Advertising and consumer choice: A model for the Spanish automobile industry of the 90´s

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Abstract

This paper assesses the role of advertising in the demand of a differentiated and infrequently purchased good market. Advertising enters directly in the demand as goodwill stock with decreasing returns. Demand is specified and estimated in a discrete choice model approach, which allows us to compute the predatory and spillover effects of advertising and different sensibilities to advertising across market segments. The model is applied to the Spanish automobile industry during the nineties, that turns out to be a suitable environment to perform the study (differentiated good market with high advertising intensity). Results suggest an important sensibility of the demand to advertising, that changes across automobile segments, and a significant carryover effect and a predatory component of advertising. Moreover, I show that the price elasticities of demand are overestimated when advertising is not included in the estimation.


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1 Introduction

Differentiation is a phenomenon more and more presents in markets. Firms supply different varieties of their products, which are perceived as close substitutes by consumers. In these markets advertising plays a fundamental role not only in the product perception, but also as an information transmission device. In a market, advertising intensity mainly depends on the demand sensibility to advertising. However, the strategic role of advertising is also important. Advertising expenditures can be huge in the differentiated markets. For example, TNS Media Intelligence/CMR\textsuperscript{1} report that, during the first nine months of 2004, General Motors spent $1.99 billions to advertising its cars and trucks and Procter and Gamble devoted $2.13 billion to the advertisements of its detergents and cosmetics. In this paper, the role of advertising from demand side of a differentiated markets is assessed.

The Spanish automobile industry during the nineties turns out to be a suitable environment to perform the analysis. First of all, it is differentiated market with a high advertising intensity. In addition, a high rate of model introduction and turnover, a continual drop of price and a significant increase in advertising expenditures are observed during the period, especially from starting in 1992, year where advertising expenditure rose by about 80\% respect to the last year.

The purpose of this paper is to study the effect and nature of advertising on the demand of Spanish automobile industry of the 90\’s. To address this goal, demand is specified and estimated in a discrete choice model approach, where advertising enters directly as a goodwill stock with decreasing returns and might have different sensibilities to advertising across the automobile segments. Results suggest an important demand sensibility to advertising, that changes across the automobile segments, and a significant long-run effect on sales and a predatory component of advertising. Moreover, I show that the price elasticities of demand are overestimated when advertising is not included in the estimation.

Prior to the 20th-century economists paid little attention to advertising. 19th-century economic research is devoted largely to the development of the theory of perfect competition, framework where the conventional assumptions that consumers have fixed preferences and perfect information involve no role for advertising (there is no reason for consumers to respond to advertising). Early empirical research mainly appeared between 1950 and 1980. Much of this work looks for inter-industrial empirical regularities, employing regression methods and using inter-industry data. One topic studied is the measurement of the long-run impact of advertising on sales, where advertising is studied as an accumulated stock that depreciates in the course of time (goodwill stock). Two important papers are Clarke (1976) and Assmus, Farley and Lehmann (1984), who find evidence of a goodwill effect of advertising for U.S. industries with a depreciation rate of about 0.4 and 0.3, respectively. Other topic arises from Bor-

\textsuperscript{1}TNS Media Intelligence/CMR is a group dedicated to worldwide media analysis, provides advertising expenditure tracking, evaluation and consultative services for broadcast, Internet and print media, in addition to news monitoring capabilities.
den (1942). He makes a distinction between advertising that increase selective (i.e., firm/brand) and primary (i.e., industry) demand. He studies a cross-section of U.S. industries and suggests that advertising mainly affects selective demand. The overall effect of advertising on primary demand, according to the studies, appears to vary across industries. For example, a positive relationship is reported for the U.S. auto industry by Kwoka (1993). Cowling, Cable, Kelly and McGuiness (1975) report no evidence of it for the instant-coffee market. This distinction is closely linked to predatory and spillover effects, introduced by Roberts and Samuelson (1988). The effect of own advertising might be due both to the fact that advertising attracts customers of rival products, business stealing or predatory effects, and to the fact that new customers enter the market (choose to buy a product instead of not buying any product at all), spillover or market enlargement effect. In a particular market both effects, one effect or even none of them may be observed.

At the beginning of 80s, with the new empirical industrial organization a second group of research emerged using data at more disaggregated levels (brand and even household levels), more sophisticated econometric methodology and models where consumer’s and firm’s conduct is emphasized, specifying and estimating explicit structural models. Many of them examine the impact of advertising on brand purchase decisions and focus on a narrow set of consumer goods: frequently purchased consumer goods (like cereals, toilet tissues, detergent, coffee, yogurt and ketchup)\(^2\). In broad terms, these studies point towards the conclusion that advertising has little effect in the purchasing behavior, above all if advertising is compared with the effect of previous consumption of the good (see, for example Ackerberg (2001)).

The main contribution of this research is the assessment of the role of advertising for the demand of a differentiated and infrequently purchased good market, using a structural model and recovering some topics studied by the first empirical research, and forgotten by modern analysis. To analyze the effect of advertising on selective and primary demand, an outside good is included on the consumer’s choice set. And in order to study its long run impact on sales, advertising enters as a goodwill stock in the consumer’s problem. The model is applied to the Spanish automobile industry using a unbalanced monthly panel data which runs from January 1990 to December 2000 (132 months), with a “car-model” as unit of analysis (257 distinct models were sold in the market, offered by 33 different multiproduct firms). The information gathered for each model includes price, registrations, segment, brand, advertising expenditures and mechanic, design and equipment characteristics. The main finding are advertising has a significant effect in influencing purchase behavior, that changes across the automobile segments, the existence of goodwill stock of advertising and a predominant combative role\(^3\) of advertising in the automobile industry.

\(^2\)Advertising may be measured as current expenditure or goodwill stock. Maybe because of the considered set of consumer goods, modern (second-group) empirical analyses often consider current expenditure.

\(^3\)It’s said that advertising has a combative role when its main goal is attracting rival firms’ customers.
although its effects on primary demand are significant. Many of the differentiated markets contain a large number of products. If there are J products and we attempt to fit a linear approximation to the demand system for this products, we will be required to estimate on the order of $J^2$ parameters. Given this dimensionality problem, one alternative, that dates back to Lancaster (1971), is the theory of demand models that treat products as bundles of characteristics. The standard approach in the literature pioneered by McFadden (1974) is the use of discrete choice models. Nowadays, discrete choice models are the most popular alternative to model and estimate demands in markets with product differentiation, due to their advantages (see Berry(1994)). They allow us to avoid the problem of dimensionality and move easily between consumer utility and aggregate demand. For the automobile industry, discrete choice models have been frequently employed to assess policies and mergers (welfare effects). This evaluation is carried out through simulation analysis, where a fit estimated pattern of substitution is needed. Among these works Goldberg (1995) stands out. He evaluates the effect of the V.E.R.\footnote{Voluntary Export Restrict.} and exchange rate changes for the U.S. automobile industry. Using a similar approach Ivaldi and Verboven (2000), study the refused merger between Volvo and Scania in 1999. It is important to emphasize that neither of them include advertising.

In this paper, I use a discrete choice model with income effect, introduced by Jaumendreu and Moral (2001), which considers a appropriate heterogeneity between consumers in markets, as automobile, with vertical and horizontal differentiation. The model is estimated in a nonlinear GMM framework (seen Nevo (2001)), where advertising, just like pricing, becomes an endogenous variable. Sensible patterns of substitution of advertising and pricing are estimated. I show that ignoring advertising leads to biases in the estimated effects of price.

The remainder of this paper is organized as follows. In Section 2 examines how advertising affects product choice. Section 3, presents the demand model utilized in the analysis. This Section is followed by a description of the data, the estimation strategy and the empirical specification in Section 4. The estimation results are contained in Section 5 and Section 6 assesses the effects of advertising. The principal conclusions and future research make up the final section.

2 Advertising and consumer choice

As Marshall (1919) first explains, advertising may affect product consumer choice in two ways: either conveying information concerning the existence, functions or qualities of the product, changing her choice set (informative advertising, $a^I$), or altering consumer’s tastes, creating spurious product differentiation (persuasive advertising, $a^P$). Given two products $j$ and $r$, consumer $i$ purchases product $j$ if

$$U_{ij}(a^P_j) + f_i(a^I_j) \geq U_{ir}(a^P_r) + f_i(a^I_r)$$  \hspace{1cm} (1)

4 Voluntary Export Restric.
where $U_{ij}$ is the utility of consumer $i$ from purchasing product $j$ and $f_i(a^t)$ is the impact of informative advertising on consumer $i$ choice.

The data of advertising collected by firms mainly are the advertising expenditure, and sometime the numbers of ads, without distinguishing between informative and persuasive advertising. For this reason in empirical research for markets with both kinds of advertising, the effect of advertising is not structurally specified. Then the total effect of advertising is modeled in an only function $h(a)$:

$$U_{ij}^* + h(a_j) \geq U_{ir}^* + h(a_r)$$

(2)

where $U_{ij}^*$ is the utility of consumer $i$ from purchasing product $j$ without containing a possible increase of utility caused by advertising and $a_j$ is total advertising of product $j$.

Nelson (1970) makes a distinction between search and experience goods. A search good is one for which quality can be determined prior to purchase (but perhaps after costly search), whereas the quality of an experience good can be evaluated only after previous consumption. Goods that are consumed infrequently and correspond to a large part of the budget are likely to be search goods, as in the case of automobiles. Such goods are mainly linked to informative advertising, but, as in the most markets, both kinds of advertising likely coexist.

As well as affected by current advertising, consumer choice is also affected by previous advertising. Although, its effect is in general smaller. This intertemporal dependence is formalized through a goodwill stock, denote by $A_t$. In the literature\(^5\), the goodwill stock of advertising is defined as a distributed lag of advertising:

$$A_{jt} = a_{jt} + \lambda A_{jt-1} = a_{jt} + \sum_{\tau=1}^{t} \lambda^\tau a_{jt-\tau}$$

(3)

where $a_{jt}$ is current period $t$ advertising for product $j$ and $\lambda \in [0, 1]$ is the carryover effect of advertising from one period to the next. Clarke (1976), and Assmus, Farley and Lehmann (1984) estimate an inter-industry average of around 0.6 and 0.7, respectively, although in this paper a greater carryover effect is expected, given the smaller frequently of their data (quarterly).

In short, the impact of advertising on product consumer choice is modeled using an only function that depend on the goodwill stock of advertising, $\Phi(A)$. When this function is chosen, it’s important to bear in mind that this function imposes assumptions regarding the impact of advertising on demand (returns of advertising). On the whole, the studies that evaluate the marginal effect of advertising suggest that advertising often entails dismissing returns (the marginal effect of goodwill stock of advertising on sales diminished with the stock of advertising level)\(^6\). We model the impact of advertising in this paper as

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\(^5\)See Clarke (1976), who provides a detailed summary of measurement of carryover effects of advertising.

\(^6\)See Alboion and Forris (1981) for a review on the effects of advertising.
\[
\Phi(A_j) = \frac{A_j}{k + A_j}
\]  

(4)

where the advertising’s effectiveness is subject to diminishing returns and the parameter \( k \) allows that results are independent to the advertising measure. The lineal function \( \Phi(A_j) = A_j \) is often used in empirical work that examine the impact of advertising on product purchase decisions, in spite of the fact that it imposes increasing returns\(^7\).

The impact of advertising on product consumer choice means changes on the selective demand of the advertised product and the selective demands of its rivals, that are usually measured using the advertising-demand elasticity (own and cross, respectively).

3 Utility and demand

Discrete choice models have recently shown to be a successful tool to estimate demand in market with product differentiation. The most popular model are: the vertical differentiation model (see Bresnahan (1987)), the logit model, the nested logit model and the full random coefficient model, developed by Berry, Levinsohn and Pakes (1995), which differ over the consumer heterogeneity assumptions.

The vertical differentiation model and the logit model are suitable for markets with an only kind of differentiation (vertical and horizontal differentiation, respectively). When vertical and horizontal differentiation coexist in a market the nested logit model and the full random coefficient model, are using. In some of these market the vertical differentiation mainly arises from the different income levels or the marginal utility of income (the disagreement about the value of quality comes from the consumers’wealth), and only the full random coefficient model (BLP model) considers a appropriate heterogeneity between consumers. When demand is only considered (without supply side), identification problems usually arise with the BLP model. A alternative model is developed by Jaumandreu and Moral (2001): a discrete choice model with income effects, characterized by imposing different price effects among market segments, and in this way a different marginal utility of income is associated with each segment. In markets where the differentiation among group is sufficiently clear and the income is the most important source of consumer heterogeneity, the discrete choice model with income effects allows us to obtain a sensible demand estimation. So, in order to apply the analysis to the Spanish automobile industry, the discrete choice model with income effects is used.

Let the consumer utility, derived from the consumption of a composite good \( m \) (rest of consumption) and her good chosen \( j \), be additively separable in the utility of the rest of consumption\(^8\) and product attributes, both observed

\(^7\) See Appendix 2.

\(^8\) Normalising the price of the composite good to unity, its consumption can be written as the consumer income \( y_i \) minus the price of the chosen good \( p_j \).
the mean value theorem, the indirect utility function obtained:

\[ V(y_i - p_j, x_j, \xi_j, z_i) = h(y_i) - \alpha(y_i, p_j) + X_j \beta + \xi_j + u(x_j, \xi_j, z_i) \]  \hspace{1cm} (5)

where \( \alpha(.) \) is the marginal utility of income\(^9\) and the relevant part of the utility in the choice\(^11\), that is called “contribution” of good \( j \), is written

\[ U_{ij}^* = -\alpha(y, p_j) + X_j \beta + \xi_j + u(x_j, \xi_j, z_i) \]  \hspace{1cm} (6)

The model clearly establishes that when consumers are heterogenous in income and prices of goods are a large part of the budget, marginal utility of income must be considered non-constant across consumers and is likely to be a major source of heterogenous choice.

Model with a specification\(^12\) of \( \alpha(.) \) corresponds to BLP model and the interactions between product and consumer characteristics make very difficult the identification when demand is only considered.

Model with \( z=0 \) can be called the “vertical differentiation model” (Berry and Pakes, (2002)), which predicts a deterministic association between income levels and chosen good (including the alternative of non buying). So each product has an associated a marginal utility of income, \( \alpha_j = \alpha(y, p_j) \). The addition of \( z_i \) likely overrides the association income-chosen product. If the product can be clustered in known and vertical differentiated classes of varieties (varieties of good which have similar attributes), varieties included in a class will be associated to a similar income levels and therefore a similar marginal utility of income.

Assume individual behavior cannot be completely predicted (see Anderson, Palma and Thisse (1992)), an additive random term must be include. So, according to the discrete choice model with income effect, the utility of consumer \( i \) from purchasing product \( j \), belongs to group \( g \), is:

\[ U_{ij} = X_j \beta + \alpha_g p_j + \xi_j + \zeta_{ig} + (1 - \sigma) \epsilon_{ij} \]  \hspace{1cm} (7)

where \( \epsilon_{ij} \) is an extreme-value-distributed error term, which is identically and independently distributed across products and consumers. \( \zeta_{ig} \) represents the consumer’s utility common to all products of group \( g \), and \( \sigma \in [0, 1] \) is a parameter that measures the correlation of utility within each group (if \( \sigma = 1 \) products within a group are perfect substitutes, whereas if \( \sigma = 0 \) they are independent).

\(^9\)It’s assumed that utility is linear in product attributes, too.

\(^10\)\( \alpha(.) \) is a continuos function with derivatives \( \frac{\partial \alpha}{\partial p} < 0 \) and \( \frac{\partial \alpha}{\partial y} > 0 \).

\(^11\)For a given consumer \( V(y_i - p_j, x_j, \xi_j, z_i) > V(y_k - p_k, x_k, \xi_k, z_i) \), \( \forall k \neq j \), if and only if \(-\alpha(y_i, p_j) + X_j \beta + \xi_j + u(x_j, \xi_j, z_i) > -\alpha(y_k, p_k) + X_k \beta + \xi_k + u(x_k, \xi_k, z_k)\)

\(^12\)For example \( \alpha(.) \) is specified as \(-\ln(y_i - p_j)^{12}/p_j \) in BLP (1995).
The functional form is similar to nested logit model, but assuming that the price coefficient is constant across consumers who purchase in the same group or segment. Both of them imply the same pattern of substitution:

- consumers faced with a change of prices substitute more toward other products within the same segments (substitute with a different proportion to market shares depending on the segment of the products). Unlike the nested logit model, the discrete choice model with income effects allow us to distinguish between the vertical differentiation from the disagreement about the value of segment independently of their wealth ($\zeta_{ig}$) and from income level or budgetary restriction ($\alpha_g$).

The impact of advertising is assumed to be additive to the valuation of each product and identical across all goods belong to the same segment ($\gamma_g$) to study differences in demand sensibility across the segments. This impact depends on the goodwill stock of the advertised product according to the function $\Phi(A)$. In this approach, the probability of choosing the product $j$ is given by:

$$S_j = P_r (U^*_ij + \gamma_g \Phi(A_j) \geq U^*_ir + \gamma_g \Phi(A_r), \forall r \in J)$$  (8)

where product $r$ belongs to group $g'$ and $J$ is the total set of products in the market (included the outside product).

There are two equivalent alternatives to make the aggregation:

- $\zeta_{ig} + (1 - \sigma)\epsilon_{ij}$ is an extreme value random variable, or
- $(1 - \sigma)\epsilon_{ij}$ is an distributed extreme value and $\zeta_{ig}$ is a segment effect that is estimated by means of segment dummies:

$$U^*_ij \gamma_g + \gamma_g \Phi(A_j) = X_j\beta + \alpha_g p_j + \xi_j + \gamma_g \Phi(A_j) + \sum_{g \in G} d_{jg} \zeta_{ig} + (1 - \sigma)\epsilon_{ij}$$  (9)

where $d_{jg}$ is a dummy variable of segment $g$ and $G$ is the whole of segments in the considered market. In the discrete choice model with income effects the second option is used to avoid identification problems.

Given consumers’ mean utility $\delta_j$ from consumption of good $j$ is defined as:

$$\delta_j \equiv X_j\beta + \alpha_g p_j + \xi_j$$  (10)

the market share for product $j$ (purchase probability) corresponds to

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13 See Appendix 3.
14 The economic theory suggests that persuasive advertising leads to product differentiation which reduces consumer’s price sensitivity (See Kaldor (1950)). In terms of the model considered, this means to replace $\alpha_g$ with: $\alpha_{gj} = \alpha_{0g} + \alpha_{1g} \Phi(A_j)$, where we expected that the negative initial effect of price ($\alpha_{gj} < 0$) will be smaller (absolute value) with advertising ($\alpha_{1g} > 0$). However, in my data set, this effect is not present. A possible explanation is that in the considered market predominates informative advertising. Moreover there are not empirical regularity of this effect in previous studies. Jedlic, Mela and Gupta (1999) use scanner data for a nonfood mature product category and find that this effect isn’t significant, while Kaul and Wittink (1995) summarize works which find evidences of it.
15 See Berry (1994).
\[ S_j = \frac{\exp[(\delta_j + \gamma_g \Phi(A_j))/(1 - \sigma)]}{\sum_{g} D_g} \] (11)

where:
\[ D_g = \sum_{k \in \psi_g} \exp \left[ \left( \delta_k + \gamma_g \Phi(A_k) \right)/(1 - \sigma) \right] \] (12)

and \( \psi_g \) is the set of models that belong to group \( g \).

The specification of demand system is completed with the introduction of an outside good or the alternative of not buying any of the models, only member of its group that is included in \( G \). The mean utility of the outside good is normalized to zero, so its market share is:
\[ S_0 = \frac{1}{\sum_{g} D_g} \] (13)

The estimation equation for the market share of product \( j \) is obtained by taking logarithms and subtracting the logarithm of the market share of the outside good from the market share of each product, i.e.:
\[ \ln S_j - \ln S_0 = \zeta_j^* + X_j \beta^* + \alpha_g^* p_j + \gamma_g^* \Phi(A_j) + \xi_j^* \] (14)

where the asterisk indicates that the coefficients must be understood to be divided by the factor \( (1 - \sigma) \).

\( \sigma \) is estimated independently (in a second step) by means of an auxiliary regression:
\[ \ln S_g - \ln S_0 = (1 - \sigma) \ln \widehat{D}_g^* \] (15)

where \( S_g \) is the market share of the group \( g \) and \( \widehat{D}_g^* \) is the estimated \( D_g \) constructed with the price and advertising impact values predicted using the instruments (to avoid simultaneity biases):
\[ \widehat{D}_g^* \equiv \sum_{k \in \psi_g} \exp \left[ \frac{\delta_k}{(1 - \sigma)} \right] \] (16)

4 Estimation

4.1 Data

The analysis is performed for the Spanish car market, using a unbalanced panel data\(^\text{16}\) on a monthly basis from January 1990 to December 2000 (132 months), with “model” as elemental unit of analysis. The original sources of the data set are A.N.F.A.C.\(^\text{17}\), “Guía del comprador de coches” magazine and “Infoadex”.

\(^\text{16}\) During the sample period, there are entries and exits of car models.

\(^\text{17}\) Asociación Nacional de Fabricantes de automóviles y camiones.
firm\textsuperscript{18}, which report new car registrations (sales), characteristics and advertising expenditure for all models, respectively.

In the data for every model the most representative (sold) version is considered, and the characteristics of the model are taken from it. This rule leads to 257 distinct models, sold in the home market and offered by 33 different brands (multiproduct firms). Finally, treating a model/month as an observation, the total sample size is 16,362, observations arranged as a “data pool” (temporal observations of the model are consecutive). The information gathered for each model include price, new car registrations, segment, brand, advertising expenditures and mechanic, design and equipment characteristics.

A important feature of the data is its high frequency, which helps to overcome the data−interval−bias. Clarke (1976) finds that estimated effects and degree of carryover of advertising are sensitive to the frequency of data used, denoted the data-interval-bias problem. The use of annual advertising data when the effects of advertising on sales depreciate over a shorter period of time can lead to biased estimations of advertising effects.

The evolution of the Spanish car market over the sample period (the nineties) is summarized in Figure 1, using adjusted price, registrations and advertising expenditure indexes. During the first half of the decade, total registrations fluctuate considerably with an important downturn by year 1993. From 1995 on, it shows a more stable and growing trend. However, the car price continuously reduced since 1991. As expected, advertising expenditure parallels the evolution of sales, with the exception of 1992\textsuperscript{19}. Finally, it’s observed a important increase of new model and version with improved characteristics.

The seasonality component of advertising expenditure is similar to the seasonality of sales. On August and September the Spanish car market is stopped, while on June and July are the months with highest sales (see Figure 3). This evolution provides a strong evidence of the expected endogeneity of advertising (firms choose advertising considering variables that determine their demand).

Figure 2, which links advertising expenditure and the log of sales, strongly suggests that advertising has diminishing returns, consistently with our assumed effect of advertising.

The Spanish car market could be divided in 5 or 8 categories, given by the own industry. This paper uses the 5 segment definition: small, compact, intermediance, luxury and minivan. Using 5 segments, instead of 8, allows us to associate for each segment characteristics and behaviors that are very different among them. Table 1 shows average characteristics of each segments. Attributes increase with the category of the segment and advertising expenditure is quite greater in the models that belong to lower categories (for example, on average, advertising expenditure in small cars is 8 times higher than in luxury cars).

The potential market size (measure of consumers in a market) is given by the

\textsuperscript{18}Infosadex computes advertising expenditure, monitoring daily communication markets and their prices.

\textsuperscript{19}Possible firms’ reaction to car tariffs dismantling at the begining of the decade
number of Spanish households\textsuperscript{20}. This quarterly data is provided by E.P.A.\textsuperscript{21}. Market shares are computed as sales of each model divided by the total market size and the market share of the outside good is one minus the sum of model market shares.

4.2 Estimation strategy

Supply decisions for differentiated products can be seen as taken in two stages: first, firms determine the quality of their products, then producers set price and advertising given product characteristics. Therefore advertising expenditure invested by firm, just like price, is a short-term strategic variable, too. Both are chosen by the firm considering the rest of variables which determine the firm’s demand, including characteristics that are unobserved by researchers but known by market agents (producers or firms and consumers). These unobserved product-specific characteristics \((u_j)\), unobserved brand-specific characteristics \((u_g)\), together with model and time specific disturbance\textsuperscript{22} \((u_{jt})\), are treated as error term \((\xi_{jt})\) in the discrete choice model approach:

\[
\xi_{jt} = u_g + u_j + u_{jt}
\]

Therefore, in the demand regression the explanatory variables advertising and price will be correlated with the error term, making these variables endogenous.

Firms-specific dummies can be included to control unobserved brand characteristics \((u_g)\) that affect the consumer’s choice (prestige, credit terms,...)\textsuperscript{23}. But given \(u_j\) the endogeneity problem still remains.

In the context of discrete choice model, the endogeneity problem has been addressed in one of two ways: focusing only on the demand side and instrumenting for endogenous variables (Nevo (2001)), or postulating a behavioral rule by which firms set their prices and advertising (given optimizing behavior of the firm), and use this information in the estimation of the demand parameters (Besanko, Gup and Jain (1998)). The second method imposes a restricted competitive assumption (in advertising and price) on the supply side, and an incorrect specification of the firms’ decisions could lead to biased estimates. Given that in our sample there are not obvious behavior rules, this paper chooses the first alternative, in a GMM framework.

Given that price and advertising are endogenous in the demand equation, it is critical to identify a set of instrumental variables which are correlated with unobserved characteristics (independence condition) but correlated with pricing and advertising (relevance condition). In the literature, there are essentially

\textsuperscript{20}The potential market size is often observed as the population of a market (population or household), although it can be left as a parameter to be estimated (see Berry(1990)).

\textsuperscript{21}Encuesta de población activa.

\textsuperscript{22}The model and time specific disturbance is assumed uncorrelate across model and time

\textsuperscript{23}Other likely source of endogeneity is brand and time specific disturbance \((u_{jt})\). To test its importance, the model was estimated including brand-time dummies. The result shows no significantly changes on advertising and price effects.
three potential sources of instrumental variables: variation in marginal cost across firms, measurement resulted from the joint ownership structure of product in the market (multiproduct firms) and measures of the level of competition.

The time dimension of the data is short in relation to the pace of variation of these measures whereas price and advertising change frequently, then they are not likely much correlated with advertising and price\textsuperscript{24}. Other way is to estimate the equation taking differences in order to difference out the individual component of error term ($u_j$) and to use lags of the endogenous variable in order to set valid moment restrictions (see Arellano and Honoré (2001)). The differentiation of the characteristics eliminates crucial information, given their small monthly variation, exacerbating the variance of the disturbances. In this approach the instrument more desirable are: the differences of the prices (or advertising) with respect to their individual time means, $\hat{p}_{jt} = p_{jt} - \left(\frac{1}{T}\right)\sum p_{js}$, lagged a number of periods. Instruments of this type were first proposed by Bhargare and Sargan (1983), and its moment restrictions have been studied in Arellano and Bover (1995).

Given that the demand equation is nonlinear in the carryover effect of advertising and the parameter of advertising impact $k$, the model is estimated in a nonlinear GMM framework. The GMM objective function is minimized using the algorithm of Broyden, Fletcher, Goldfarb, and Shanno and the step method of Dennis and Schanabel (1983). The initial parameters values are taken of a preliminar linear estimation: for each values of the carryover effect of advertising ($\lambda$), the GMM estimated coefficients are obtained ($\hat{\beta}_{GMM}(\lambda)$). In a second step the carryover effect of advertising is estimated. To estimate it, the objective function is evaluated with these estimated coefficients and again minimized

\[
\hat{\lambda}_{GMM}(\lambda) = \arg \min \ S_N(\hat{\beta}_{GMM}(\lambda)) = b_N(\hat{\beta}_{GMM}(\lambda))\ A_N\ b_N(\hat{\beta}_{GMM}(\lambda))
\]

where\textsuperscript{25} $b_N(\hat{\beta}_{GMM}(\lambda)) = \frac{1}{N}Z(y - X\hat{\beta}_{GMM}(\lambda))$ are the sample moment conditions and $A_N = (Z'Z/N)^{-1}$ is the optimal weight matrix.

To obtain inferences robust to serial correlation, a robust estimate of the variance-covariance matrix is used (see Newey and West (1987)). Then statistics are computed:

\[
V(\beta) = (DA_N D)^{-1} D A_N V A_N D (DA_N D)^{-1}
\]

where $D = Z\frac{\partial f(x, \beta, \lambda, k)}{\partial \beta}$ and $V' = Zu u Z$, using consistent estimation obtained of the preliminar linear estimation.

\textsuperscript{24} All instruments have been considered, with the exception of cost because these are not available, and the independence and relevance conditions are worse checked.

\textsuperscript{25} Where I use the notation $y = f(X, \beta, \lambda, k) + u$, $y = (y_1, ... y_N)$, $X = (x_1, ..., x_N)$, and $Z = (z_1, ..., z_N)$.
4.3 Econometric specification

The dependent variable consists of the log of model monthly share minus the log of the outside good monthly share, both computed taking the current number of households as the market size. Among the explanatory variables, we can distinguish the model attributes, price, goodwill stock of advertising, and a set of month, year, brand and segment dummies to control for seasonality, unspecified time effects, firm-specific factors and segment effect, respectively.

The specification employs the same attributes of BLP, replacing the air conditioning for the maximum speed. Then the employed attributes are: size, ratio cubic centimeters to weight, ratio km to litre and maximum speed, as measures of size and safety, power, fuel efficiency and luxury, respectively. The use of other characteristics or more complete list does not change the main results.

In the car industry, it’s known the existence of the models ‘life cycle, which suggests that valuation of a model is associated to model’s age (time of permanence of the car model on the market). The change of consumers’ value over the age can be explained by the fact that consumers have preference for the novelty or latest design and at same time they valuate the prestige or good reputation which old models posses. To control these preference, model’s age and its square are included in the demand equation.

Given the car market is divided in 5 categories, the specification employs 5 segment, price and advertising26 effects.

Several instrument sets were tested using price and advertising differences with respect to the individual time means lagged a different number of periods. The instruments of price and advertising lagged between 4 and 9 months have same characteristics (correlation with the error term and current variable). The reported estimate uses as instruments the third, sixth and ninth lags of the (segment) price variables in differences, and sixth lag of the (segment) goodwill variables in differences. Other combination of these instruments does not mean significant changes of the results.

After the estimation of the demand equation, the parameter $\sigma$ is computed from the auxiliary regression (14), employing month, year and segment dummies (and a constant).

Appendix 1 contains definitions and measure units of the variables employed in the estimation.

5 Demand estimation

Estimation results of four specifications of the model are presented in Table 2. The first column corresponds to the model without advertising. The second column corresponds to the specification suggested in this paper, where advertising is included as a goodwill stock, considered endogenous variable and using a concave and enclose function. The next two columns include advertising but using 26 Advertising and price effects are specified by interaction between segment dummies and respective variable.
lineal function (column III) or considering it as exogenous variable (column IV).

Regardless of the specification, monthly dummies fit correctly the seasonal component of the sales (June and July are the months with the highest sales, while on August and September are minimum). The sales downturn in 1993 and its growing trend from 1995 until 1999 is confirmed by the years time dummies. The brand dummies show the prestige of firms as Mercedes, Audi, Alfa Romeo, Porsche, Jaguar and BMW. The Sargan test confirms the validity of the employed instruments, rejecting the overidentification at 95% on all cases.

The estimated coefficients on attributes always have the expected sign, with the exception of the measures of fuel efficiency (Km/l) which is negative, although, not significant.

Price effects exhibit, regardless of the specification, the expected pattern: negative and with a lower coefficient (marginal utility) for higher segment. When advertising is not included, the price effects are overestimated. The price bias is greater in the lowest segments, and comparing with specification suggested, on average, is 60%.

The age parameter, that contains the preference for novelty, is negative and its square, that contains the effect of model’s prestige, is positive. Moreover, in automobile market the new models are severely advertised and over the time its advertising expenditure reduces. The negative correlation between advertising and model’s age makes that the age parameter increases in economical and statistical significativity when advertising is no included.

For the suggested specification, advertising coefficients have positive sign and, just like price, are different among segments and decreasing with the category of the segment. The estimated parameter $\sigma$ is 0.7, which is close to estimations obtained in similar studies. For the Spanish car market from 1991 to 1996, Jaumandreu and Moral (2001) report 0.842, and 0.706 is found by Brenkers and Verboven (2002) for five European car market during 1970-1999.

When the goodwill stock of advertising is included with a lineal function, instead of a concave one, the advertising coefficients follow an opposite pattern, being increasing with the category of the segment. If the advertising returns are decreasing, then in the segments with bigger advertising expenditures the associated returns will be smaller, and using a lineal function means underestimated the advertising effect. Table 1 shows that advertising expenditures are bigger in lower range segments and therefore the above pattern is explained.

If advertising is included as an exogenous variable, the price effects are underestimated.

The pattern of substitution due to changes of prices, given estimated parameters, are summarized in Table 3 and Table 4, which report average price-demand elasticities and average price-demand semi-elasticities (own and cross) by the segments, respectively. Semi-elasticity is the percent change in the demand when the price of model changes by ten thousands of euros. The estimated elasticities and semi-elasticities are below previous studies, which don’t include

\[27\] The model predicts that superior segment have associated a larger income, so a smaller marginal utility of income.
advertising. For example, in Jaumandreu and Moral (2001) the average own price elasticity reported is larger. This difference may be explained by the overestimating of price effects without advertising. The Table 4 reports semi-elasticities that are rather than elasticities to control for large price differences between models that would create the illusion that relative price increases of expensive cars are associated with large substitution effects. The pattern is as expected: price semi-elasticities tend to be lower the higher the segment and the magnitude of cross-price semi-elasticities depend on the degree of similarity between models (automobiles that belong to the same segment have bigger cross-price elasticities).

6 Assess the effects of advertising

The marginal effect of current advertising on sales is computed from the market share of each product (first derivative of market share respect to it). Depending on advertised product the effect will be different (own product, product belong to same segment or product belong to different segment). In particular:

\[
\frac{\partial S_j}{\partial a_j} = \gamma_g S_j \frac{\partial \Phi(A_j)}{\partial A_j} \left[ \frac{1}{1 - \sigma} - S_j \left( 1 + \frac{\sigma}{(1 - \sigma) S_g} \right) \right] \tag{17}
\]

\[
\frac{\partial S_j}{\partial a_k} = -\gamma_g S_j S_k \frac{\partial \Phi(A_k)}{\partial A_k} \left[ 1 + \frac{\sigma}{(1 - \sigma) S_g} \right] \tag{18}
\]

\[
\frac{\partial S_j}{\partial a_s} = -\gamma_m S_j S_s \frac{\partial \Phi(A_s)}{\partial A_s} \tag{19}
\]

where the product \( j \) and \( k \) belong to the same segment \( g \), and the product \( s \) belongs to the different segment \( m \).

From the above equations, current advertising-demand elasticities are obtained as

\[
\varepsilon_{jj} = \gamma_g \frac{\partial \Phi(A_j)}{\partial A_j} a_j \left[ \frac{1}{1 - \sigma} - S_j \left( 1 + \frac{\sigma}{(1 - \sigma) S_g} \right) \right] \tag{20}
\]

\[
\varepsilon_{jk} = -\gamma_g \frac{\partial \Phi(A_k)}{\partial A_k} a_k S_k \left[ 1 + \frac{\sigma}{(1 - \sigma) S_g} \right] \tag{21}
\]

\[
\varepsilon_{js} = -\gamma_m \frac{\partial \Phi(A_s)}{\partial A_s} a_s S_s \tag{22}
\]

where \( \varepsilon_{jj} \) is the own-advertising elasticity, \( \varepsilon_{jk} \) is intra-segment cross-advertising elasticity and \( \varepsilon_{js} \) is cross-segment cross-advertising elasticity. The two first elasticities depend on \( \sigma \) (parameter that measures the substitutability across products which belong to the same group). So in less differentiated markets (greater \( \sigma \)) the own-advertising elasticity and intra-segment cross-advertising elasticity (absolute value) will be large.

\[\text{See Appendix 3.}\]
Estimated elasticities of advertising are reported in Table 5. Consistently with the literature, advertising elasticities are smaller than price elasticities. Estimated own-advertising elasticities are in a range from 0.1 to 0.044 and the market average is 0.07. These estimates are similar to previous studies, for example: the average elasticity for mature good in Lodish (1995) is 0.05, Assmus, Farley and Lehmann (1984) report 0.15, and in Jediti, Mela and Gupa (1999) is 0.08.

Given the definition of market share,

\[ S_j + \sum_{r \neq j, r \in J} S_r + S_0 = 1 \]  \hspace{1cm} (23)

where \( J \) is the set of products in the market, besides the outside good. Then, the effect of own advertising might be due both to the fact that advertising attracts customers of rival products (business stealing or predatory effect), and to the fact that new customers choose to buy a product instead of not buying at all (spillover or market enlargement effect). In order to disentangle these effects one should look at the marginal effect of advertising on the other product and on the outside good:

\[
\frac{\partial S_j}{\partial a_j} = - \left[ \sum_{r \neq j, r \in J} \frac{\partial S_r}{\partial a_j} + \frac{\partial S_0}{\partial a_j} \right] \tag{24}
\]

Both effects are measured by the cross effects on other products; the spillover effect will be measured by the cross effect on the outside good, and the business stealing effect by the cross effect on rival goods:

\[
\sum_{r \neq j, r \in J} \frac{\partial S_r}{\partial a_j} = \sum_{k \in \varphi_g \setminus \psi_g} - \gamma_g \frac{\partial \Phi(A_j)}{\partial A_j} S_j S_k \left[ 1 + \frac{\sigma}{(1 - \sigma)} \frac{1}{S_g} \right] + \sum_{s \in \varphi_g \setminus \psi_g} - \gamma_g \frac{\partial \Phi(A_j)}{\partial A_j} S_j S_s \]  \hspace{1cm} (25)

\[
\frac{\partial S_0}{\partial a_j} = - \gamma_g \frac{\partial \Phi(A_j)}{\partial A_j} S_j S_0 \]  \hspace{1cm} (26)

The results discussed in the previous section show that advertising increases sales of advertised car. In Table 6, the overall effect of a million (euros) of advertising expenditure is divided in business stealing effect and spillover effect, measured in unit of car\(^{29}\). For all segments, the results show that both effects

\(^{29}\)Multiplying by potential market \( M \):
are present, but the business stealing effect (on average, 70%) dominates over the market expansion effect (on average, 30%).

The fact that the business stealing effect is the dominate effect, means advertising plays a combative role in the Spanish automobile market. This result is consistent with previous empirical works: Lambin (1976) holds that advertising is mainly combative in nature. However the effect advertising on primary demand is significant (changes on primary demand can be then derived from changes on total advertising expenditure, and no only from underlying social and environmental considerations, as Borden (1942) declares).

Moreover the estimated carryover effect of advertising is 0.875. So, firm’s current advertising is associated with increases in its future sales, and this effect runs out on average in 15 months (depending on segment)\(^{30}\).

\section{Conclusion}

This paper assesses the role of advertising from demand side of a differentiated and infrequently purchased good market, that is the Spanish automobile industry of the 90s, in a discrete choice model approach. Specifically, three questions are addressed: the demand sensibility to advertising, the effects of current advertising on future sales (carryover effect of advertising) and the nature of advertising in the market (spillover and business stealing effect).

Unlike frequently purchased good, I obtain an important demand sensibility to advertising, that changes across the automobile segments (like price, diminishing with the category), and a significant carryover effect. The average own-advertising elasticity estimated is about 0.7 and the estimated carryover effect of advertising is 0.875, that means firm’s current advertising is associated with increases in its future sales which runs out on average in 15 months. Moreover, the effect of own advertising is mainly due to the fact that advertising attracts customers of rival products (70%), although the fact that new customers choose to buy a product instead of not buy any product at all, is observed too (30%). So the predominant component of advertising in the Spanish automobile market is predatory.

In the demand estimation, using the discrete choice model with income effects, it’s show a significant overestimation of the price effects when advertising is no included. The price effects are overestimated , on average, 70%. Finally, if a lineal function, instead of concave one, is employed to specify advertising (assuming dismissing returns) the advertising effects are underestimated.

Future works may test the differences of the carryover effect and nature of advertising between frequently and infrequently purchased good. And the possibility to have access to data with distinction between informative and persuasive

\begin{equation}
M \frac{\partial S_j}{\partial a_j} = -M \sum_{k \neq j} \frac{\partial S_k}{\partial a_j} + \frac{\partial S_0}{\partial a_j} = \frac{\partial q_j}{\partial a_j}
\end{equation}

\(^{30}\)That is: \(\frac{\partial q}{\partial a} \approx 0 \text{ at } \tau = 18 + t\), where \(q\) is sales.
advertising, will allow us to make a structural specification of advertising impact and to make conclusions about its Microeconomic implications.
Appendix 1: Variables definitions

Variables employed

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market share for product $j$ ($S_j$)</td>
<td>units sales of model / No. households</td>
</tr>
<tr>
<td>Market share for outside good ($S_0$)</td>
<td>$1 - [\text{all units sales} / \text{No. households}]$</td>
</tr>
<tr>
<td>Market share for segment $g$ ($S_g$)</td>
<td>units sales of model belonged to segment $g$ / No. households</td>
</tr>
<tr>
<td>Price for product $j$ ($P_j$)</td>
<td>Market price in ten thousand of euros circa 1995</td>
</tr>
<tr>
<td>Goodwill stock of advertising ($A_j$)</td>
<td>Stock of advertising for product $j$ in millions of euros circa 1995$^1$</td>
</tr>
<tr>
<td>Sales for product $j$ ($q_j$)</td>
<td>units sales of model</td>
</tr>
<tr>
<td>CC/Kg</td>
<td>Auto cubic capacity per kg of car</td>
</tr>
<tr>
<td></td>
<td>($\text{cm}^3/\text{kg}$)</td>
</tr>
<tr>
<td>Size</td>
<td>length times width ($\text{m}^2$)</td>
</tr>
<tr>
<td>Max. speed</td>
<td>Maximum speed (kph)</td>
</tr>
<tr>
<td>Km/l</td>
<td>Kms covered at a constant speed of 90 kph with a litre of gasoline</td>
</tr>
<tr>
<td>Age</td>
<td>Model age (months)</td>
</tr>
</tbody>
</table>

Notes: 1. From 1990 to 1992 available data is annual, so to have monthly frequency it is divided by 12. The fit of suggested function of goodwill and the data depends of the measure of advertising, then a previous analysis is necessary. When the entry of model in the market is before 1990, the considered $A_0$ is equal to the goodwill that model has if the previous advertising expenditures had been the average expenditure in 1990, given the estimated carryover effect of advertising.
Appendix 2: Advertising specification

Market shares in the model are:

\[ S_j = \frac{e^{\delta_j + \gamma \Phi(A_j)}}{1 + \sum_{r \in J} e^{\delta_r + \gamma \Phi(A_r)}} \]

and given the outside good share\(^{31}\), then the demand of the product \( j \), taking log, can be written:

\[ \frac{S_j}{S_0} = e^{\delta_j + \gamma \Phi(A_j)} = \frac{S_jM}{S_0M} = \frac{q_j}{q_0} \]

\[ q_j = Qe^{\gamma \Phi(A_j)} \]

The returns of advertising are measured by second derived of demand with respect to advertising:

\[ \frac{\partial q_j}{\partial A_j} = \gamma \frac{\partial \Phi(A_j)}{\partial A_j} Qe^{\gamma \Phi(A_j)} \]

\[ \frac{\partial^2 q_j}{\partial^2 a_j} = \gamma \left[ \left( \frac{\partial \Phi(A_j)}{\partial A_j} \right)^2 + \left( \frac{\partial^2 \Phi(A_j)}{\partial^2 A_j} \right) \right] Qe^{\gamma \Phi(A_j)} \]

Given estimated parameters, the returns for each considered function are:

• Lineal function (\( \Phi(A_j) = A_j \)):

\[ \frac{\partial q_j}{\partial a_j} = \gamma Qe^{\gamma A_j} > 0 \]

\[ \frac{\partial^2 q_j}{\partial^2 a_j} = \gamma^2 Qe^{\gamma A_j} > 0 \]

• Concave and enclosed function (\( \Phi(A_j) = \frac{A_j}{k + A_j} \)):

\[ \frac{\partial q_j}{\partial a_j} = \frac{k}{(k + A_j)^2} Qe^{\gamma A_j} > 0 \]

\[ \frac{\partial^2 q_j}{\partial^2 a_j} = \left[ \gamma \left( \frac{k^2}{(k + A_j)^4} - \frac{2k}{(k + A_j)^3} \right) \right] Qe^{\gamma A_j} = -\gamma kQe^{\gamma A_j} \left( \frac{A_j}{(1 + A_j)^4} (2k^2 + [2A_j - \gamma] k) \right) < 0 \]

Given the estimated coefficients, the second derivative is negative.

\(^{31} S_0 = \frac{1}{1 + \sum_{r \in J} e^\delta e^{\gamma \Phi(A_r)}} \)
Appendix 3: Demand elasticities

Given the indirect utility function: \( u_j = -\alpha (y, p_j) p_j + u(x_j) + \epsilon_j \). Price and advertising (own and cross) effects can be written as\(^{32}\):

\[
\frac{\partial S_j}{\partial p_j} = E_y \frac{\partial S_j}{\partial p_j} = -\int \tilde{\alpha}(y, p_j) S_{j/y} (1 - S_{j/y}) f(y) dy
\]

\[
= -\alpha S_{j/y} (1 - S_{j/y}) (1 + w_j)
\]

\[
\frac{\partial S_k}{\partial p_j} = E_y \frac{\partial S_k}{\partial p_j} = -\int \tilde{\alpha}(y, p_j) S_{j/y} S_{k/y} f(y) dy
\]

\[
= -\alpha S_{j/y} S_{k/y} (1 + w_{jk})
\]

\[
\frac{\partial S_j}{\partial \alpha_j} = E_y \frac{\partial S_j}{\partial \alpha_j} = \int \gamma_j \frac{\partial \Phi(A_j)}{\partial \alpha_j} S_{j/y} (1 - S_{j/y}) f(y) dy
\]

\[
= \gamma_j \frac{\partial \Phi(A_j)}{\partial \alpha_j} S_{j/y} (1 + w_j)
\]

\[
\frac{\partial S_k}{\partial \alpha_j} = E_y \frac{\partial S_k}{\partial \alpha_j} = \int \gamma_j \frac{\partial \Phi(A_j)}{\partial \alpha_j} S_{k/y} f(y) dy
\]

\[
= \gamma_j \frac{\partial \Phi(A_j)}{\partial \alpha_j} S_{k/y} (1 + w_{jk})
\]

Cluster products in groups, indexed \( g \) and assume:

\[
w_j = \frac{\sigma}{1 - \sigma} \frac{S_g - S_j}{1 - S_j}
\]

\[
w_g = \frac{\sigma}{1 - \sigma} \frac{1}{S_g}
\]

\[
w_{gm} = 0
\]

where a product \( j \) belongs to group \( g \)^{33}, \( w_g \) is common for cross-price effects between products belonging to the group and \( w_{gm} \) for the cross-price effects that involving two different groups. If it’s assumed that \( \alpha_j = \alpha \), it easy to see that price and advertising effects are now the nested Logit price and advertising effects. And if it’s assumed that \( \alpha_j \) is constant only between models belong to the same segment, price and advertising effects are now the discrete choice model with income effects price and advertising. Therefore both models have similar price and advertising effects with the exception of \( \alpha_j \) that is assumed constant only between products belonged to same segment in the discrete choice model with income effects.

\(^{32}\)where \( \alpha_j = \int \tilde{\alpha}(y, p_j) f(y) dy \), \( \tilde{\alpha}(y, p_j) = \alpha(y, p_j)(1 + \frac{p_j}{\sigma} \frac{\partial \alpha}{\partial p_j}) \), \( w_{jk} = \text{Cov}[\alpha S_{j/y}, S_{k/y}] / \alpha_j S_j S_k \) and \( w_j = \text{Cov}[\alpha S_{j/y}, S_{j/y}] / \alpha S_{j/y}^2 \). See, Jaumandreu and Moral (2001).

\(^{33}\)Define \( S_g = \sum_{k \in \psi_g} S_k \), where \( \psi_g \) is the set of model belong to segment \( g \).
References


Table 1: Segment in the Spanish car market

<table>
<thead>
<tr>
<th></th>
<th>Small</th>
<th>Compact</th>
<th>Intermediate</th>
<th>Luxury</th>
<th>Minivan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales$^2$</td>
<td>1,401.5</td>
<td>1189.1</td>
<td>607.3</td>
<td>111.8</td>
<td>133.6</td>
</tr>
<tr>
<td>Advertising$^3$</td>
<td>0.603</td>
<td>0.567</td>
<td>0.339</td>
<td>0.065</td>
<td>0.121</td>
</tr>
<tr>
<td>Price</td>
<td>7.42</td>
<td>11.53</td>
<td>16.44</td>
<td>28.96</td>
<td>17.50</td>
</tr>
<tr>
<td>CC/Kg</td>
<td>1.46</td>
<td>1.53</td>
<td>1.56</td>
<td>1.73</td>
<td>1.43</td>
</tr>
<tr>
<td>Size</td>
<td>5.78</td>
<td>6.96</td>
<td>7.61</td>
<td>8.23</td>
<td>7.86</td>
</tr>
<tr>
<td>Km/l</td>
<td>0.20</td>
<td>0.18</td>
<td>0.16</td>
<td>0.14</td>
<td>0.14</td>
</tr>
<tr>
<td>Max. speed</td>
<td>155.37</td>
<td>181.77</td>
<td>195.44</td>
<td>215.70</td>
<td>174.68</td>
</tr>
</tbody>
</table>

Notes:
1. Monthly average of model
2. Unit sales
3. Advertisement expenditure in millions of euros circa 1995
4. The rest of variables are described in Appendix 1
Table 2: Demand for car model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Without advertising</th>
<th>(1/A) endogenous</th>
<th>With 3(1/A)</th>
<th>A (1/A)</th>
<th>With 7(1/A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-17.71 (-6.46)</td>
<td>-14.32 (-8.89)</td>
<td>-14.71 (-7.82)</td>
<td>-14.27 (-9.20)</td>
<td></td>
</tr>
<tr>
<td>Attributes:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CC/Kg</td>
<td>0.62 (1.26)</td>
<td>0.34 (1.08)</td>
<td>0.41 (1.79)</td>
<td>0.26 (0.85)</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>0.47 (2.13)</td>
<td>0.22 (1.60)</td>
<td>0.32 (1.96)</td>
<td>0.14 (1.11)</td>
<td></td>
</tr>
<tr>
<td>Km/l</td>
<td>2.03 (0.39)</td>
<td>-2.42 (-0.69)</td>
<td>-2.68 (-0.65)</td>
<td>-2.86 (-0.87)</td>
<td></td>
</tr>
<tr>
<td>Max. speed</td>
<td>0.04 (3.51)</td>
<td>0.02 (3.58)</td>
<td>0.02 (3.31)</td>
<td>0.02 (3.59)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.005 (-2.17)</td>
<td>-0.002 (-1.40)</td>
<td>-0.003 (-1.85)</td>
<td>-0.003 (-1.67)</td>
<td></td>
</tr>
<tr>
<td>Age(^2)</td>
<td>0.00003 (2.70)</td>
<td>0.00002 (3.03)</td>
<td>0.00002 (3.11)</td>
<td>0.00002 (3.24)</td>
<td></td>
</tr>
<tr>
<td>Price effect:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>-5.28 (-1.73)</td>
<td>-3.01 (-2.09)</td>
<td>-3.86 (-1.97)</td>
<td>-2.16 (-2.14)</td>
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<tr>
<td>Compact</td>
<td>-4.47 (-2.85)</td>
<td>-2.05 (-2.54)</td>
<td>-2.84 (-2.87)</td>
<td>-1.68 (-1.81)</td>
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</tr>
<tr>
<td>Intermediate</td>
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<td>-1.62 (-3.71)</td>
<td>-1.85 (-3.49)</td>
<td>-1.56 (-3.68)</td>
<td></td>
</tr>
<tr>
<td>Luxury</td>
<td>-1.22 (-3.24)</td>
<td>-0.90 (-3.52)</td>
<td>-1.20 (-3.48)</td>
<td>-0.81 (-3.24)</td>
<td></td>
</tr>
<tr>
<td>Minivan</td>
<td>-2.56 (-1.65)</td>
<td>-1.59 (-1.95)</td>
<td>-2.12 (-2.20)</td>
<td>-1.24 (-1.70)</td>
<td></td>
</tr>
<tr>
<td>Advertising effect:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>4.70 (9.55)</td>
<td>0.15 (8.50)</td>
<td>3.93 (11.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td>4.61 (7.98)</td>
<td>0.15 (8.43)</td>
<td>3.59 (8.23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate</td>
<td>4.42 (7.65)</td>
<td>0.16 (4.18)</td>
<td>3.35 (10.59)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Luxury</td>
<td>4.32 (9.26)</td>
<td>0.32 (5.92)</td>
<td>2.06 (6.67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minivan</td>
<td>3.47 (4.60)</td>
<td>0.26 (3.30)</td>
<td>1.93 (3.60)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carryover effect of advertising ((\lambda)):</td>
<td>0.8751</td>
<td>0.9</td>
<td>0.896</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concave parameter ((k)) :</td>
<td>6.53</td>
<td></td>
<td>1.61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sustituibility ((\sigma)) :</td>
<td>0.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: 1. Instruments: differences of variable with respect to their time lagged 3, 6 and 9 months, for price, and 6 for advertising when is considered and as endogenous variable.
2. Instrument lagged 7 months imply that model with 7 and fewer observations must be removed.
3. (.) : Standard errors are robust heteroskedasticity and serial correlation.
4. Segment effects and brand, time and seasonal dummies are included in the estimation.
### Table 3: Average\(^1\) price elasticities

<table>
<thead>
<tr>
<th></th>
<th>Own</th>
<th>Intra segment</th>
<th>Cross segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>2.093</td>
<td>-0.054</td>
<td>-0.85e-04</td>
</tr>
<tr>
<td>Compact</td>
<td>2.201</td>
<td>-0.055</td>
<td>-0.83e-04</td>
</tr>
<tr>
<td>Intermediate</td>
<td>2.55</td>
<td>-0.031</td>
<td>-1.00e-04</td>
</tr>
<tr>
<td>Luxury</td>
<td>2.478</td>
<td>-0.005</td>
<td>-1.28e-04</td>
</tr>
<tr>
<td>Minivan</td>
<td>2.644</td>
<td>-0.008</td>
<td>-1.08e-04</td>
</tr>
<tr>
<td>Market*</td>
<td>2.393</td>
<td>-0.032</td>
<td>-1.08e-04</td>
</tr>
</tbody>
</table>

**Note:**
1. Average of elasticities of the models, obtained from estimated parameters and average values of the models.
2. Average of elasticities of the segments.

### Table 4: Average\(^1\) price semi-elasticities\(^2\)

<table>
<thead>
<tr>
<th></th>
<th>Own</th>
<th>Intra segment</th>
<th>Cross segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>2.931</td>
<td>-0.069</td>
<td>-0.59e-04</td>
</tr>
<tr>
<td>Compact</td>
<td>1.951</td>
<td>-0.049</td>
<td>-0.79e-04</td>
</tr>
<tr>
<td>Intermediate</td>
<td>1.598</td>
<td>-0.022</td>
<td>-1.04e-04</td>
</tr>
<tr>
<td>Luxury</td>
<td>0.898</td>
<td>-0.002</td>
<td>-1.23e-04</td>
</tr>
<tr>
<td>Minivan</td>
<td>1.585</td>
<td>-0.005</td>
<td>-1.02e-04</td>
</tr>
<tr>
<td>Market(^3)</td>
<td>1.793</td>
<td>-0.029</td>
<td>-0.93e-04</td>
</tr>
</tbody>
</table>

**Note:**
1. The percent change in sales when price increases ten thousand of euros.
2. Average of semi-elasticities of the models, obtained from estimated parameters and average values of the models.
3. Average of semi-elasticities of the segments.
Table 5: Average\(^1\) advertising elasticities

<table>
<thead>
<tr>
<th></th>
<th>Own</th>
<th>Intra segment</th>
<th>Cross segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.085</td>
<td>-0.0030</td>
<td>-0.06e-04</td>
</tr>
<tr>
<td>Compact</td>
<td>0.101</td>
<td>-0.0033</td>
<td>-0.04e-04</td>
</tr>
<tr>
<td>Intermediante</td>
<td>0.087</td>
<td>-0.0017</td>
<td>-0.06e-04</td>
</tr>
<tr>
<td>Luxury</td>
<td>0.033</td>
<td>-0.0001</td>
<td>-0.07e-04</td>
</tr>
<tr>
<td>Minivan</td>
<td>0.042</td>
<td>-0.0002</td>
<td>-0.06e-04</td>
</tr>
<tr>
<td>Market*</td>
<td>0.009</td>
<td>-0.0016</td>
<td>-0.06e-04</td>
</tr>
</tbody>
</table>

Note:
1. Average of elasticities of the models, obtained from estimated parameters and average values of the models.
2. Average of elasticities of the segments.

Table 6: Average\(^1\) effect in current sales of a advertising expenditure of a million of euros

<table>
<thead>
<tr>
<th></th>
<th>Business Stealing</th>
<th>Spillover</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>135</td>
<td>59</td>
<td>194</td>
</tr>
<tr>
<td>Compact</td>
<td>132</td>
<td>58</td>
<td>190</td>
</tr>
<tr>
<td>Intermediante</td>
<td>104</td>
<td>31</td>
<td>149</td>
</tr>
<tr>
<td>Luxury</td>
<td>41</td>
<td>17</td>
<td>58</td>
</tr>
<tr>
<td>Minivan</td>
<td>41</td>
<td>17</td>
<td>58</td>
</tr>
<tr>
<td>Weigh</td>
<td>70%</td>
<td>30%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Note: Average of effects of the models, obtained from estimated parameters and average values of the models (rounded number).
Figure 1: Evolution of the Spanish automobile market

Figure 2: Dispersed graphic between log of sales and goodwill stock of advertising
Figure 3: Monthly advertising expenditure