial \alpha}{\partial p_s} > 0$ implies $\overline{y}_k > \overline{y}_j$.

is given by the well known logit formula. Indexing by 0 the alternative of "buying nothing," and giving to this alternative null utility contribution, probabilities can be written as

$$P(j|x,p,y,z) = \frac{e^{u_j}}{1+\sum_s e^{u_s}} \tag{5}$$

A useful interpretation of the role of this addition can be easily done in relationship to the example of Figure A1. The utility lines and the critical income values y^s now only hold as relations for average utility contributions (i.e., at the zero mean of the random terms). But they allow us to easily follow the evolution of consumer's relative probabilities of buying different goods along the different income levels. For example, variety j presents the highest probability of being chosen when consumer's income belongs to the interval (y^j, y^k), followed by the probabilities of acquiring k and then l. The previous deterministic associations of choices with y and z have become probabilistic.

Model (4) can encompass many industry settings. In particular, it is able to deal with any combination of "vertical" and "horizontal" differentiation of the goods. Assume, for example, that supply shows a clustering of the produced goods in a certain number of income-related classes of varieties (classes which group horizontally-differentiated varieties of goods which exhibit similar quality-price pairs[23]). Varieties included in a class will show identical utility lines in Figure 1, and will tend to be associated to typical income levels. But consumer's taste for variety modelled by the error term, and the possible inclusion of consumer characteristics, will induce a diversity of choices for each income level.

In the analysis of price effects it is useful to focus on the particular relationship of probabilities with income. With this purpose, let us write $P(j|x,p,y,z)$ as $P(j|y)$, where it is assumed that x,p,z remain fixed. With our assumptions on $h(.)$ and on the ranking of the products, as far as the probabilities' evolution is concerned, it is easy to show the following

Lemma. $P(0|y)$ is continuously decreasing in y and $P(j|y)$ is, for each j, either a continuously increasing function of y or reaches a maximum and then decreases. The alternatives whose probability reaches a maximum are the lowest priced ones, and they reach it in a sequence of y values that reproduce the price ordering.

[23] Many markets show this pattern, although this type of producers choice reains unexplored.

Proof. See below.

Market demand elasticities.

Models with heterogeneous consumers leave us with conditional probabilities as $P(j|x,p,y,z)$. With market data, no consumer individual decisions are observed and aggregated information is given by product shares, which may be related to product attributes and price. With many consumers, market shares converge in probability to aggregated probabilities. Given a joint distribution for income and consumer characteristics $f(y,z)$, aggregated probability for good j is $P(j) \equiv E\left[P(j|x,p,y,z)|x,p\right] = \int\int P(j|x,p,y,z)f(y,z)dydz$.

If firms are supposed to set prices according to market wide price effects[24], the relevant effects to take into account are the partial (for given x,p) derivatives in equilibrium of these aggregated probabilities. Focussing on income (generalization is straightforward), and adopting again the simplified notation $P(j|y)$ for $P(j|x,p,y)$, the relevant own and cross price effects can be written as

$$\begin{aligned}
\frac{\partial P(j)}{\partial p_j} &\equiv E_y\left[\frac{\partial P(j|y)}{\partial p_j}\right] = -\int \widetilde{\alpha}(y,p_j)P(j|y)[1-P(j|y)]f(y)dy \qquad \forall j=1,...,J \\
\frac{\partial P(k)}{\partial p_j} &\equiv E_y\left[\frac{\partial P(k|y)}{\partial p_j}\right] = \int \widetilde{\alpha}(y,p_j)P(j|y)P(k|y)f(y)dt \qquad \forall k \neq j
\end{aligned}$$

These expressions have simply the general form corresponding to logit price effects under consumer heterogeneity (see, for example, Nevo 2000)[25]. They can be rewritten in the more useful form

$$\begin{aligned}
\frac{\partial P(j)}{\partial p_j} &= -\alpha_j P(j)[1-P(j)] + Cov\left[\alpha P(j|y), 1-P(j|y)\right] \qquad (6) \\
&= -\alpha_j P(j)[1-P(j)](1+\omega_j) \qquad \forall j \\
\frac{\partial P(k)}{\partial p_j} &= \alpha_j P(j)P(k) + Cov\left[\alpha P(j|y), P(k|y)\right] \\
&= \alpha_j P(j)P(k)(1+\omega_{jk}) \qquad \forall k \neq j
\end{aligned}$$

[24] That is, a unique price for each good.

[25] We use $\widetilde{\alpha}(y,p_j)$ for $\alpha(y,p_j)\left(1+\frac{p_j}{\alpha}\frac{\partial\alpha}{\partial p_j}\right)$ in order to simplify algebra. The change induced by the elasticity of marginal utility with respect to the product price may be considered a second order effect.

where $\alpha_j = \int \widetilde{\alpha}(y, p_j) f(y|j) dy$, $\omega_{jk} = Cov\left[\alpha P(j|y), P(k|y)\right] / \alpha_j P(j) P(k)$, ω_j can be defined similarly and, in addition, fulfils the constraint $\omega_j = \sum_{k \neq j} \frac{P(k)}{1-P(j)} \omega_{jk}$. Notice that α_j is average marginal utility of income for buyers of good j (integration is defined in terms of conditional density $f(y|j)$), covariances measure the degree by which buying probabilities covariate across different incomes and the constraint is a consequence of the consistency of the demand system[26]. Expressions (6) are independent of the heterogeneity that is integrated over in addition to income and only depend on the logit assumption for the additive random effect of equation (4).

These price effects (and therefore the corresponding elasticities) show two important changes with respect to the standard logit effects. Firstly, marginal utility parameters are now product-specific. This reflects the different average marginal utilities of income associated to consumption of each product, with the practical consequence of augmenting the variability of the own-price demand effects. Proposition 1 below establishes that this variability goes in the direction of a lower price elasticity for high quality goods. Secondly, cross-demand effects of a change in price of good j now change even across substitute goods with identical $P(k)$ share. Variation induced by the ω_{jk} term reflects that the model is now distinguishing among products "closer" and "farther" to product j in a very precise meaning, cast in the covariance term. Products which exhibit a high probability of being chosen at the same income levels will show a higher substitutability for product j, while products which are the typical choices at other income levels will show a lower substitutability.

Changes are easy to interpret. When logit formulas refer to an individual characterized by some income, it is simply natural to expect that a reduction in one probability will benefit proportionally to all other alternatives (this may eventually change the individual's most probable alternative). This effect is what is given by the first part of the equations, which can be interpreted as referred to a hypothetical consumer with average utilities. When changes are referred to the large number of buyers clustered around alternatives, changes will reflect also aggregate changes in the clustering. This is what is reflected in the covariance term, raising what can be called "aggregated" price effects or elasticities (this

[26] Elasticities can respectively be written as $\eta_j = -\alpha_j p_j [1 - P(j)](1 + \omega_j)$ and $\eta_{jk} = \alpha_j p_j P(j)(1 + \omega_{jk})$.

name can be already found in Ben-Akiva and Lerman, 1985).

Remark. The above price effects include the Nested Logit price effects as a particular case.

Proof. See below.

The Nested Logit model may be interpreted as a particular case in which buying probability covariances are strong for products inside a nest and zero for products belonging to different nests. This shows that the simple Nested Logit defines clusters of products but does not introduce any rank among these groups. The above price effects reflect an ordering among products or groups of products derived from the role of consumers' income in determining their consumption. This ordering is reflected in the result stressed for the following proposition.

Proposition . With marginal utility of income decreasing at a non-decreasing rate, products with higher prices have lower average marginal utilities.

Proof. See below.

(To be completed, note on IIA at the individual level)

Estimation of a general demand model with panel data.

BLP propose a simulation estimator for their model. Let δ_j be the part of the utility specification of good j which does not depend on consumer unobservables although it does depend on the product unobservable ξ_j. The method consists of finding the δ vector which makes the consumer-heterogeneity simulated shares equal to the observed shares, by estimating the parameters which make the moments for ξ as close as possible to zero. Berry, Linton and Pakes (2004) analyze the asymptotic properties of this type of estimator when the number of products grows large. With panel data (product characteristics, prices and sales are observed over time), however, some arrangements become available.

The first part of the average price effects (6) only depend on aggregated probabilities and the product specific (averaged) parameter α_j (j is the index of the product whose price effects are examined). The set of own and cross first terms corresponding to the J products

$(j = 1...J)$, suggest that may exist a system of J "representative" probabilities which are able to generate the first part of the derivatives with respect to the price (and eventually other characteristics). And this is effectively the case: the probabilities of a hypothetical consumer, with utility for each good equal to an average utility defined as follows, generates this part of the derivatives. Extend the definition of δ_j to include all the relevant averages of consumer unobservables interacted with product characteristics, given the observables. In particular, include the average α_j $(\equiv \int \widetilde{\alpha}(y, p_j) f(y|j) dy$) interacted with the price, and the unobservables ξ_j.

Result. The vector δ of mean utilities which matches the aggregated probabilities is unique and it is the unique whose associated probabilities generate the desired average partial derivatives.

Proof. See below.

As observed shares converge to probabilities ($p \lim \ln \frac{S_j}{S_0} = \ln \frac{p \lim S_j}{p \lim S_0} = \ln \frac{P(j)}{P(0)}$), parameters α_j can then be consistently estimated in equations as

$$\ln s_j - \ln s_0 = x_j \overline{\beta} - \alpha_j p_j + \xi_j$$

where unobserved consumer heterogeneity is likely to generate also product specific "fixed" effects components of ξ_j (the result of averages $\int v f(v|j) dv$, with non-zero mean, interacted with product characteristics, for example $(\int v f(v|j) dv) x_{jk} = \beta_{jk} x_{jk} \equiv \overline{\xi}_j$).

(To be completed).

Proofs.

Proof of the Lemma.

Notice that the e^{u_s} are increasing in y. Hence $P(0|y) = 1/(1 + \sum_s e^{u_s})$ is continuously decreasing in y. On the other hand, each probability $P(j|y)$ will be increasing if $\frac{\partial P(j|y)}{\partial y} = -\frac{\partial \alpha(y,p_j)}{\partial y} P(j|y) \left[p_j - \sum_s \theta_{js} P(s|y) p_s\right] > 0$, where the terms θ_{js} have the form $\theta_{js} = \frac{\partial \alpha(y,p_s)}{\partial y} / \frac{\partial \alpha(y,p_j)}{\partial y} > 0$ and fulfil $\theta_{js} > \theta_{ks}$ if $p_k > p_j$.What we need is the positiveness of the term between brackets. With J varieties ranked according to prices (from the lowest to the highest), the positiveness conditions from 1 to J form a system of inequalities in which the constraints will be violated in turn as y grows (the constraints are easier to be fulfilled the bigger the price). The the corresponding probabilities will begin to decrease.

Proof of the Remark.

Take $\alpha_j = \alpha$ for $\forall j$, and form groups of products indexed $g = 1...G$. Let J_g represent the set of products in group g and define $P(J_g) = \sum_{s \in J_g} P(s)$. Assume a common ω_g for cross-price effects between products belonging to the group, $\omega_g = \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)}$, and $\omega_{gm} = 0$ when the cross-price effect involves two different nests. Define ω_j consistently for a product j which belongs to group $g : \omega_j = \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)}\frac{P(J_g)-P(j)}{1-P(j)}$. It is easy to see that price effects are now $\frac{\partial P(j)}{\partial p_j} = -\alpha P(j)[\frac{1}{1-\sigma} - P(j)(1 + \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)})]$ for $\forall j = 1...J$, with $j \in J_g$; $\frac{\partial P(k)}{\partial p_j} = \alpha P(j)P(k)(1 + \frac{\sigma}{1-\sigma}\frac{1}{P(J_g)})$ for $k \neq j$, with $k \in J_g$, and $\frac{\partial P(k)}{\partial p_j} = \alpha P(j)P(k)$ for $k \neq j$, with $k \in J_m$, which are the Nested Logit price effects.

Proof of the Proposition.

Marginal utility of income decreases at a non-decreasing rate. We want to show that, if $p_k > p_j$, then $\alpha_k < \alpha_j$.Write $\alpha_j - \alpha_k = \int \alpha(y, p_j)f(y|j)dy - \int \alpha(y, p_k)f(y|k)dy$. Using integration by parts and the fact that $F(0) = 0$ and $F(y^{\max}) = 1$, we have that $\alpha_j - \alpha_k = \alpha(y^{\max}, p_j) - \alpha(y^{\max}, p_k) + \int \left[-\frac{\partial\alpha(y,p_j)}{\partial y}F(y|j) + \frac{\partial\alpha(y,p_k)}{\partial y}F(y|k)\right] dy$. On the one hand, the difference between the two first terms can be considered negligible for $y^{\max}$ enough large with respect to prices. On the other, the difference between brackets under the integral sign may be written as $-h''(y, p_j)\,[F(y|j) - F(y|k)] + [h''(y, p_k) - h''(y, p_j)]\; F(y|k)$. Given the previous Lemma, it is easy to check that the ratio of probabilities of alternative k to j is increasing in income, that is $\frac{\partial[P(k|y)/P(j|y)]}{\partial y} > 0$. This implies $\frac{P(k)}{P(j)} > \frac{\int_0^{y^{\max}} P(k|y)f(y)dy}{\int_0^{y^{\max}} P(j|y)f(y)dy}$ or $\int_0^y f(y|j)dy > \int_0^y f(y|k)dy$, and hence $F(y|j) > F(y|k)$. On the other hand, $h''(y, p_k) - h''(y, p_j) \geqslant 0$ by assumption. Thus, $\alpha_j - \alpha_k > 0$.

Proof of the Result.

Which is unique follows from Berry (1994), which establishes the conditions under which δ solves uniquely the system $P = P(\delta(P))$. Then, we must show that this is the only δ

which generates the desired derivatives. Notice that, by dividing u_j in two parts: δ_j, which includes the averaged heterogenity and v_j, say, wich includes the remaining deviations, aggregated probabilities factorize in two terms. For simplicity, we use again the simplified notation for heterogeneity based on y

$$E\left[P(j|y)\right] = \frac{e^{\delta_j}}{1+\sum_s e^{\delta_s}} \int \frac{1+\sum_s e^{\delta_s}}{1+\sum_s e^{\delta_s+v_s}} e^{v_j} f(y)dy = P(j|\delta)w_j(y)$$

Then, by choosing δ such that $P(j|\delta)$ match the aggregated probabilities $P(j)$, factors $w_j(y)$ will become unity. Hence derivatives will take the form

$$\frac{\partial E\left[P(j|y)\right]}{\partial p_j} = -\alpha_j P(j)\left[1-P(j)\right] + P(j)\frac{\partial w_j(y)}{\partial p_j}$$

Formulas (6) give the interpretation of the averages.

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Table 1
The Spanish car market in the 90s: basic statistics

Year	Sales	Sales index	Models entry	Models exit	No. of models[1]	Share of domestic producers[2]	[Of which imported cars]	Share of European producers[2]	Share of Asian producers[2]
1990	971,466	100.0	19	2	96	82.0	[14.3]	16.0	2.0
1991	878,594	90.4	10	3	103	80.0	[13.7]	16.9	3.1
1992	973,414	100.2	16	7	112	81.3	[14.3]	14.6	3.9
1993	735,993	75.8	12	8	116	80.7	[19.1]	13.9	5.2
1994	897,492	92.4	13	13	116	78.6	[16.2]	15.8	5.3
1995	822,593	84.7	17	12	121	77.0	[15.2]	15.7	6.8
1996	897,906	92.4	16	14	123	75.0	[15.2]	15.8	8.4

[1] At the end of the year.
[2] See notes to Table 2.

Table 2
The Spanish car market in the 90's: competitors, brands and model entry and exit

Producer type	End of 1989		1990-1996				1996
	No. of brands	No. of car models	Brand entry	Models entry	Models exit	Models net entry	No. of car models
Domestic[1]	7	33	-	26	16	10	43
European[2]	14	38	.	45	30	15	53
Asian[3]	5	8	4	28	12	16	24
American[4]	-	-	1	4	1	3	3
Total	26	79	5	103	59	44	123

[1]Citroen-Peugeot, Ford, Opel(GM), Renault and Seat-VW

[2]Audi, Alfa-Romeo, BMW,Fiat, Jaguar, Lada, Lancia, Mercedes, Porshe, Rover, Saab, Skoda, Volvo and Yugo.

[3]Honda, Hyundai,Mazda,Nissan and Toyota before 1990; Mitsubishi, Suzuki, Subaru and Daewo since 1990 and after.

[4]Chrysler

Table 3
Results from model estimation and testing

Dependent variable: $p_{jt}/(1 + tariffs_{jt})$
Sample period[1]: $I - 1991$ to $XII - 1996$; Observations[1]: $7,122$; N^{o}of models[1]: 164
Estimation method: GMM[2]

Variable	Coefficient	t-ratio[3]	Coefficient	t-ratio[3]	Coefficient	t-ratio[3]
Constant	2.151	13.74	2.036	11.69	1.985	11.33
Attributes:						
CC/Weight	2.034	7.85	2.068	8.06	1.859	6.89
Maxspeed	1.144	2.26	1.043	2.05	0.832	1.75
Km/l	0.360	0.76	0.364	0.76	1.031	2.17
Size	-0.146	-0.75	-0.162	-0.84	-0.381	-2.05
Weight	3.610	5.41	3.814	5.54	3.908	6.04
Air	-0.085	-0.77	-0.091	-0.80	0.037	0.31
$(\text{CC/Weight})^2$	1.570	3.90	1.560	3.90	1.440	2.70
$(\text{Maxspeed})^2$	3.220	4.21	3.193	4.25	3.589	4.11
$(\text{Size})^2$	0.100	1.82	0.099	1.87	0.088	1.69
Behaviour[4]						
Always Bertrand						
Small	-0.16	-0.09				
Compact	-1.67	-1.55				
Intermediate	3.45	2.80				
Luxury	2.64	1.70				
Minivan	-4.26	-1.69				
Always Collusion						
Small			0.084	0.23		
Compact			-0.219	-0.91		
Intermediate			0.827	3.10		
Luxury			0.667	1.93		
Minivan			-1.358	-2.12		
D+E switch from collusion to Bertrand						
Small					-1.102	-2.22
Compact					-0.952	-1.05
Intermediate					3.013	3.08
Luxury					3.487	3.35
Minivan					-4.445	-2.46
Sargan test (28 degrees of freedom)	49.46		50.19		36.22	
Voung-type test					-8.51,-9.21	

Notes:
1. Instruments lagged 12 months imply that models with 12 and fewer observations must be removed.
2. Instruments: differences of segment-shares with respect to their time mean lagged 6 and 12 months, 31 brand dummies.
3. Standard errors are robust to serial correlation and heteroskedasticity across individuals.
4. Coefficients of behavioural variables are constrained to add up to zero.

Table 4
Testing behaviour

Behaviour sequences			
	1992-1996		
1990-1991	Collusion	Coal. European	Bertrand
Collusion	1		
Coalition Domestic+European		2	3
Coalition Domestic			4
Bertrand			5

Test results (Vuong type test)				
	2	3	4	5
1	5.54	-9.21	-1.64	-1.20
2		-34.27	-6.70	-6.40
3			9.12	8.51
4				1.28

Model # versus model #. A row value above (below) the critical value of 1.96 (-1.96) means that the row model is better (worse) than the column model.

Table A.1
Results from demand estimation

Dependent variable: $\ln \hat{P}_j - \ln \hat{P}_0$
Sample period[1]: I − 1991 to XII − 1996
Observations[1]: 7,122
N^o of models: 164
Estimation method: GMM[2]

Variable	Coefficient	t-ratio[3]
Constant	−15.840	−6.70
Attributes:		
CC/Weight	1.332	2.46
Maxspeed	0.034	2.92
Km/l	0.071	1.61
Size	0.651	3.42
Prices:		
Small	−4.916	−2.67
Compact	−3.374	−2.65
Intermediate	−0.931	−3.53
Luxury	−0.593	−2.97
Minivan	−2.575	−3.12
Segment effects[4]:		
Small-domestic	5.152	3.49
Intermediate	−2.831	−1.97
Luxury	−4.969	−3.57
Seasonal effects	included	
Time dummies	included	
Age polynomial	included	
Age-price interactions	included	
σ estimate	0.842	7.51
Sargan test[5] (25 degrees of freedom)	35.86	

Notes:
1. Instruments lagged 12 months imply that models with 12 and fewer observations must be removed.
2. Instruments: differences of segment-prices with respect to their time mean lagged 6 and 12 months, 20 age dummies (years) and interactions of the age dummies with the price differences lagged 12 months.
3. Standard errors are robust to heteroskedasticity and serial correlation.
4. Small-mini, compact and minivan coefficients constrained to be equal to the average effect.
5. Two-step statistic.

Figure 1
Sales evolution in the Spanish car market

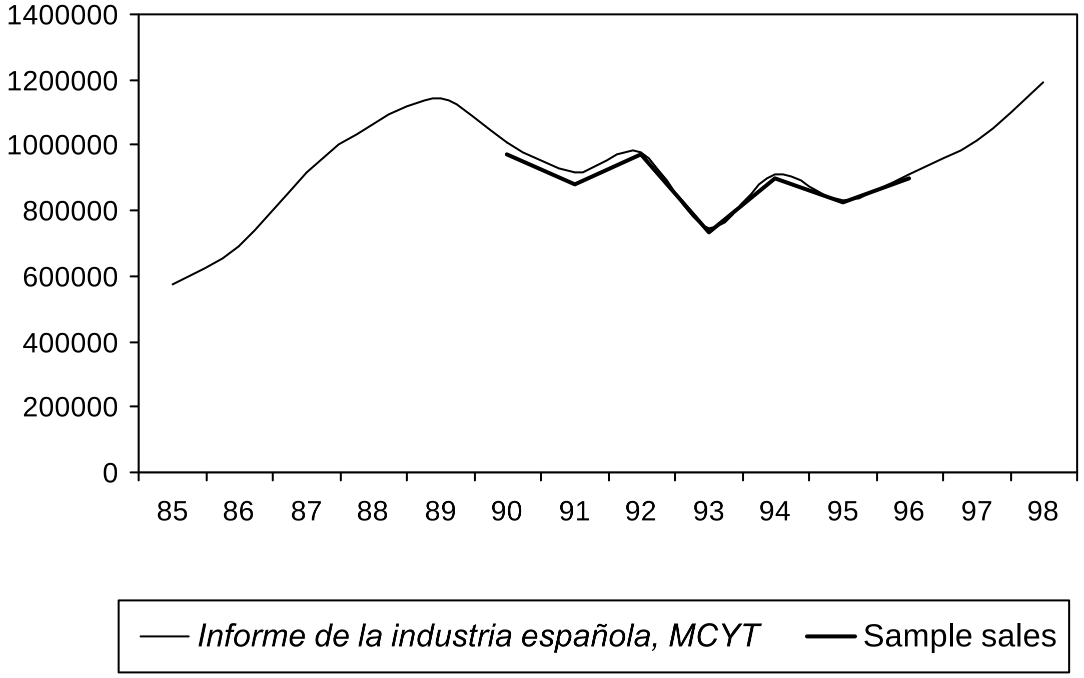

Figure 2: Prices and received prices

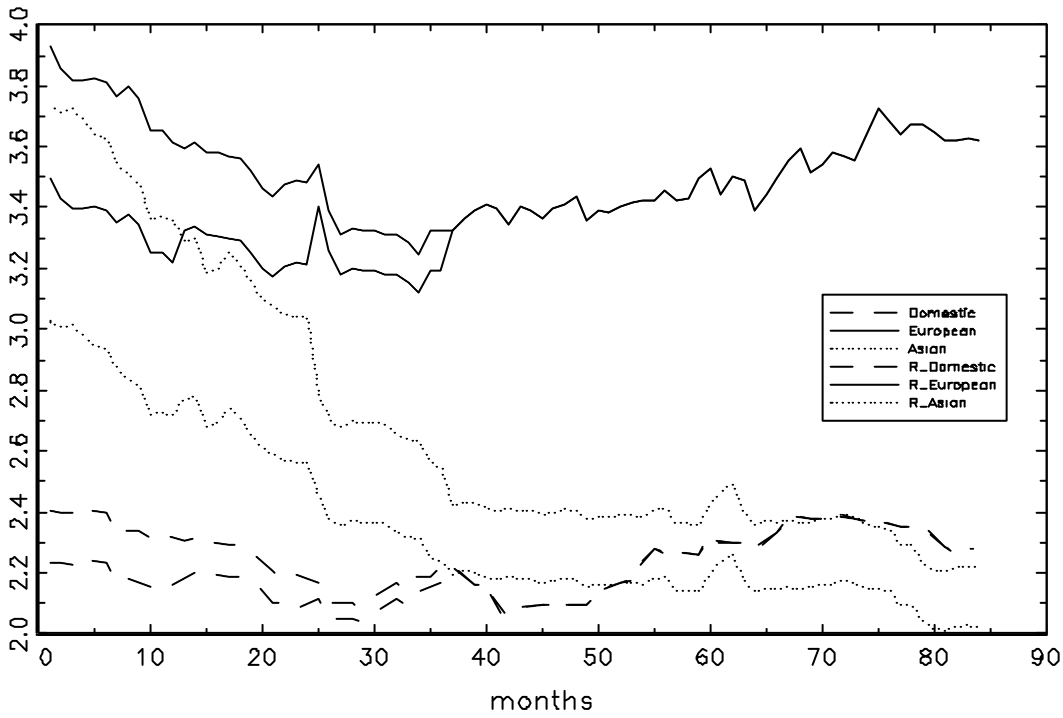

Figure 3: Quality adjusted price index

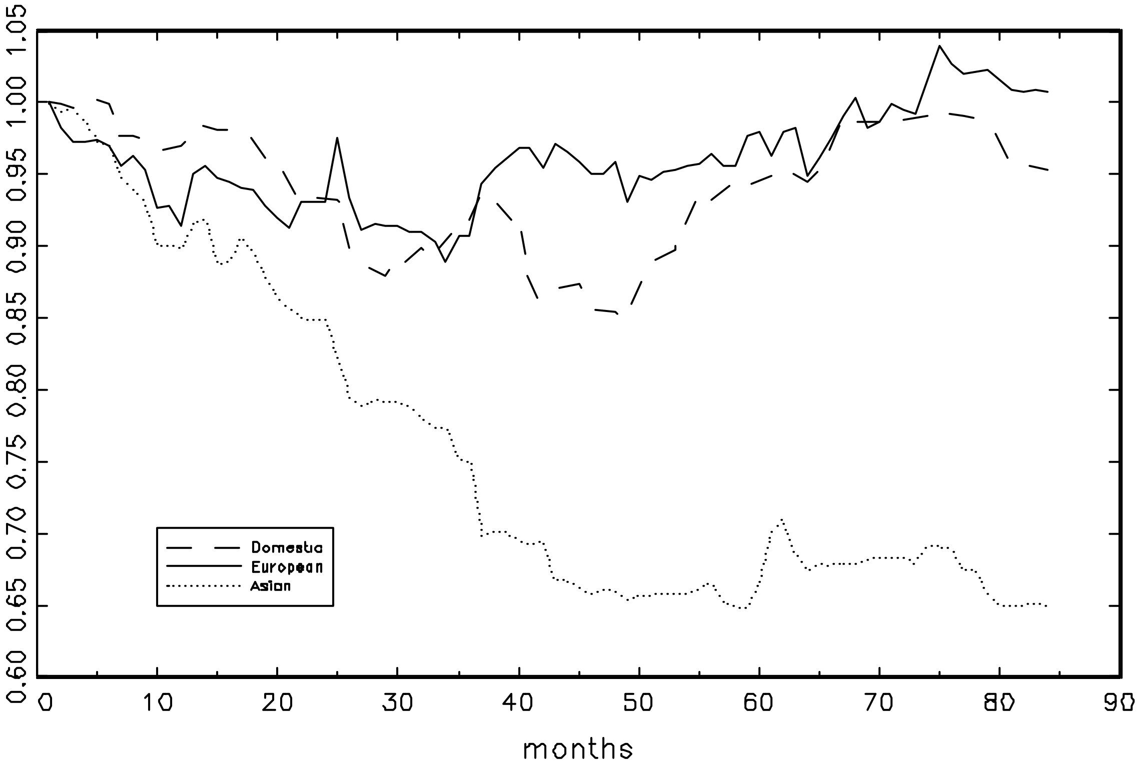

Figure 4: Entry and quality change adjusted price index