AUTOMOBILE DEMAND, MODEL CYCLE AND AGE EFFECTS[1]

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Abstract

This paper is aimed at exploring the existence of typical patterns of automobile model life and the formal specification and test for age effects in a discrete-choice demand framework estimated with data on the models sold in the Spanish market. Estimates show that market shares' evolution entails age effects, clearly distinguishable from the impacts generated by changes in attributes and in the firms' pricing, and quantifies them. These effects bring in an autonomous factor of modification of the relevant model elasticities, full of implications for firm behavior. On average, own-price elasticities are observed to decrease until the fourth year of a model life, and then to increase again.

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1. Introduction

Car model turnover is an important characteristic of the automobile market. The entry of new models and the exit of others over time are quantitatively important. Moreover, the exit of a model and the entry of another are often the two sides of a unique operation synchronized by their manufacturer. All this raises life cycles of models. Some are short, others longer. The life of extremely successful models is boosted by producers at certain moments in time with changes in the current version, but old models are often simply replaced by new ones.

Models' life cycles are the result of the interaction between consumers' preferences and producers' decisions, but consumers' demand characteristics are likely to play a crucial role. The presence of very defined patterns of demand over the cycle of models suggests that consumers' average valuation of models is associated with model age (the time that a model has been marketed), what raises an explanation for market shares evolution over time. And consumers' age-related valuation impacts the elasticities of demand with respect to the own-price of models and the cross-prices of competitor models. The resulting equilibrium elasticities are of course endogenously determined, but the evolution of consumers' valuations brings in an important firm's non-controlled factor of modification given the remaining factors.

The purpose of this paper is to explore the effects of the age of a model on automobile demand, using techniques of the discrete-choice approach to market demand estimation with a particularly suitable panel data set. In particular, we begin by looking at the characteristics of the life cycle of models by means of a non-parametric description of the relationships between model shares and model ages. Then we specify and test for age effects on the demand for models using the discrete-choice framework (see Berry (1994), and Berry, Levinsohn and Pakes (1995) –hereafter BLP- for a paramount application to the automobile market.[1])

Consumers' change of valuation with model age is likely to have important consequences for firm behaviour. Firstly, firms are likely to respond to these changes in the short run with pricing changes. Secondly, firms are likely to carry out minor model changes in order to try to enhance the durability of the models. Thirdly, firms will adopt their models' exit-entry decisions according to the impact of evaluation on profits. Models' entry decisions are associated with large sunk costs (design, plant adaptation, launch,…), and the decisions of substituting a model for another (cannibalisation) will be adopted only when the evolution of valuations makes this change profitable. All this rends the study of the age effects on demand a necessary step previous to undertaking more complete specifications of the forces underlying product decisions.

The study relies on a newly constructed panel data set for the Spanish car market, particularly useful for studying model dynamics. Over the seven years 1990-96, we observe the monthly registrations (sales) of a total of 182 models, which account for virtually the entire market and experiment a high turnover. The data have been elaborated and matched to a database on prices and technical characteristics.

Results show that age effects exist and are important in explaining shares patterns: once model attributes and time demand determinants are accounted for, age explains a significant part of shares' evolution. Firstly, shares tend to increase until the course of the fourth year in the life of the model. Secondly, shares subsequently tend to decrease as time goes by, and this deterioration may account on average for one third of its value. Thirdly, shares of surviving models tend to be higher on average, denoting that firms decide to discontinue the models with the worst evolution. On the other hand, equilibrium elasticities betray the impact of model age: average elasticities decrease during the three first years of model life and increase afterwards.

The rest of the paper is organized as follows. Section two discusses with more detail the meaning of age effects and relates this study to other empirical findings. Section three introduces the data. Section four is devoted to a description of model's life cycles by means of non-parametric analysis. Section five explains the specification of age effects in a discrete choice framework, and section six presents the estimation strategy and results. Finally, section seven concludes. A data appendix gives some details on the sample and variables.

2. Age effects

Consumers' demand characteristics have presumably an important role in models' life cycles.[2] The existence of very defined patterns of demand over the cycle of models suggests that consumers' average valuation of models is associated to models' age, i.e., the time of permanence of the car model on the market. Shares, in fact, tend to change over time much more pronouncedly than what can be explained by observed relative model attributes.[3] One explanation is that consumers also valuate the degree by which new models possess disembodied attributes as "newness" or "latest design," and old models possess "prestige" or "good reputation," all of them attributes that change with age. Another is that consumers like a series of minor embodied but unobservable technical features included in the newest models and judge them to be incorporated (or not) in enduring models. In fact, consumers probably valuate some mix of these two types of characteristics. In any case, the evolution of valuation with models' age seems an important explanation for the evolution of market shares over time.

The effects of model age through changes of consumers' valuation can be summarized in their impact on the elasticity of demand with respect to the own-price of the model (and on the cross-price elasticities, i.e., the elasticities with respect to the prices of the competing models.) Model price resulting elasticities are of course variables endogenously determined in equilibrium, because they also depend on the firms' pricing, decisions of changing attributes and introducing models. But the evolution of consumers' valuations brings in a firms' non-controlled factor of modification of elasticities, given the remaining factors, as time goes by. Equilibrium elasticities are an important tool of description and analysis (e.g., in the study of mark-ups), and hence the impact of age on (equilibrium) elasticities is worthy of assessment.

In the short-run, changes in the price elasticities of models will be associated with differences in the firm's pricing over time in a single market, gaps between the price of the same model of the same brand in two markets in which the stage of the cycle is not the same and, particularly, firms' decisions on the entry and exit of models in their mix of products. In the long–run, the evolution of elasticities as the effect of age are likely to be linked to all product decisions, from model improvements[4] to entry/exit decisions.[5]

Only a few papers have directly addressed the life cycle of products introduced by multiproduct firms in a differentiated product industry. And, among the few, most have been devoted to industries experiencing a high product turnover derived from an intense process of innovations. Bresnahan, Stern and Trajtemberg's (1997) is the closest to our objectives. They study, in a discrete choice demand framework, how two disembodied attributes of IBM-compatible personal computers (being a "frontier" product, being branded) impact demand elasticities and hence temporary market power, finding a role for these two sources of differentiation. Other studies have instead focussed directly on the description of the entry and exit process, trying to assess determinants and choices. Among them, Stavins (1995) describes the positioning in the attributes' space and the probabilities of exit in personal computers, and Greenstein and Wade (1998) the product introduction determinants and hazard rates of mainframes. An important exception to the highly changing technological setting is Asplund and Sandin (1999), which studies the Swedish beer market during the nineties, also characterised by a rapid product turnover. Studying hazard rates, they find patterns of product life and turnover that are very similar to the ones we obtain in our demand framework.

New car models during the nineties undoubtedly embodied many small innovations, but model turnover can hardly be attributed exclusively to changes in technology. On the other hand, the non customer-configurable character of the product (like beer and unlike personal computers) seems to make it prone to the operation of disembodied effects as a source of differentiation. In this setting, the specification and estimation of age-related demand effects is an improvement which enriches demand and elasticities estimation. In addition, if age effects are important, their estimation is a necessary step in the direction of structurally addressing the question of firms' product decisions as a reaction to market developments.

3. Car models turnover in the Spanish market

This section briefly introduces the data and then characterises model turnover during the nineties in the Spanish car market. Car producers distinguish models, characterised by a model name, from the versions of these models, which they present as slight variations in the characteristics of the model. Our data set takes models, just as they have been defined by producers, as the elemental units of analysis. The basic data consists of the breakdown by models of the monthly new car registrations (sales) from January 1990 to December 1996 (an entry occurs when a new models appears.)

The information gathered for each model includes price (list retail price), attributes (for the attribute variables used in this paper see Table A.1) and the variable that is crucial to our analysis: *age*. This variable measures in months for how long, at time t, a model has been marketed on the Spanish automobile market.

We group models into 5 categories that closely resemble common industry and marketing classifications. The classes considered are: small, compact, intermediate, luxury and minivan. For some purposes we will distinguish additionally between the small "mini", and the small "domestic", the very popular somewhat superior models produced domestically. The number of models in each segment are, respectively, 33, 37, 56, 47 and 9.[6] In Spain there are 7 big (export oriented) multinational manufacturers that produce domestically, but whose domestic output is subject to complex transnational decisions about how to allocate the production of the models geographically.[7] We will distinguish between "domestic" and "foreign" cars, mainly by employing standard demand (not supply) criteria. Thus, we will call domestic the models sold by these brands, neglecting the fact that some of them are really produced abroad and imported. And we will call foreign the cars sold by the firms without any domestic production.[8] Grouping together the models manufactured by the same producer gives a total of 31 firms or brands, 7 with domestic production and 24 foreign producers.

Models seem to be a basic product category, both for demand and supply reasons. On the one hand, models have a name and an image, and firms invest heavily in advertising their models. This implies that consumers basically choose among models, and that firms incur some demand-rooted sunk costs in launching models. But, on the other hand, models also have some basic attributes that remain fairly stable over time. As Table 1 illustrates, for our 182-model sample, these attributes seem to be mainly related to size and power characteristics. This strongly suggests that model launching also implies technology related sunk costs (design, manufacturing facilities adaptation, etc.). Demand and cost side sunk costs provide a rationale for firms to stick to their living models. In fact life spans are, as we will see below, heterogeneous, and they can be spotted by minor modifications in the models' characteristics. Producers try to boost the life of models at certain moments with small changes.[9]

The evolution of the market over our sample period shows three main facts (see Table 2): firstly, a significant demand variability; secondly, a fall in tariffs followed by the corresponding increase in foreign car penetration; thirdly, an increase in the number of models and a rather high rate of model turnover. In what follows, we briefly comment on these characteristics.

Table 2 shows total yearly registrations. There was an important demand downturn by the year 1993 and, to a lesser extent, by the year 1995 (and also a fall in prices.) Table 2 also details the evolution of sales of domestic models. In the years 1990, 1991 and 1992 the tariffs for the EEC imports and for the non-EEC countries were gradually reduced.[10] As a result, the share of domestic models tends to fall since 1992, while the share of foreign models increases (from 18% to almost 25%.)

Let us concentrate on model increase and turnover. Table 2 reports an important increase in the number of marketed models (36%) and the corresponding fall, given the detrended demand, in sales per model. The net entry of models is especially important in the first half of the period, but continues until the end. Table 3 details gross entry and exit and the age distribution evolution. As can be seen in the last two rows, a high, rather stable yearly rate of turnover underlies net entry (entry+exit over the existing models is about 20%.[11]) As a result, only one fourth of the models marketed by 1997 are models that were already on the market at the beginning of the nineties.

This market context implies that the study of model turnover must be carried out in a situation of increasing product competition interwoven with a market opening (which probably triggered the new competition intensity.) Accordingly, some remarks are pertinent. Firstly, it must be noted that the increase in the number of products is mainly an endogenous outcome generated by all the participants. For example, Asian producers account for a somewhat disproportionate share of gross (and net) entry of models, but all firms contribute to the increase in the number of models.[12] Secondly, most of the product entry and exits come from the decisions of replacement of a model by another. Table 4, which reports all the models' entries and exits, depicts the firms' entry-exit pairs that are only separated by one or, at most, two years delay. These pairs amount to more than 90% of the number of exits.

Given the two characteristics cited above, increased competition seems to have influenced the pace of model introduction more than changed its form. In principle, this justifies treating all the models symmetrically. However, it is important to bear in mind that the estimated age effects are conditional on the life spans that are present in the sample.

4. Exploring model life cycle

The data set provides us with rich information on the different phases of the life of models. We observe the entry of models, the market evolution of models that have been marketed for different time intervals, and exit. In this section, we focus the attention on the simple description of the evolution of market shares over model ages, to detect and characterize average properties of the life cycle of models. To do this, we will employ non-parametric regression techniques.

Let s be the market share of a model at a given moment of time (we drop model and time subindices for simplicity), and let t be its age or time elapsed from the moment that it was released on the market.[13] Our first aim is to describe model shares as a function of model age, that is, the expectation of model shares conditional on t,

$E(s|\boldsymbol{t})$. However, the conditional expectation of s may be written by the law of iterated expectations as

$$\begin{aligned} E(s|\boldsymbol{t}) &= P(s>0)\, E(s|\boldsymbol{t}, s>0) + P(s=0)\, E(s|\boldsymbol{t}, s=0) \\ &= P(s>0)\, E(s|\boldsymbol{t}, s>0) \end{aligned} \tag{1}$$

where the second equation follows from $E(s\,|\,\boldsymbol{t}, s=0)=0$. This expression shows that the expected share is the result of two factors: the probability of still being on the market for each age, or probability of survival, and the expected share conditional on age and survival. Therefore, to interpret the expectation of s conditional on age, we will also estimate and study the survival function $P(s>0|\boldsymbol{t})$ and the expectation of s conditional on age and survival $E(s|\boldsymbol{t}, s>0)$.

We will estimate $E(s\,|\,\boldsymbol{t})$ and $E(s\,|\,\boldsymbol{t}, s>0)$ by means of the econometric model $s = g(\boldsymbol{t}) + e$, where e is a zero mean disturbance, using the entire sample and the subsample of positive shares, respectively, employing a non-parametric regression estimator.[14] To estimate the survival function, we will compute the ratios at each $\boldsymbol{t}$ of the number of models with positive shares to the total number of observations for this age (see Kiefer, 1988).

Figure 1 shows the result of estimating the expectation of s conditional on age. Figure 2 depicts the results of estimating the two components according to expression (1) of this expectation. Panel a of Figure 2 shows the estimation of the survival function and Panel b reports the result of estimating the expectation of s conditional on age and survival. In appendix, the different panels of Figure A.2 give the results of estimating the expectation of shares conditional on age in four car subsamples (small, compact, intermediate and luxury) of domestic and foreign models.

The curves show many things about model life cycles. Firstly, the expectation of s conditional on age shows that models invariably come out on the market with relatively high sales, probably due to the advertising campaigns that precede their entry. However, for most models, it takes some time to reach the maximum market share. This time seems to range between 24 and 48 months (shares peak over the course of the third and fourth years), though it is clearly less for foreign cars.

Secondly, according to the survival function, the probability of leaving the market before the first 24 months is negligible, and only 10% of the models exit before the first 48 months. Therefore, the first part of the conditional expectation function must also be considered a good approximation to the own evolution of the surviving models.

Thirdly, the survival function shows that the probability of leaving the market increases steadily from the age corresponding to the maximum share to the twelfth year, while the expected share conditional on age and survival tends to increase slightly during the same period. In fact, 50% of the models have disappeared from the market by the end of the eighth year, and 75% by the completion of the twelfth, but the average share of the surviving models tends to be somewhat higher (but note that here the estimates are more imprecise: the small number of observations entails a high variance.) On balance, the expectation of shares conditional on age during this particular interval is dominated by a decreasing probability of survival that curves it down. At the same time, the expectation of shares conditional on age and survival shows that exit particularly affects shares under the average size.

Fourthly, the small fraction of models that reaches the age of twelve years can endure longer maintaining high relative shares.

As far as the differences between domestic and foreign cars are concerned, there are two main points that are worthy of comment. Firstly, the sharpest contrast is between the shares reached by the domestic models and the smaller shares reached by foreign models. Furthermore, smaller domestic cars and bigger foreign cars tend to last longer on the market than their respective counterparts.

This simple description of average model life cycles does not pretend to determine the different forces at work and, in particular, whether there is any role for the age of the model separate from the role of the observed model attributes and their evolution over time. However, the reported evidence makes apparent strong share evolution patterns that suggest a positive answer. The following sections are devoted to the specification and estimation of age effects in an explicit demand framework to confirm this hypothesis.

5. The demand for models over time

Discrete-choice demand models seem the natural context to introduce and investigate changes in consumers' valuation over time (see the references in the introduction). On the one hand, these models build up the demand equations based on explicit links between product market shares and the framework of consumers' utility. On the other, the standard employed model can be easily enlarged to account for this type of changes. Let us explain our specification.

The discrete choice approach obtains the demand equations by relating observed market shares with the shares predicted by the utility framework. Following Berry (1994), and employing the usual linear utility specification, a demand equation for model *j* can be written relating a non-linear transformation of the vector of observed market shares *s* to the mean utility level for model *j* as

$$\boldsymbol{d}_j(s) = x_j \boldsymbol{b} - \boldsymbol{a} p_j + \tilde{\boldsymbol{x}}_j \qquad (2)$$

where p_j is the price of the model, x_j is the vector of observed product characteristics, and $\tilde{\boldsymbol{x}}_j$ represents the effect on utility of product characteristics unobserved by the econometrician. In particular, if consumer utility is assumed to be $u_{ij} = \boldsymbol{d}_j + \boldsymbol{e}_{ij}$, with $\boldsymbol{e}_{ij}$ identically and independently distributed across products and consumers with the extreme value distribution, the market share equals the probability of a logit model. Then $\boldsymbol{d}_j(s)$ is the simple transformation $\ln s_j - \ln s_0$, where s_0 stands for the share of the so-called outside good or the alternative of not buying any of the models, which provides a useful linear estimable model.[15]

The simplest logit specification imposes strong constraints on the pattern of substitution among goods, but several model extensions have been developed in order to relax these constraints. The constraints follow from the exclusive additive specification of consumers' heterogeneity. BLP type model specifications reinforce heterogeneity through random attribute and price coefficients. One sensible alternative which relaxes constraints incurring lower computational costs are nested logit models, where alternatives are grouped using a-priori information (a good source of discussion about this is Nevo (2000)). In this study we combine coefficients varying across segments with a type of nested logit estimation, which turns to be a simple theoretically suitable specification when income effects are expected and, in practice, gives sensible demand elasticity estimates. Car model demands are likely to entail important income effects, with consumers tending to cluster around model-classes (segments) according to their income level, and average segment-specific marginal utilities are expected to reflect this heterogeneity. This preserves the useful linear form of equation (2) and will allow us to focus on the instrumental variables estimation choices (see the next section).

In order to account and test for the presence of age effects, we will specify (2) explicitly including two possible consumer utility effects of the age of the model. Firstly, we will include a direct effect. This effect can be understood as the average impact on utility of a set of unobservable time varying attributes. The standard specification of (2) already takes $\tilde{x}_j$ as disturbances to account for, among other things, such factors. Our specification can be simply seen as splitting these unobserved utility effects in three components: $x(t_j)$, the time varying effect of unobserved attributes measured through the impact of model age; x_j, a time invariant component related to the stable unobservable characteristics of the model; and x_{jt}, the remaining time varying unobserved effects on mean utility of model j.

Secondly, we will include an additional possible age effect through marginal utility of income. The a parameter of the linear utility model is marginal utility of income. Often treated as a constant, this parameter is likely to reflect at least the different marginal utility corresponding to the different income levels associated to buying different car models (this is why we specify and estimate different segment parameters $\boldsymbol{a}_g$.) At the same time, $\boldsymbol{a}$ is also likely to reflect the marginal utility associated with buying models with different degrees of penetration in the market. Consumers can valuate new models positively because of their "newness," but can also consider that they imply a higher sacrifice in terms of the utility of alternative expenditure allocation. To test for these age effects we will specify marginal utility of income as $\boldsymbol{a}_g + \boldsymbol{a}(\boldsymbol{t}_j)$.

Finally, we will use a nested logit specification by including segment-specific dummies in order to pick-up the segment effects $\boldsymbol{h}_g$. We interpret their values as the realisations of the random variables conjugate to the extreme value errors that raise nested probabilities (Cardell, 1997).

The enlarged logit specification can be written, allowing for a time subscript, as

$$\ln s_{jt} - \ln s_{0t} = x_{jt}\boldsymbol{b}^* - (\boldsymbol{a}_g^* + \boldsymbol{a}^*(\boldsymbol{t}_j))p_{jt} + \boldsymbol{h}_g^* + \boldsymbol{x}^*(\boldsymbol{t}_j) + \boldsymbol{x}_j + \boldsymbol{x}_{jt} \qquad (3)$$

where the asterisk indicates that the corresponding coefficients must be understood to be divided by the factor $(1-\boldsymbol{s})$. Equation (3) can be estimated subject to the constraint that the coefficients of segment dummies add up zero, which gives an estimate of the effects up to a constant. Then mean utilities can be estimated up to a constant (and hence "inclusive values" up to a multiplicative factor), and $\boldsymbol{s}$ can be obtained in a second step by means of an auxiliary regression.[16] Relationship (3) is the equation that we estimate in the next section.

6. Econometric estimation and results

6.1 Estimation strategy

As it is well known, one of the main problems to be solved in the specification and estimation of demand equations is the treatment of the endogeneity of prices. In addition, our data consist of unbalanced panel observations for a rather standard number of individuals (182 models) but with a more unusual data frequency: monthly during a seven-year period. This implies some advantages to estimating the parameters of interest, but also the need for specific methods to address some estimation problems: the heterogeneity of the time information content (T is large, but only with respect to the frequency of change of some variables), and the serial correlation of the disturbances. In what follows, we briefly explain our estimation choices.

Prices are likely to be correlated with the x_j and x_{jt} components of the disturbance (the time invariant impact of unobserved model characteristics and the shocks.) In the first case this happens because there are presumably many unobserved characteristics that enter the determination of the models' marginal cost, and hence their prices, which simultaneously influence consumers' utility. In the second case, it occurs because prices are determined at the same time as consumers' demand, and both variables are likely to be influenced by common market shocks.[17] Accordingly we will use as instruments, in a GMM framework, the differences of the prices with respect to their individual time means, $\tilde{p}_{jt} = p_{jt} - (1/T)\sum_s p_{js}$, lagged a number of periods. This is likely to pick up just the time variations of prices (and not across models), and just the ones occurring prior to the contemporaneous market events.[18,19] In addition, to test the validity of the employed instruments, we will employ the Sargan test statistic of the overidentifying restrictions.

Monthly data are likely to contain useful information about reactions of shares to prices, which change frequently, but much less about reactions to attributes, which change rarely and have mainly long-term effects. On the other hand, monthly market shares will contain a lot of short-term movements we are not interested in modelling or even in conditions to model. Individual effects and short-term movements will induce autocorrelated errors. To obtain inferences robust to serial correlation, we will need to use a robust estimate of the variance-covariance matrix. To obtain such an estimate, we will use an average across individuals of Newey-West type computations of the individual autocovariances that take advantage of the size of T (see Newey and West (1987)).

6.2. Econometric specification and results

The dependent variable consists of the (log of the) model monthly share observations minus the (log of the) monthly shares of the outside good. Both shares are computed, as in BLP, taking the current number of households as the market size.[20] Among the explanatory variables we can distinguish three groups: control variables, model attributes and price, and variables aimed at picking up the age effects. To control for seasonality and unspecified time effects (for example, the fall in demand), we include a set of monthly dummies and another of yearly time dummies, respectively. Let us detail the second and the third group of variables.

Looking for maximum comparability, we have tried to specify the same attributes as BLP. This has almost been possible, although we have had to replace the BLP's air conditioning "luxury" proxy for the *maximum speed in km/h (Maxspeed)*, probably a better proxy for quality in Spain during the nineties. The other employed attributes are the power measure *ratio cubic centimetres to weight* (*CC/Weight*), the fuel efficiency *ratio km to litre* (*Km/l*), and the measure of size and safety *length times width* (*Size*). The use of other characteristics or a more complete list does not change the main results. The price effects are specified for the main five segments used in the estimation: Small, Compact, Intermediate, Luxury and Minivan. We expect lower coefficients (in absolute value) the higher the segment. At the time of specifying the segment dummies, however, we consider additionally the division of small cars in two subgroups: small-mini and small-domestic.

The direct age effects are included as a polynomial of order three of the age measured in months (higher order terms turned out not to be significant.) The marginal utility effects of age are specified by including the set of dummies interacted with price and corresponding to the age intervals (in years) observed in the sample. After some experimentation, we established the age interval corresponding to 36 to 48 months as the reference interval.

Several instrument sets were tested with very similar results, invariably using price differences with respect to the individual time means, with different lags.[21] The reported estimate uses as instruments the sixth and twelfth lags of the (segment) price variables in differences, 20 age dummies (in years) and twenty interactions of the ages and the twelfth lag of the variable price in differences. The number of overidentifying restrictions of our preferred estimation is hence 25, although very similar results can be obtained with a smaller number of instruments. As we employ twelve period lagged variables, we must discard all the individuals with twelve or fewer observations, retaining 164, and use a maximum of 72 time observations. Note that this implies that we are not able to estimate the age effects during the first year of the model life (the year 0).

The reported coefficient estimates are one step GMM estimates, obtained by employing the standard weighting matrix[22] (the inverse of $E(Z_j^{'}\bar{x}_j\bar{x}_j^{'}Z_j)$, where $\bar{x}_j = (x_j + x_{j1},...,x_j + x_{jT})'$ and Z_j represents the set of instruments for individual j, which is estimated by $(\sum_j Z_j^{'}Z_j)^{-1}$). All the statistics are then computed using the robust to heteroskedasticity and serial autocorrelation "two-step" weighting matrix (see below). The reported Sargan test is also a two-step statistic.

To estimate a robust inverse of $E(Z_j^{'}\bar{x}_j\bar{x}_j^{'}Z_j)$ we assume that $\bar{x}_j\bar{x}_j^{'} = \Omega_j$ are matrices corresponding to conditional homoskedastic errors, and we obtain $\hat{\Omega}_j$ values using the Newey-West Bartlett kernel computations for the autocovariances of individual j. Then we employ the usual "two-step" estimate $(\sum_j Z_j^{'}\hat{\Omega}_j Z_j)^{-1}$. We use 72 time observations as the maximum lag that we take into account in the Bartlett kernel.

Table 5 presents the results of our preferred estimation. The statistics and estimated coefficients are sensible. The implications concerning the role of age are reasonable. We comment in turn.

The Sargan test confirms the validity of the employed instruments. Regression residuals show a strong autocorrelation, but the use of a robust covariance matrix make the inferences reliable. Control variables present sensible patterns. Seasonality is strong, with August-September showing the lowest sales after a peak in June-July. The regression confirms that yearly sales reached a relative maximum in 1991 and fell sharply in 1993.

Attributes are significant and show the expected sign. The price effects exhibit the expected pattern (the higher the segment, the lower average marginal utility is) and all demands are elastic. Relative elasticities[23] show a sensible pattern: small and compact cars show similar average higher elasticities, while intermediate and luxury car elasticities are lower. Average own-price elasticity across all models ranges over ages from 2.4 to 5.3 (see Table 6, column 5).

Let us concentrate on the age effects, focussing on the first twelve years of life. First of all, the direct effect implied by the age polynomial is clearly significant. Additionally, marginal utility of income is also influenced by age, although to a limited extent. Only the first two price-age interaction terms before the reference interval are individually significant. That is, age influences marginal utility of models before they reach their 36th month on the market. All the other interaction terms individually present statistically non-significant values and show no defined pattern. The age polynomial plus the two first indirect age effects, evaluated at the median price, give a clear pattern of change of mean utility, which is summarised in the third column of Table 6. In contrast to the non-parametric regressions of section 3, notice that here we are measuring net age impacts on shares, free of price and attribute change effects, reflecting how average consumers' valuation changes with age.

When a model is brought out on the market, time favours the increase of their market share. Consumers have a high initial valuation of the attributes embodied in the new model but, at the beginning, they are reluctant to choose it when offered similar alternatives. The tendency of shares to increase with the passing of time finishes, however, when the model has been marketed for three years. From this moment on, the simple age of models ceases to favour them and begins to show the opposite effect until the moment the car reaches its eighth year of life. The average market share's damage attributable to the course of time during this stage is more than one third of the share.

But models that surmount this time threshold (and remember that only 50% do), show higher market shares. And the 30% that go beyond the age of twelve years continue showing high shares for a number of years.

As a consequence of age effects, the course of time influences model equilibrium elasticities. Columns fourth to sixteenth of Table 6 give segment averages of elasticities across ages, using models that fit two groups: models that survive less than seven years and models that survive between seven and thirteen years. This splitting is used to highlight the evolution of elasticities with age: as models that survive more years tend to show somewhat lower elasticities, putting all models together tends to blur the trends. The table shows that own-price elasticities clearly decrease steadily the first years of models life, as can be expected from the impact of age on utility. On average, own-price elasticity decreases until the fourth year of life. Next, elasticities tend to rise more or less steadily with the age of the model.[24]

7. Conclusion

Car model turnover is an important characteristic of the automobile market. The entry by firms of new models to replace old ones is quantitatively important and, in our Spanish sample as probably in most countries, entry has recently been increasing over time. Model life cycle is reflected in typical patterns of evolution of their market shares, hardly explainable with only the help of the evolution of their attributes and price. These patterns suggest links between consumers' valuation of models and their marketing age. And these links are likely to have important consequences for firm strategies, as far as firms face consumer and market evolution by means of pricing, change of attributes and, finally, model exit-entry decisions.

This paper has been aimed at exploring the existence of typical patterns of model life and the formal specification and test of age effects in a framework of demand for car models. We have used a suitable data set which includes detailed model sales over time, in addition to information on model attributes, price and age, in a period of high entry and exit. Age effects have been specified using the discrete-choice approach to the estimation of market demands to explain the evolution of market shares. Estimations have shown that shares' evolution includes age effects, clearly distinguishable from the impacts generated by changes in attributes and firms' pricing.

Our study has shown that models' shares tend to increase the three first years they are marketed and then begin to deteriorate as time goes by. Firms can boost the models' presence on the market with different version improvements and, if the model survives, its reputation is likely to give new inertia to shares at later stages. But age effects bring in an autonomous factor of modification of the relevant model elasticities, to which firms must react with their pricing and product strategies. Average elasticities betray these age effects firstly decreasing and then increasing. Corresponding (opposite) age price movements have already been documented.

The full understanding of age effects and the interaction of age with firms' strategies deserve further research. The testing and specification of age effects must be considered a first step towards the development of structural models for the product decisions.

Data Appendix

This work uses a newly constructed data set created for the analysis of the automobile market during the nineties.[25] The basic data consist of the breakdown by models of the monthly new car registrations (sales). Registrations come from an administrative source, the *Dirección General de Tráfico*, and have been supplied by *ANFAC*. The data set has been cleaned, retaining 99% of the registrations, and has been matched to a database on prices and technical and physical characteristics of the models, collected and elaborated from a specialized review (*Guía del Comprador de Coches.)*

The data set takes models just as they have been defined by producers. Only super-luxury and marginal models have been dropped from the sample, and some similar models with extremely small sales have been aggregated in a single model. On the other hand, to meaningfully fix the date of exit of models, we have selected the month in which the previous six-month mobile average of unit registrations of a model falls below 10 units. This leaves a total of 182 car models, with an average of 110 models marketed per month and an average of 50 monthly observations per model.

The matching of the model sales data with model attributes has been carried out using, when possible, the characteristics of the model version with the highest sales. Unfortunately, detailed sales per version are not available for imported cars. In these cases, an intermediate version has been selected, sometimes based on fragmentary information on the versions' sales.

The information gathered for each model includes prices (list retail price and manufacturer's price), power-related variables, performance characteristics, consumption, size-related variables and, finally, the presence of standard equipment and the availability of options. In addition, the variable age measures for how long a model has been marketed on the Spanish automobile market. For the models already existing at the beginning of the sample, the marketing age at the starting observation (January 1990) has been approximated by relying on external used cars market information and by considering a maximum of 180 months (15 years.) Table A.1 reports the content of each variable that we use in this work. Table A.2 provides some descriptive statistics for the whole sample and for five market segments: small, compact, intermediate, luxury and minivan.

Footnotes

[1] The discrete-choice approach to demand estimation, developed for differentiated products markets, has been recently enlarged, enriched, and applied extensively to the modelling of several markets, in particular to the automobile market. Bresnahan's (1987) automobile article can be considered a precedent of this type of model. Goldberg (1995), Feenstra and Levinsohn (1995), Verboven (1996), Berry, Levinsohn and Pakes (1999) and Petrin (2002) include automobile demand estimations related to the discrete-choice method.

[2] In general, demand change and technological progress interact in raising product life cycles (for a general presentation of cycles, mainly at the industry level, see Klepper (1996)). However, product cycles present many industry-idiosyncratic characteristics.

[3] Most marketing literature on product life cycle uses the adoption approach, in which the path of sales over product age is explained by the purchasing behaviour over time of consumers that act as "innovators" while other behave as "imitators." See Kwoka (1996) for an application of this approach to the life cycle of minivans. In practice, it can be assumed equivalently that is the average valuation of the product by consumers what changes over time.

[4] Management literature stresses the importance of adopting techniques to enhance the durability of products.

[5] Assume that a multiproduct firm, which sets prices taking into account the cross effects of its marketed products, faces own-price product elasticities whose absolute value increases over time, and cross-price elasticities of each product with respect to substitutes that decrease, as well as sunk costs of product entry. It is in the firm's interest to eventually substitute new products for the oldest ones in order to preserve the maximisation of the expected profitability of the product mix that it sells.

[6] This classification is close to the ones used by Verboven (1996) for European cars (mini and small, medium, large, executive, luxury and sports), and Goldberg (1995) for the American car market (subcompact, compact, intermediate, standard, luxury and sports.) The main differences are the aggregation of luxury and sports cars in a single class, and the specification of a class for minivans.

[7] Citroen, Ford, Opel, Peugeot, Renault, Seat and Volkswagen.

[8] As Goldberg (1995) points out, cars are usually classified into "domestic" and "foreign" according to different criteria depending on whether the analysis refers to the demand or supply side. In demand analysis, it is customary to classify cars according to the character of the brand rather than the location of the production of a particular car. In supply analysis, cars should be classified by the country of production. The rationale for this distinction is that consumers are not expected to pay relatively much attention to the side of production.

[9] BLP define models in their twenty-year US sample by requiring, in addition to the same name, that the width, length, horsepower or wheelbase do not change by more than ten percent. Comparing our data with BLP data, it turns out that we observe more or less the same cross-sectional average number of models

(110 vs. 118), but also that a model lasts on average 4.2 years, while they observe a model lasting only 2.2 years. Of course, our definition of model is not the same (we only rely on the name) but, from Table 1, it can be checked that the adoption of similar criteria to BLP would have a small effect (in fact it would only reduce our average number of years from 4.2 to 3.3). This seems to say that our turnover level is not so high by US standards.

[10] The tariffs for the EEC imports were gradually reduced to 13.1%, 8.7% and 4.4%, disappearing the following year. The tariffs for the non-EEC countries were reduced during the same years to 23.1%, 18.8% and 14.4% and remain fixe d at 10.3% since 1993.

[11] In total, many more models (103) enter than the number of models marketed before the beginning of the period (98-19=79.) But the exit of models is equally important (59), increasing after the two first years of the period, and tends to concentrate along some ages (from 4 to 8 years, say).

[12] Asian producers bring in the market a number of new models (28) that almost doubles the initial number accounted for them (15), while the entry of models by domestic producers (28), and non-Asian foreign producers (48), matches approximately their initial contribution of models (respectively 35 and 48).

[13] For each model/month in the sample, we have a market share value that is associated with the age of the model, which gives a total of 9,251 non-zero share-age observations. Moreover, for each model that exits the sample before December 1996, we complete its sample observations with the assignment of a zero market share until reaching the maximum age that we will consider (180+84=264 months.) This is all we observe, because we have two types of censoring. On the one hand, for the non-exiting models, we cannot observe their shares from their last observation onwards (right censoring). On the other, we also cannot observe the early life observations of the models, which were already on the market by January 1990 (left censoring). To perform our descriptive exercises, we will pool together all the non-censored (positive and zero) observations, which gives a total of 19,528 observations. Interestingly enough, the density of these observations is rather uniform along the considered ages (see Figure A.1)

[14] We use the simple Nadaraya-Watson estimator; see, for example, Wand and Jones (1995).

[15] The logit model also provides a simple theoretical context in which the relative deterioration of an attribute of a good implies, in a Bertrand equilibrium context, a higher (absolute value) own-price demand elasticity and a fall in the market share of the good. The price set by the firm reacts in order to soften the direct share effect, but the firm finds optimal do not offset it completely.

[16] Estimation of (3), using the constraint $\sum_g (\boldsymbol{h}_g - \boldsymbol{h}) = 0$ to specify all the segment effects ($\boldsymbol{h}$ represents the average of these effects), gives coefficient estimates up to the scale factor $(1 - \boldsymbol{s})$ and mixes two unidentifiable components in the regression constant. Then, to estimate the σ parameter, we construct estimates of the "inclusive values" $D_g = \sum_{j \in J_g} e^{\frac{u_j}{(1-s)}}$ up to a multiplicative constant and

perform the regression $\ln \hat{P}(g) - \ln \hat{P}(0) = c + (1 - \sigma) \ln \hat{D}_g^{*}$. To avoid simultaneity biases, the "inclusive values" are constructed with the price values predicted using the instruments.

[17] The most standard way of treating such a setting is the estimation of the equation taking first differences in order to difference out the individual correlated component, and the use of lags of the endogenous variable to set valid moment restrictions (see, for example, Arellano and Honore (2000).) In our case, this is an undesirable alternative because T is short in relation to the pace of variation of attributes (many attributes change very little or not at all in the seven years). The differentiation of the attributes would eliminate crucial information contained in the levels equation and would exacerbate the variance of the disturbances.

[18] 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 application of moment restrictions that involve differenced instruments and level equations to treat persistent data is Blundell and Bond (1999).

[19] The differences of a predetermined or endogenous variable with respect to its time mean introduce some correlation of the lags of the variable with the differenced error term that is likely to generate estimation biases in short panels (this is the type of bias analysed by Nickell (1981).) However, this bias is likely to be negligible as T grows large enough.

[20] Collected from the population survey *Encuesta de Población Activa*. The monthly shares are multiplied by 12 in order to facilitate comparability with the elasticities obtained with yearly data.

[21] We also experimented with sums of characteristics across own-firm products and rival firm products, in their totality and by segments. In general they revealed to be poorer instruments than the lagged price differences and tended to produce worse values for the Sargan statistic.

[22] GMM estimation of panel linear models is summarised in Arellano and Honore (2000).

[23] We compute for each time observation own-price elasticities of model j as $\eta_j = \alpha_g p_j (1 - s_j + \frac{\sigma}{1 - \sigma}(1 - s_{jg}))$, where s_{jg} is the share of model *j* in segment g.

[24] This coincides with the general findings of marketing literature. See, for example, Parker (1992).

[25] Details on the construction of the data set can be found in Moral (1999).

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Table 1: Degree of stability in model characteristics [1,2]

(No. and percentage of models with significant changes)

Characteristics	Extent of the change					
	2%		5%		10%	
Stable:						
No. cyl	7	(3.85)	7	(3.85)	7	(3.85)
Length	21	(11.54)	7	(3.85)	0	(0.00)
Width	16	(8.79)	5	(2.74)	2	(1.10)
Varying:						
Fiscalp	42	(23.08)	29	(15.93)	15	(8.24)
CC	44	(24.17)	39	(21.43)	29	(15.93)
Luggage	47	(25.82)	40	(21.97)	29	(15.93)
Greatly varying:						
HP	77	(42.31)	69	(37.91)	55	(30.22)
RPM	64	(35.16)	49	(26.92)	18	(9.89)
Maxspeed	74	(40.66)	38	(20.88)	11	(6.04)
C90	83	(45.60)	64	(35.16)	39	(21.42)
C120	81	(44.50)	59	(32.42)	39	(21.42)
Ctown	79	(43.41)	62	(34.07)	38	(20.88)
Weight	73	(40.11)	59	(32.42)	25	(13.73)

Notes:

1. Every column reports the number (percentage) of models that fail to pass the corresponding stability test. The test is passed if the characteristic does not change by more than, respectively, two, five or ten percent in a period of twelve months or less.
2. Definition of variables is in Table A.1. of the Data Appendix.

Table 2: The Spanish car market in the 90s

Year	Registrations	Index[1]	No. of models	Average monthly sales by model	Price[2]	Sales of domestic models[3]
1990	971,466	109.7	98	851	1.976	82.0
1991	878,594	99.2	106	712	1.948	80.0
1992	973,414	109.9	117	700	1.876	81.3
1993	737,938	83.3	120	520	1.928	80.2
1994	901,754	101.8	124	616	1.925	78.7
1995	829,797	93.7	127	556	1.982	77.2
1996	906,444	102.3	133	580	1.986	75.2

Notes:
1. Index=100 at the time average of registrations.
2. Sales weighted mean price, in millions of pesetas circa 1992. The weight for each model monthly observation is the average share of the model in the corresponding year.
3. Models sold by firms with domestic production, irrespectively of whether they are imported.

Table 3: Entry, age distribution of models and exit.

Age (in years)	1990	1991	1992	1993	1994	1995	1996	Exit[3]: until 1995+1996
age[1,2] $\leq$ 1	19	10	16	12	13	17	16	
1 < age $\leq$ 2	3	19	10	16	12	13	17	1
2 < age $\leq$ 3	7	3	19	10	16	11	13	4
3 < age $\leq$ 4	18	7	3	18	10	14	10	5
4 < age $\leq$ 5	5	18	6	3	18	7	13	6 + 2
5 < age $\leq$ 6	8	4	15	6	3	16	7	3 + 1
6 < age $\leq$ 7	6	8	4	13	6	3	15	5 + 3
7 < age $\leq$ 8	5	6	8	3	12	4	2	7
8 < age $\leq$ 9	6	4	6	6	2	10	3	8
9 < age $\leq$ 10	4	6	4	4	3	2	7	+ 1
10< age $\leq$ 11	4	4	6	4	4	3	2	4
11< age $\leq$ 12	0	4	4	5	2	3	3	2
12< age $\leq$ 13	1	0	3	3	5	2	3	2
13< age $\leq$ 14	4	1	0	3	2	5	1	1 + 1
14< age $\leq$ 15	3	4	1	0	3	2	4	+ 1
15< age $\leq$ 16	5	3	4	1	0	3	2	
16< age $\leq$ 17		5	3	4	1	0	3	
17< age $\leq$ 18			5	3	4	1	0	
18< age $\leq$ 19				5	3	4	1	1
19< age $\leq$ 20					4	3	4	1
20< age $\leq$ 21						3	3	
21< age $\leq$ 22							3	
No. of models	98	106	117	119	124	127	133	
								Totals:
Entry	19[4]	10	16	12	13	17	16	103
Exit	2	5	10	9	14	10	9	59

Notes:

1. The first category represents a number of months equal to or less than 12.
2. Each entry is the number of models of a given age observed during the year.
3. Exits are equal to the difference between the number of models belonging to the interval of *s* years at time *t* and the number of models in the interval *s+1* years at time *t+1*.Exits during 1996 cannot be observed in this way and we report them separately.
4. Includes the entry of 8 models in January 1990. Four of them stay until the end of the sample and the other four exit before December 1996.

Table 4: Entry and exit of models by firms[1].

	1990		1991		1992		1993		1994		1995		1996	
	Ent.	Exit	Ent.	Exit	Ent.	Exit	Ent.	Exit	Ent.	Exit	Ent.	Exit	Ent.	Exit
ALFA					**1**	**1**			**1**	**1**	**1**	**1**		
AUDI	**1**					**1**			**3**	**1**		**1**	**1**	**1**
BMW	**1**										**1**	**1**		
CHRYSLER					**2**					**1**	**2**			
CITROEN			**1**				**1**	**1**	**1**				**1**	
DAEWOO											**2**			
FIAT	**2**	**1**			**1**				**1**		**4**	**2**	**1**	**2**
FORD						**1**	**2**	**1**	**1**				**2**	
HONDA	**2**									**1**				
HYUNDAI					**4**				**1**	**1**			**1**	**1**
JAGUAR														
LADA										**1**				
LANCIA	**1**							**1**	**1**			**1**	**1**	
MAZDA				**1**	**1**									
MERCEDES							**3**	**1**				**1**		
MITSUBI	**1**										**1**		**1**	**1**
NISSAN	**1**		**1**	**1**	**1**					**1**	**3**			**1**
OPEL	**1**		**1**			**1**	**1**	**1**	**1**	**1**				
PEUGEOT			**1**	**1**			**1**	**1**	**1**		**1**			
PORSCHE														
RENAULT	**1**				**1**		**1**	**2**	**1**	**2**			**1**	
ROVER	**3**	**1**	**2**		**2**		**1**			**1**		**1**	**2**	**3**
SAAB														
SEAT			**1**			**1**	**1**						**1**	
SKODA				**1**	**1**		**1**				**1**	**2**		
SUBARU			**1**							**1**				
SUZUKI	**1**		**1**							**1**	**1**		**1**	
TOYOTA	**1**					**1**			**1**	**1**			**1**	
VOLVO	**3**		**1**		**1**	**2**							**2**	
VW					**1**	**2**		**1**						
YUGO				**1**										
Total:	**19**	**2**	**10**	**5**	**16**	**10**	**12**	**9**	**13**	**14**	**17**	**10**	**16**	**9**

Note:
1. Shaded areas highlight entry-exit pairs separated at most by two years.

Table 5: Logit demand for car models with age effects

Dependent variable: $\ln s_j - \ln s_0$		Estimation method: GMM[1]	
Sample period[2]: I-1990 to XII-1996		Observations[2]: 7,122 No. of models[2]: 164	
Variable		Coefficient	t-ratio[3]
Constant		-15.840	-6.70
CC/Weight		1.332	2.46
Maxspeed		0.034	2.92
Km/l		0.071	1.61
Size		0.651	3.42
Segment effects[4]:	Small domestic	5.152	3.49
	Intermediate	-2.831	-1.97
	Luxury	-4.969	-3.57
Price x segment:	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
Age polynomial[5]:	Age	-4.816	-2.27
	age^2	3.884	1.93
	age^3	-0.905	-1.62
Price x age[6]:	1 <age≤ 2	-0.381	-3.37
	2 <age≤ 3	-0.135	-2.01
	4 <age≤ 5	-0.015	-0.20
	5 <age≤ 6	0.023	0.24
	6 <age≤ 7	-0.085	-0.85
	7 <age≤ 8	-0.037	-0.32
	8 <age≤ 9	0.081	0.64
	9 <age≤ 10	0.161	1.27
	10 <age≤ 11	-0.052	-0.40
	11 <age≤ 12	-0.041	-0.29
	12 <age≤ 13	0.099	0.66
	....		
	21 <age≤ 22	0.100	0.51
Seasonal dummies		Yes	
Time dummies		Yes	
s estimate		0.842	7.51
Sargan test[7] (25 degrees of freedom)		35.86	
Serial autocorrelation statistic[8] (m12)		5.921	

Notes:

1. Instruments: differences of prices with respect to their time mean lagged 6 and 12 months (interacted with the segment dummies), 20 age dummies, interactions of the age dummies with the price differences lagged 12 months.
2. Instruments lagged 12 months imply that models with 12 and fewer observations must be removed.
3. Standard errors are robust to heteroskedasticity and serial correlation.
4. Small-mini, compact and minivan dummy coefficients constrained to be equal to the average effect.
5. Age in months.
6. Age intervals in years. We exclude the category 3<age≤4. Intervals from 9 to 21 years not shown.
7. Two-step statistic.
8. Constructed as Arellano-Bond m-statistics.

Table 6: Age effects and own-price elasticities

Age[1]	Survival Function[2]	Mean utility[3]	Average elasticities by age, segment and interval of survival[4]												
			Total	Total	Small mini	Small mini	Small dom.	Small dom.	Compact	Compact	Interm.	Interm.	Luxury	Luxury	Minivan
			1-6[5]	7-12[5]	1-6	7-12	1-6	7-12	1-6	7-12	1-6	7-12	1-6	7-12	1-6
1	1.00	1.00	4.52		5.64		6.56		6.73		3.27		3.32		6.51
2	0.99	1.29	3.94	2.41	5.31		6.07		6.25		2.77	2.47	2.50	2.34	5.97
3	0.96	1.34	3.78	3.21	5.19		6.43		6.34	5.57	2.45	2.22	1.94	1.84	5.15
4	0.92	1.09	3.92	3.69	5.73	6.10	6.99	5.33	6.50	7.01	2.31	2.38	2.37	2.11	5.58
5	0.81	0.96	4.13	3.50	6.17	5.60	7.09	5.10	6.32	6.40	2.21	2.41	2.28	1.98	
6	0.73	0.89	4.26	3.81	6.21	6.00	7.18	6.05	6.85	6.40	2.32	2.83	2.31	2.71	
7	0.65	0.87		3.81		6.20		6.11		6.42		2.48		2.52	
8	0.56	0.88		3.78		6.38		5.70		7.54		2.33		2.07	
9	0.48	0.93		3.77				5.49		6.78		2.40		1.74	
10	0.39	0.99		4.55				6.00		6.07		3.30		2.98	
11	0.37	1.08		4.99				6.18		6.38		3.60		3.08	
12	0.29	1.18		5.31				6.12				3.73			

Notes:
1. Age x is a shorthand for the numbers of months comprised between x and x+1 years.
2. Age effects are conditional on survival.
3. Ratio of mean utility at the specified age to age 1, keeping everything constant but age. The significant marginal utility effects are computed at the sample median price (2.5).
4. Averages of the elasticities observed at the indicated age and segment for models belonging to the specified survival interval.
5. Intervals of survival: 1-6, cars which survive from 1 to 7 years; 7-12, cars which survive from 7 to 13 years.

Table A.1: Variables

Price	Market price in millions of pesetas circa 1992. It includes indirect tax, transport and registration cost.
CC	Cubic centimeters
HP	Horsepower
Fiscalp	Fiscal power, fiscal horses according to Spanish legislation.
RPM	Revolutions per minute
Maxspeed	Maximum speed (in kph)
C90	Consumption (in litres) to cover 100 km at a constant speed of 90 kph.
C120	Consumption (in litres) to cover 100 km at a constant speed of 120 kph.
Ctown	Consumption (in litres) to cover 100 km in town at a constant speed of 90 kph.
Length	Length in cm
Weight	Weight in kg
Width	Width in cm
Luggage	Luggage capacity in cm^3
No. cil	Number of cylinders
Age	Time (measured either in months or years) elapsed since the model was introduced in the Spanish market.

Table A.2: Sales-weighted average attributes by car classes[1]

	Price	CC/Weight	Maxspeed	Km/l	Size	Age
Small (33 models)						
1990	1.371	1.546	155.746	20.755	5.766	7.583
1991	1.351	1.532	157.361	20.853	5.785	7.190
1992	1.274	1.539	158.936	21.193	5.796	7.912
1993	1.300	1.552	159.042	20.986	5.845	8.100
1994	1.317	1.551	159.325	20.449	5.873	8.308
1995	1.381	1.530	160.842	19.853	5.869	9.386
1996	1.367	1.473	160.840	19.904	5.892	9.623
Compact (37 models)						
1990	1.917	1.624	176.034	19.089	6.934	5.879
1991	1.871	1.587	176.239	18.762	6.929	5.489
1992	1.823	1.662	177.153	18.914	6.899	5.229
1993	1.894	1.689	179.108	18.813	6.897	5.657
1994	1.899	1.655	177.115	18.929	6.871	5.995
1995	1.960	1.609	176.921	18.545	6.895	6.320
1996	1.965	1.549	178.162	18.891	6.926	5.697
Intermediate (56 models)						
1990	2.620	1.733	189.423	17.269	7.428	4.516
1991	2.477	1.732	186.844	17.618	7.396	4.622
1992	2.287	1.713	186.831	17.502	7.402	4.931
1993	2.405	1.655	189.290	17.675	7.511	3.779
1994	2.529	1.585	190.471	17.077	7.589	4.148
1995	2.572	1.535	191.647	16.963	7.635	3.961
1996	2.568	1.493	194.025	17.209	7.655	4.280
Luxury (47 models)						
1990	4.658	1.755	208.407	15.414	8.223	4.571
1991	4.408	1.736	209.436	15.368	8.201	5.597
1992	4.129	1.744	209.246	15.168	8.169	6.238
1993	4.128	1.699	209.744	15.020	8.169	6.727
1994	4.109	1.684	208.638	14.820	8.168	5.988
1995	4.184	1.649	211.300	14.975	8.204	6.582
1996	4.389	1.690	212.982	14.532	8.217	8.104
Minivan (9 models)						
1990	3.845	1.642	178.000	14.706	7.429	5.000
1991	3.733	1.641	176.250	13.905	7.711	6.000
1992	2.690	1.690	169.283	15.455	7.465	2.854
1993	2.217	1.679	166.409	16.780	7.208	2.682
1994	2.621	1.671	170.254	15.119	7.568	3.246
1995	3.279	1.608	175.773	13.331	7.988	3.354
1996	3.376	1.618	175.891	13.462	8.038	3.046
All classes (182 models)						
1990	1.976	1.622	171.988	19.209	6.611	6.217
1991	1.948	1.609	173.126	19.121	6.660	5.947
1992	1.876	1.636	174.858	19.145	6.705	6.165
1993	1.928	1.631	175.991	19.093	6.746	6.069
1994	1.926	1.600	174.656	18.881	6.711	6.443
1995	1.983	1.563	175.453	18.495	6.727	6.974
1996	1.987	1.514	176.506	18.662	6.760	6.942

Note:
1. Definition of variables is in Table A.1.. The weight for each model's monthly observation is the average share of the model in the corresponding year.

Figure 1: Shares' conditional expectation function.

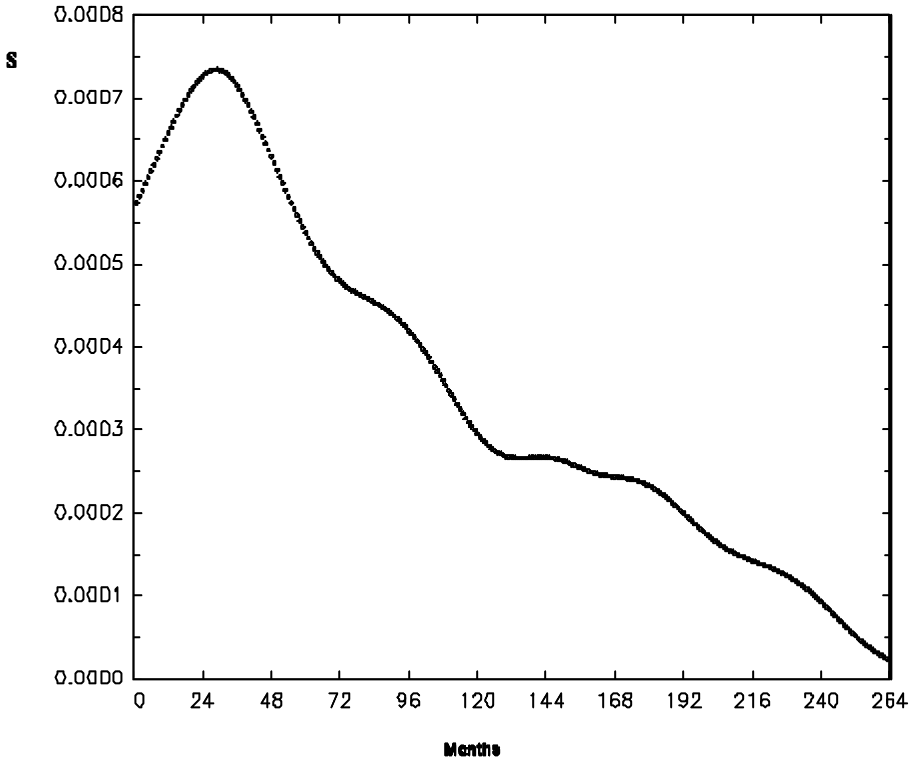

Figure 2.a: Models' survival function.

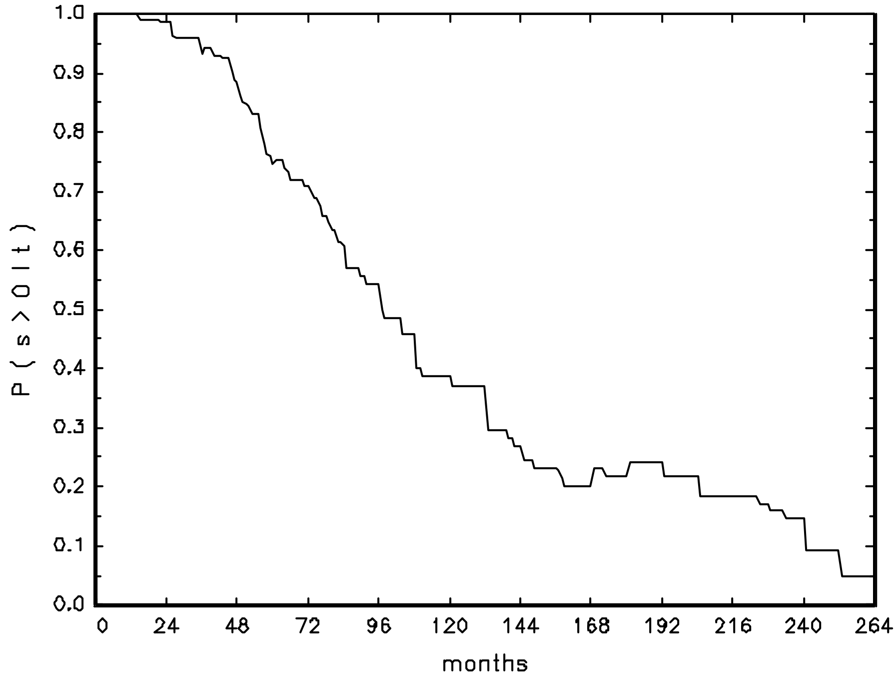

Figure 2.b: Expectation of market share conditional on age and survival

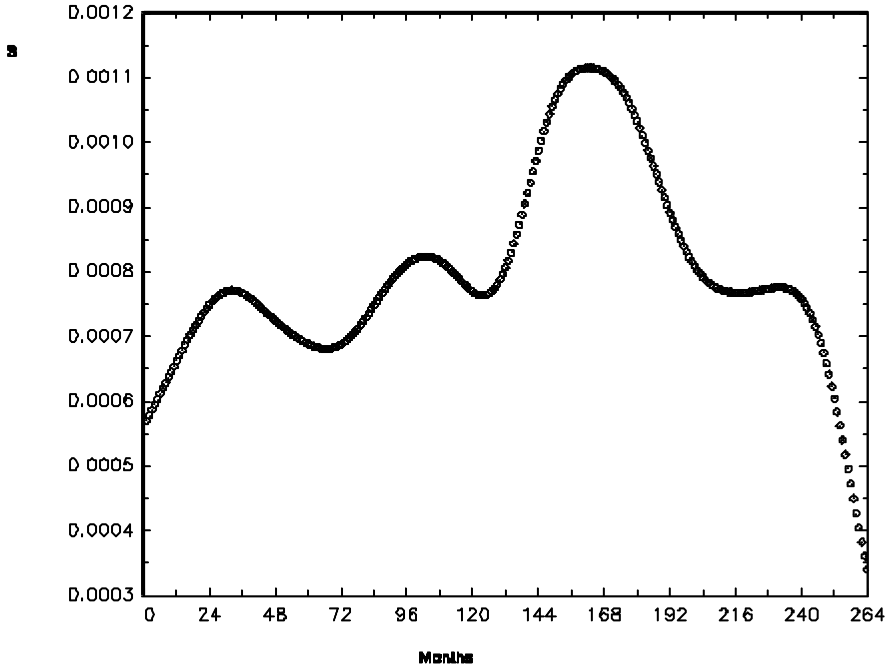

Figure A.1: Frequencies of the non-censured observations.

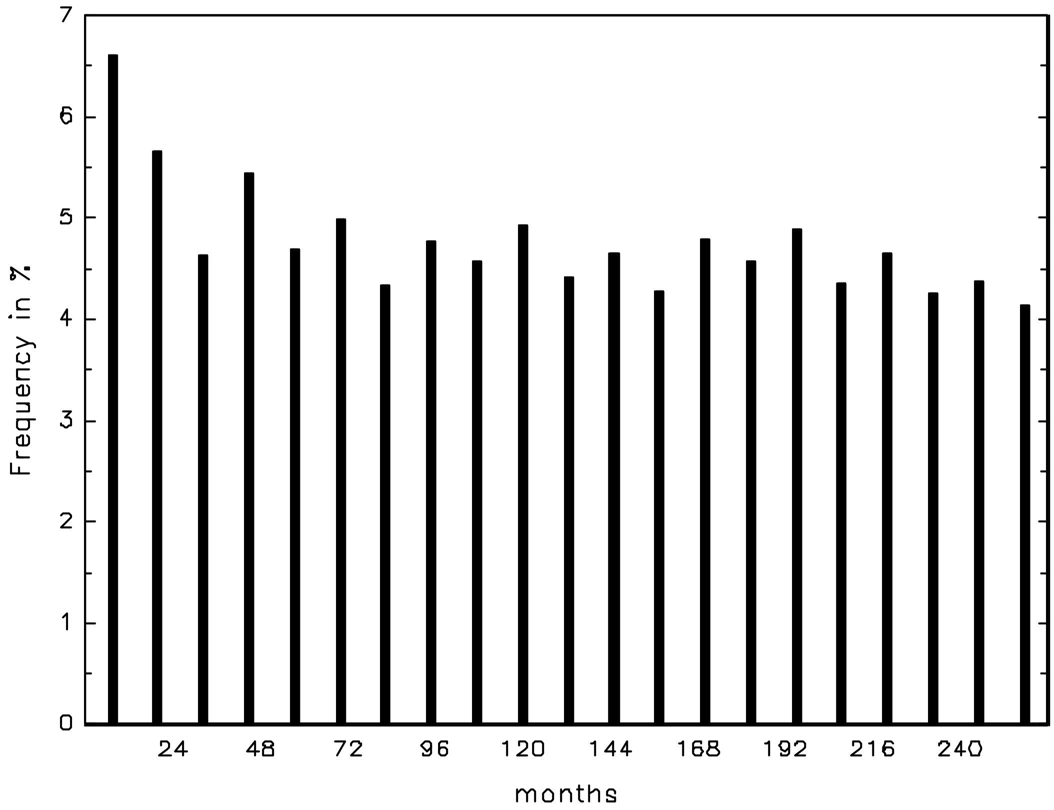

Figure A.2a: Shares' conditional expectation functions of domestic models.

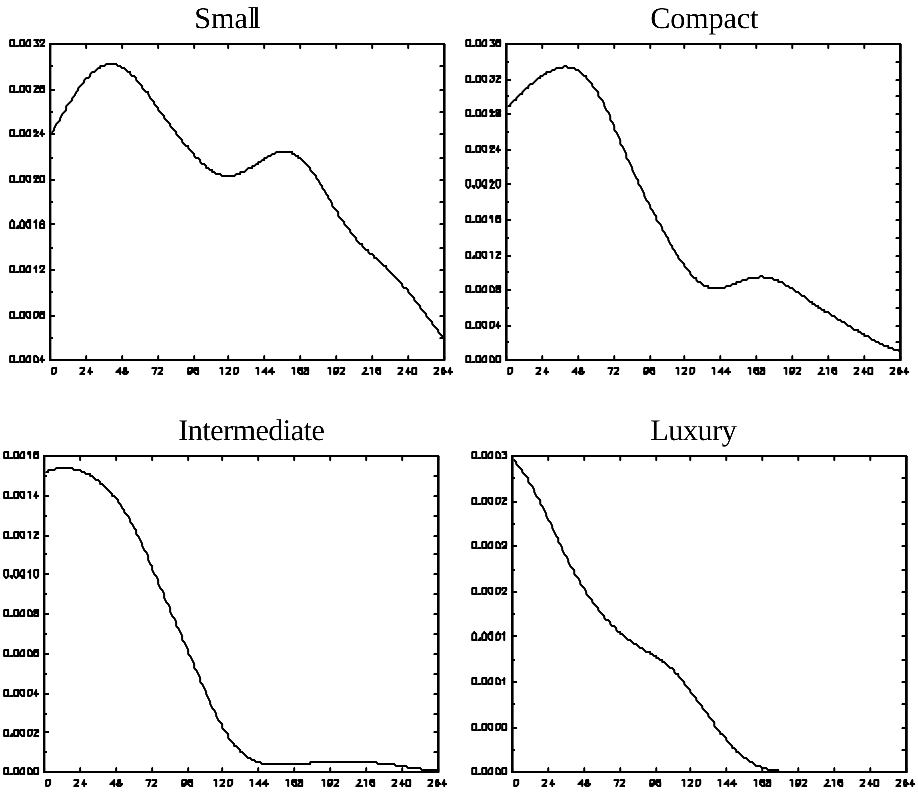

Figure A.2.b: Shares' conditional expectation functions of foreign models.