Advertising and Consumer Awareness of New, Differentiated Products *

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Abstract

This article proposes a novel approach to assess the dynamic effect that advertising expenditures have regarding which products consumers include in their choice sets. In a discrete-choice model consumers face choice sets that evolve according to their awareness of each product. Advertising expenditures have a dynamic effect in the sense that they raise consumer awareness of a product, increasing present and future sales. To estimate this effect the authors explicitly model the firms' dynamic advertising decisions and illustrate the model using data from the Spanish automobile market. The results show that the effect of advertising on awareness is dynamic and that accounting for it is crucial in explaining the evolution of product sales over its life cycle. Furthermore, we show that the awareness process can be significantly sped up by advertising. Thus there is a great heterogeneity in the awareness process among products depending on the level of advertising expenditures and it may range from one to six years.

JEL codes: L13, L62, M11, M37.
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Advertising is a primary tool for firms to affect the performance of their products, specially in markets for consumer goods such as cars, computers, cell phones, and digital cameras. Such markets are characterized by the continuous turnover of multiple relatively close substitute products. Therefore, advertising becomes crucial in making consumers aware of the existence and characteristics of new products.

Marketing literature therefore acknowledges how advertising influences consumers, beyond the traditional effects on their preferences. That is, a second channel is important inasmuch as it changes the consumer awareness of a product. This awareness determines consumers' *choice sets*; among the large number of products in the market, consumers are only aware of a few of them when they make their choice. Although most of the literature has focused on the static effect of advertising in the consumer choice set, this assumption is not very compelling when we aim to study the entry of new products in markets for infrequently purchased goods. To the extent that consumers currently aware of a product are more likely to keep it in their choice set in the future the awareness of a new product increases over time. We denote this dynamic effect as the awareness process for new products. Of course, this awareness process makes advertising a dynamic firm choice. This dynamic effect, together with the entry of new (and better) competing products in the future, can explain why firms concentrate their advertising expenditures early in a product's life cycle, where the novelty and its innovative features might compare favorably with competitors' offerings, and reduce them over time.[1]

In recognition of these effects, we propose an empirical model to measure the dynamic effect of advertising on consumers' product awareness and the evolution of their choice set over time. To disentangle this effect of advertising from the effect that operates through the utility function we use the importance of the effect of advertising on awareness early in the life cycle of a product whereas for mature products the awareness process has finalized and the effect on the utility is more dominant. An illustration, using data from the Spanish automobile market, suggests that the awareness process may vary significantly among products. We show that the effect of advertising on awareness is dynamic and that accounting for it is crucial in explaining the evolution of product sales over its life cycle.

The results of our model have significant implications from a managerial point of

[1]This stylized fact also has been explained with models in which agents know about the existence of a product but they learn about its quality from repeated purchases (Ching and Ishihara 2010) or according to the existence of a goodwill stock in the utility function. In the product markets we focus on these effects are likely to be second order; Repeated purchases are a weak source of learning for durable goods and the goodwill effect is likely important for brand level advertising but less so in the case of products with high turnover.

view. First, understanding the dynamic effect of advertising on consumer awareness is important to the extent that firms make significant investments early in the life of a product aiming that consumers include it in their choice set. Second, understanding how much of the effect of advertising derives from changing consumer awareness versus changing their preferences has important consequences, for example, for the competition that is likely to emerge among firms. Sutton (1991) suggests that when advertising improves perceptions of the quality of a product it can pose a barrier to entry and lead to high concentration in the market. Instead, if advertising expenditures mainly affect awareness, Fershtman and Muller (1993) argue that it might increase competitition and, even might lead firms to curtail their expenditures to prevent fierce price competition.

There is an extensive literature that emphasizes the dynamic effects of advertising for the consumer utility (usually understood as a stock). However, papers that have studied how advertising helps in developing a consumer's awareness of a product, such as Draganska and Klapper (2011) or Goeree (2008), have overlooked its dynamic component. One of the few exceptions is Clark, Doraszelski, and Draganska (2009) who empirically show, using evidence across markets, that the dynamic effect of advertising operates mainly through the awareness channel. Evaluating the previous effect is important because, as Doraszelski and Markovich (2007) theoretically show, it has implications on the structure and the dynamics of an industry.

We propose a structural demand-and-supply model for differentiated products that explicitly accounts for the dynamic effect of advertising on the choice set. The demand side of the market is modeled using a conditional logit model of discrete choice, based on the standard setup developed by McFadden (1974). However, each consumer's choice set depends on how long each product has been in the market and the advertising expenditures on each of them. Of all the products the consumer is aware of (that is, products in the consumer's choice set), he or she chooses the one that leads to the highest utility. This utility is determined by product characteristics, the price, and the advertising expenditures by the firm.

On the supply side, we explicitly postulate the problem that each firm faces when deciding the price and advertising expenditures for each of its products. These multi-product firms maximize the present value of future profits, and take into account that advertising not only affects the consumers' utility but also the configuration of their choice set. The firm's problem leads to a closed-form equilibrium condition obtained using the technique proposed by Berry and Pakes (2001). This technique is based on the estimation of the optimality conditions using dynamic controls, i.e. advertising in our application, which enables us to consider dynamic strategic interactions among firms. Other methodologies developed to study dynamic oligopoly problems (e.g. Ericson and Pakes 1995; Aguirregabiria and Mira 2002; Bajari, Benkard, and Levin 2007) explicitly solve the value function and/or the optimal policy function of the firm. Instead, Berry and Pakes (2001) has computational properties similar to those of Euler equation estimation techniques (Hansen and Singleton 1982) but still can be derived for problems that involve interactions among agents. Our analysis constitutes one of the first applications of this methodology.

By combining the two sides of the market, we obtain three equilibrium relationships: demand, price, and advertising. As Chintagunta, Kadiyali, and Vilcassim (2006) suggest, we explicitly model both advertising and pricing decisions to overcome the potential problems of endogeneity and simultaneity.[2] We estimate these equations simultaneously with aggregate data using the Generalized Method of Moments and simulation techniques, following the algorithm proposed by Berry, Levinsohn, and Pakes (1995).

To illustrate this methodology, we estimate the model for the Spanish automobile market using monthly data from January 1990 to December 2000 (132 months) with a "car model" as the elementary unit of analysis. Our data include monthly advertising expenditures attributed to each car model. Overall, 257 distinct car models were sold in the market during the sample period, offered by 33 multi-product manufacturers. The Spanish automobile market is representative of many consumer markets for several reasons. First, sales of new car models tend to increase up to the third year in the market and then tail off. Second, firms follow a typical pattern of advertising a car model mostly at entry. This behavior is especially remarkable in the first year, when the median expenditure in advertising is 137% higher than in the fifth year. In contrast, median sales in the first year are approximately 13% lower. Third, during the 1990s, 180 car models entered and 98 exited the Spanish automobile market. This large turnover of car models enables us to capture the determinants of the process by which consumers become informed about new products.

Our estimates indicate that the dynamic effect of advertising in the choice set is particularly important for new products, the awareness process of which can be significantly sped up. We estimate that though this process takes three years on average, there is a

[2]Endogeneity issues arise because researchers only observe a subset of variables, such as price and advertising, but a firm's choice is based on a larger set of attributes, such as product design or style. As a result, the explanatory variables of the model are likely correlated with the error term, giving rise to an endogeneity problem. The simultaneity problem arises when a firm's choice variables and quantities sold are set simultaneously in the market.

great heterogeneity among products depending on the level of advertising expenditures and it may range from one to six years. We also show that by including the effect of advertising on both consumer utility and the inclusion of a product in the consumer's choice set, we can reproduce the evolution of product sales over its life cycle. Furthermore, we estimate that, on average, half of the effect of advertising on sales stemming from the inclusion of a product in the choice set, can be attributed to its dynamic component.

The heterogeneity in the length of the awareness process and its different components uncovered by our analysis provides a cautionary advice against the use of observations restricted to a fixed initial period in the market to estimate the effect of advertising in the awareness process.[3] To the extent that reduced-form models typically do not endogeneize the duration of this awareness process, driven in part by advertising expenditures, the estimated effects are likely to be biased. From a managerial point of view learning both about the determinants and the end of the awareness process is important because it affects the optimal staging of the advertising expenditures.

In the next section we outline how our work fits into the literature streams on advertising and the characterization of the awareness process. We later describe how we model the consumer and producer sides of the market and we discuss some estimation and identification issues. The empirical application then leads into a discussion of our results

1 Related Literature

Following papers such as Berry, Levinsohn, and Pakes (1995), the literature on aggregate discrete choice models of demand typically assumes that consumers are aware of all products in the market and maximize their utility by choosing among them. However, an extensive marketing literature acknowledges the lack of realism of this assumption. Consumers face a restricted number of alternatives (Hoyer 1984; Mitra and Lynch 1995) that may vary over time and reflect the marketing strategy of the firm (Allenby and Ginter 1995; Siddarth, Bucklin, and Morrison 1995). Furthermore, by not accounting properly for the restricted number of alternatives that a consumer faces, researchers may underestimate the impact of marketing strategies (Bruno and Vilcassim 2008; Draganska and Klapper 2011).

A growing strand of the literature has focused on the determinants of the consumer *choice set* or the subset of products from which the consumer selects the one to purchase.

[3] As Chandrasekaran and Tellis (2007) indicate, other studies identify the end of the awareness process with the moment in which product sales reach their peak.

Many papers have tried to infer how these choice sets come about using survey data. Bronnenberg and Vanhonacker (1996) model choice sets as arising from the salience of a product (or brand). Consumers are more likely to incorporate a product in their choice set if they have purchased it in the past or if it becomes more visible, such as through price promotions or a more prominent shelf placement. Roberts and Lattin (1991) distinguish between awareness sets and choice sets. Whereas an awareness set might arise as a result of firms' strategies, for example through advertising expenditures, the choice set is shaped by consumer decisions. In their model, consumers simultaneously choose, among products they are aware of, to invest in learning about the ones that ex ante are expected to lead to the highest expected utility. Kim, Alburquerque, and Bronnenberg (2010) understand the choice set as the result of a process of sequential search. We choose to abstract away from the role of consumers in actively determining choice sets and, instead mimic Goeree (2008) or Draganska and Klapper (2011), who regard the choice set as a result of firms' advertising decisions.

Advertising expenditures affect not only the consumers' choice set but also the utility that they may obtain from purchasing a product. However, it is seldom the case that choice sets are available to researchers as in Draganska and Klapper (2011). Without this information, separating the two effects of advertising is challenging from an econometric point of view. Several strategies attempt to resolve the challenge. One of them, used in papers such as Ackerberg (2001) or Narayanan and Manchanda (2009), is to use a proxy for the choice set such as the previous purchasing decisions, mainly of frequently bought experience goods. Functional form assumptions have also proved useful in some situations (Bronnenberg and Vanhonacker 1996; Siddarth, Bucklin, and Morrison 1995; Van Nierop, Bronnenberg, Paap et al. 2010). We have access only to aggregate sales data and therefore rely mainly on this last alternative.

In their study of the mature German coffee market, Draganska and Klapper (2011) regard the effect of advertising over the choice set of a consumer to be essentially static. To separate the two effects of advertising they rely on a combination of aggregate information and data on individual choice sets from consumer surveys. In our model, instead, identification is based on the analysis of the dynamic effects of advertising that operate over the choice set of consumers after a product is first introduced in the market. To the best of our knowledge, we offer the first evaluation of the dynamic effect of advertising that comes from variations in the choice set in the context of aggregate discrete choice models of demand.

Goeree (2008) estimates a model for the personal computer market that considers the supply side of the market in order to deal with the endogeneity problem. As in our case, she does not observe individual choice sets. As a result, introducing variation in the consumers' choice set creates a dimensionality problem in the model, arising from the high number of possible choice sets.[4] One of her contributions is to provide a strategy to overcome these problems and measure the effect of advertising on the inclusion of a product in a choice set. Whereas she focuses on the static effect of advertising and abstracts from the effect that it might have on consumer utility, we consider both effects of advertising, study the dynamic implications for awareness, and provide an identification strategy to disentangle the different effects. To also accommodate the dynamic dimension of advertising necessary for this identification, we propose a generalization of Goeree's estimation strategy.

Our work also relates to extensive literature that studies the dynamic effects of advertising. Decades ago, Nerlove and Arrow (1962) pointed out that advertising affects current sales of a product but also has a long-lasting impact on future perception through the goodwill stock that it generates. The dynamic role of advertising also may relate to consumers' learning process. Consumers use information from advertising about the characteristics of a product to update their assessment on the utility that their purchase would entail. Erdem and Keane (1996) measure this effect for the laundry detergents market and Ackerberg (2003) for the yogurt market. That is, consumers learn about the quality of a product both through past experience and exposure to advertising. For products that are not purchased frequently Roberts and Urban (1988) propose a structural model and analyze the learning process using a sample that follows potential customers of a new car model over time.

Ching and Ishihara (2010) propose a dynamic model of detailing in the pharmaceutical industry. Although physicians know about the existence of most drugs, they are initially uncertain about their effectiveness. As a result, the prescription behavior of doctors has two effects on their utility. A static effect arises from the increase in the doctors' utility due to the higher quality of the drug. A dynamic effect arises because the more a drug is currently prescribed the more information a doctor will gather on its effectiveness, increasing future utility. In their model, detailing behavior provides information that accelerates the process by which doctors learn about a new drug. Their identification strategy to isolate the effect of detailing is similar to the one we use and is based on the differentiated impact of prescribing behavior throughout the life cycle of a product.

[4]In our application, a typical month contains an average observations of 130 different products. Considering each choice set explicitly is computationally unfeasible, because the number increases exponentially with the number of products.

However, in their model, the first years in the market reveal the learning component of prescription behavior. In our model, we use data from this period to identify the probability that a product will be included in a consumer's choice set.

2 Model

We describe a model of consumer purchasing behavior in which the set of products that consumers choose from is specific to each individual and evolves over time. Firms choose the price and advertising expenditure for each product. Both strategic variables affect the consumer's decision to buy one product rather than another. Furthermore, advertising affects how aware each consumer is of a product which reveals the probability that is included in a consumer's choice set.

In section 2.1 we describe the problem that consumers solve and derive the demand equation that results from their optimal decisions and that firms face for each of their products. In section 2.2, we present the firm's dynamic problem and derive the close-loop equilibrium equations for the price and advertising expenditure. In section 3 we describe a method to estimate simultaneously these three equilibrium relationships.

2.1 Consumer Problem

We divide the description of the consumer problem into two parts. We first present the preferences that determine a consumer's choice among all the products of which the consumer is aware, and then we describe how the different choice sets come about.

2.1.1 Consumer Preferences

Consider a market comprised of I consumers and J different products. Each consumer i is only aware at time t of the existence of a subset C_{it} of these products. For each product in the *consumer choice set* C_{it}, agent i obtains utility

$$U_{ijt} = \delta_{jt} - \alpha_i p_{jt} + \varepsilon_{ijt}. \tag{1}$$

The term δ_{jt} is a product and time-specific component, common to all consumers. This term is a function of a vector of observed product characteristics x_{jt}, with typical element x_{jkt}. We assume the functional form

$$\delta_{jt} = \sum_k \beta_k x_{jkt} + \gamma a_{jt} + \xi_{jt}, \tag{2}$$

where the parameter β_k is mean taste for observed product characteristic k, the coefficient γ measures the effect of advertising a_{jt} on consumer utility and ξ_{jt} captures the unobserved product characteristics.

Utility also depends on consumer-specific characteristics related to the effect of the product price on consumer utility. The price of the product, p_{jt}, has a consumer-specific effect α_i. Following Berry, Levinsohn, and Pakes (1999), we assume that this effect arises from differences in consumer income y_i, so that $\alpha_i \equiv \alpha/y_i$. If income is log-normally distributed with mean m_{yt} and standard deviation σ_y, then $\alpha_i = \alpha e^{(-(m_{yt}+\sigma_y v_{iy}))}$, where v_{iy} is normally distributed with mean 0 and variance 1.[5] Finally, the term ε_{ijt} captures consumer i's idiosyncratic taste for product j at time t. We assume this stochastic term is drawn from a type-I extreme value distribution with mean 0 and it is independent and identically distributed across products, consumers, and time.

The choice set of each consumer always includes an "outside" option (denoted as good 0) that corresponds to not purchasing any product. This utility can be written as

$$U_{i0t} = \sigma_0 v_{i0} + \varepsilon_{i0t}, \tag{3}$$

where σ_0 is the standard deviation from the mean taste for the outside option, and v_{i0} is the unobserved consumer taste for the outside good, normally distributed with mean 0 and variance 1. The random variable ε_{i0t} follows the same distribution as the rest of ε_{ijt}.

Denote $\mathbb{C}_{jt}$ as the set of all possible choice sets that include product j in period t. The assumption about the distribution of ε_{ijt} allows us to write the probability that product j maximizes consumer i's utility in period t among all the products in choice set C_{it} conditional on observing $v_i = (v_{i0}, v_{iy})$ as follows:

$$f_{ijt|C_{it}}(v_i, \delta_t, X_t; \theta) \equiv \Pr(U_{ijt} \geq U_{imt}, \forall m \in C_{it}) = \begin{cases} \frac{e^{\delta_{jt}+\alpha_i p_{jt}}}{e^{\sigma_0 v_{i0}} + \sum_{\forall m \in C_{it}/\{0\}} e^{\delta_{mt}+\alpha_i p_{mt}}}, & \text{if } C_{it} \in \mathbb{C}_{jt}, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

In this previous probability, δ_t denotes the vector of product-specific components, X_t is the matrix that includes the vector of characteristics of all products, and θ is the set of parameters of the model.

Because each consumer's choice set is unobserved, we must draw inferences from the unconditional probability that consumer i buys product j at time t. It is easy to see that this probability, denoted s_{ijt}, can be obtained as the sum of the probability that product j is preferred for a given choice set, weighted by the probability that each choice set is

[5] The complexity introduced by the dynamics of the model leads us to consider only a random coefficient on the price, based on the empirical distribution of income, and the outside good. The model could be extended to a full random-coefficient model.

realized. Thus,

$$s_{ijt} = \sum_{C \in \mathbb{C}_{jt}} f_{ijt|C}(v_i, \delta_t, X_t; \theta) \Pr\left(C | \{X_r, y_{ir}\}_{r=1}^{t}\right). \tag{5}$$

We now turn to how each possible choice set can come about.

2.1.2 Choice Set Probabilities

We assume that a product can be included in a consumer's choice set either for exogenous reasons (for example, consumers are more likely to learn about a product when it has been in the market longer) or as a result of the firm's behavior, mainly through the use of advertising.

We impose two constraints on the determinants of a consumer's choice set. First, we assume that the probability that a product is included in a consumer's choice set is independent of the other products that are also included. This assumption rules out the existence of cognitive constraints (e.g. a consumer can only remember a certain number of products) or information spillovers (e.g. a consumer aware of the existence of a product is also aware of the existence of other products sold by the same firm). Second, the probability that a product is included in a choice set is independent of the characteristics of the consumer.

Our assumptions stem from the lack of individual data. When these data are available, other works in the literature have shown that these assumptions can be relaxed. Draganska and Klapper (2011) and Van Nierop, Bronnenberg, Paap et al. (2010) use individual choice set data that makes the first concern moot. To the extent that these choice sets can be related to individual consumer characteristics, the second concern also can be overcome. Papers based on individual product choices, such as Chiang, Chib, and Narasimhan (1998) or Goeree (2008), indicate that choice sets might vary substantially across consumers.

With our assumptions, the probability that a given choice set C arises, defined in Equation 5, can be written as

$$\Pr\left(C | \{X_r, y_{ir}\}_{r=1}^{t}\right) = Pr\left(C | \{X_r\}_{r=1}^{t}\right) = \prod_{j \in C} \phi_{jt} \prod_{m \notin C} (1 - \phi_{mt}). \tag{6}$$

The function ϕ_{jt} measures the probability that product j is in choice set C at time t. That is, the probability of choice set C is the product of the probability that the consumer is aware of each product in C and is not aware of any of the products that do not belong to C. As mentioned previously, we assume that the outside option belongs to all choice sets, such that $\phi_{0t} = 1$ for all t. We further assume that ϕ_{jt} only depends on the characteristics of product j. We postulate the function,

$$\phi_{jt} = \frac{e^{\omega_{jt}}}{1 + e^{\omega_{jt}}}, \tag{7}$$

where ω_{jt} is a latent variable that captures the *awareness level* of product j at time t. This latent variable exhibits time dependence and evolves according to the following transition equation[6]

$$\omega_{jt+1} = \lambda\omega_{jt} + \varsigma_{jt}. \tag{8}$$

The awareness level in each period depends on awareness in the previous period, through the carryover coefficient λ. The last term captures the effect of advertising as a source of information, and ς_{jt} takes a value 0 or 1, according to

$$\varsigma_{jt} = \begin{cases} 1 & \text{with probability } \frac{\kappa a_{jt}}{1+\kappa a_{jt}}, \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

The parameter $\kappa > 0$ measures the impact of advertising. The higher the advertising expenditures, the more likely it is that a consumer is aware of the existence of the product.[7] The discrete outcomes of ς_{jt} can be interpreted as the outcome of a consumer being exposed (or not) to advertisements of product j. However, this discreteness is smoothed out in the aggregate, because different consumers face different choice sets resulting from different realizations of the random variable that characterizes the probability of inclusion ϕ_{jt}.

Finally, we denote $\bar{\omega}_{jt}$ as the initial awareness of product j introduced in the market in period t. This initial awareness varies across products, because firms might engage in promotion activities even before the product is sold. In particular, we postulate

$$\bar{\omega}_{jt} = \psi a^b_{ft}, \tag{10}$$

where a^b_{ft} denotes the average annual expenditure incurred by firm f (seller of product j) to advertise its brand in period t. We use brand advertising expenditure as a measure of the presence of a firm in the market. For our application, the car market, brand

[6]See Ching and Ishihara (2010) for a similar structure to model how different physicians learn about the effectiveness of a drug. Interestingly, whereas in our model choice sets are heterogeneous in the population but product information is always complete, in their setup product information sets are heterogeneous in the population but the choice set is always complete.

[7]The specification of the effect of advertising is similar to the one used in Pakes and McGuire (1994) to model the transition equation of capital as a result of investment. This specification satisfies two properties necessary to apply the methodology proposed by Berry and Pakes (2001): the transition probability of ω_{jt+1} conditional on a_{jt} is random and its support is independent of a_{jt} (see Appendix A).

advertising is meant to proxy for consumer exposure to the firm like the number of dealerships or presence in car shows. Thus, the initial awareness ψ determines how important firm exposure is and adds a source of heterogeneity across firms, depending on their previous presence in the market.

To summarize, it is important to notice that our specification assumes that the awareness level accumulates over time and it is a function of the history of advertising expenditures.[8] The dynamic component of the evolution of awareness of a product is governed by the parameter λ. A value for this parameter greater or equal to 1 would not necessarily mean that consumers do not forget, but rather that the proportion of consumers who learn about the product increases over time.

Furthermore, in our specification the awareness probability ϕ_{jt} has an S-shaped form as a function of ω_{jt}, meaning that the probability grows exponentially in initial stages but then slows down as the product becomes well-known, with an asymptote at 1. We define the end of the awareness process of a product as the moment at which awareness probability remains stable over time.

It might be useful, at this point, to compare our model of the consumer choice set with Goeree's (2008). Using individual information based on survey data related to consumer exposure to media, she constructs awareness probabilities that not only depend on advertising or product age but also are a function of demographic characteristics. Thus, she obtains consumer-specific probabilities ϕ_{ij}. However, because her focus in on the high-turnover personal computer market, she only considers the contemporaneous effect of advertising on awareness, and abstracts from its dynamic impact. In our application, products typically stay in the market for at least six years, so Goeree's simplification would be problematic. Indeed, in section 4.3 we show that accounting for the dynamic component of advertising is empirically relevant to our results.

2.1.3 Market Shares

The predicted market share of product j at time t, corrected by the awareness process, can be obtained from the individual purchase probabilities described in Equation 6 aggregating over the distribution of consumers' characteristics, $dP_v(v_i)$ with $v_i = (v_{i0}, v_{iy})$, and the random term that determines the transition process for the awareness level. Thus,

[8] We do not allow for the possibility that previous sales drive the awareness process of the product, as occurs, for example, if consumers who have bought the product actively spread information to other consumers. Making awareness a function of previous sales introduces an additional source of dynamics that would lead to computational difficulties related to the lack of close-loop equilibrium conditions for the firm's optimization problem.

the predicted market share for product j at time t can be obtained as

$$s_{jt} = \int \sum_{C \in \mathbb{C}_j} \left(\prod_{l \in C} \phi_{lt} \prod_{m \notin C} (1 - \phi_{mt}) \right) \ f_{ijt|C} \ \ dP_v(v_i) dP_\varsigma \left(\{\varsigma_r\}_{r=1}^{t-1} \right), \tag{11}$$

where $dP_\varsigma(\{\varsigma_r\}_{r=1}^{t-1})$ denotes the distribution of ς for all firms from period 1 to $t-1$. The awareness level of a product is the result of the build up of advertising expenditures in all previous periods.

Finally, the demand for product j at time t can obtained by multiplying its market share by the size of the market at time t, denoted I_t.[9].

2.2 Dynamic Problem of the Firm

We consider multiproduct firms that choose in every period the price and advertising expenditures for each of their products. These firms behave as Bertrand competitors. Their maximization problem is intrinsically dynamic, because consumer awareness of a product builds over time. In other words, the advertising expenditure at time t has an effect on future sales by making the choice sets in which the product is included more likely to be realized for each consumer. Thus, the problem that firm f maximizes can be written as

$$\sup_{a_{ft}, p_{ft}} E \left[\sum_{\tau=0}^{\infty} \rho^\tau \pi_{f \ t+\tau} | x_t, \omega_t, a_{-ft}, p_{-ft} \right], \tag{12}$$

where a_{ft} and p_{ft} are the vectors of advertising expenditures and prices, respectively, for all products offered by firm f, and a_{-ft} and p_{-ft} denote the advertising and prices of competitors. The coefficient ρ is the time discount factor. Finally, the function π_{ft} denotes the net cash flow of firm f at time t and can be written as

$$\pi_{ft} = \sum_{r \in \mathbb{F}_f} \left[(p_{rt} - mc_{rt}) \, s_{rt} I_t - a_{rt} \right], \tag{13}$$

where $\mathbb{F}_f$ indicates the set of products sold by firm f, and mc_{jt} is the marginal cost of product j at time t. The log of this marginal cost is approximated by the weighted sum of the log of the product attributes. Some attributes are observed by the econometrician, aggregated in the vector w_{jt} (with typical element w_{jkt}), whereas some are not, as represented by the random variable ζ_{jt}. Thus, the marginal cost of product j is determined

[9] As usual, market size is understood as the set of potential consumers. Some will choose not to purchase any product (they buy product 0), whereas the rest constitute the market demand. In this model, advertising affects market demand by attracting consumers that otherwise would not purchase the good, either because they were not aware of it or because their utility was low.

by

$$\ln(mc_{jt}) = \sum_k \eta_k \ln(w_{jkt}) + \zeta_{jt}. \tag{14}$$

The coefficient η_k denotes the effect of characteristic k on marginal cost.

Notice that the state variables at time t are the vector of attributes of all products, x_t, and the awareness levels of all products ω_t. In other words, we assume that when a firm chooses prices and advertising expenditures, it can observe the realization of ς_t for all products up to the beginning of period t. We also assume that each firm is only uncertain about future awareness levels but it can anticipate the entry and exit of products, as well as their characteristics.

The optimal price decision of firm f for product j arises from the first-order condition of the problem in Equation 12 which can be written as

$$s_{jt} + \sum_{r \in \mathbb{F}_f} (p_{rt} - mc_{rt}) \frac{\partial s_{rt}}{\partial p_{jt}} = 0. \tag{15}$$

Regarding advertising, we assume that each producer behaves as a single-product firm. The firm thus does not take into account the effects of advertising on the other products it sells. This assumption reflects the estimation requirements we explain in Appendix A, though our results in section 4.3 indicate that it is not likely to generate significant biases in our application. In this case, we can represent the dynamic problem that a firm faces for each of the products it sells, as in the following Bellman equation,

$$V_j(\omega_t) = sup_{a_{jt}} \left\{ \pi_j(a_t, \omega_t) + \rho E_\omega \left[V_j(\omega_{t+1}) | \omega_t, a_t \right] \right\}, \tag{16}$$

where V_j is the present value of profits of product j, the state variables ω_t evolves according to the transition Equation 8, and $\pi_j(a_t, \omega_t)$ is the net cash flow of the firm f at time t from product j, as given by

$$\pi_j(a_t, \omega_t) = \left[p_{jt} - mc_{jt} \right] s_{jt} I_t - a_{jt}. \tag{17}$$

We follow the procedure introduced by Berry and Pakes (2001). In Appendix A we show that the first-order condition for the advertising expenditure of product j at time t resulting from Equation 16 can be written as

$$\left[(p_{jt} - mc_{jt}) \frac{\partial s_{jt}}{\partial a_{jt}} I_t - 1 \right] + \sum_{\tau=1}^{\bar{T}_j} \rho^\tau \pi_j(a_{t+\tau}, \omega_{t+\tau}) \frac{1}{a_{jt}(1 + \kappa a_{jt})} = u_{jt}, \tag{18}$$

where $\bar{T}_j$ is the time product j exits the market. The advertising expenditures thus have two effects on profits. One of the effects is contemporaneous; from Equation 1 we know that an increase in advertising raises consumer utility directly and thus market share, at a higher cost. The second term captures the dynamic effect, in that firms factor the impact that their current expenditures will have on their future advertising decisions, as well as the decisions of their competitors. This interaction is reflected in changes in the distribution of future choice sets. The error term on the right-hand side, u_{jt}, arises from the difference between expected and realized future profits. With the rational expectations assumption, this error is uncorrelated with the information available at t, $E[u_{jt}|\omega_t] = 0$.

Notice that this dynamic effect can potentially reproduce a stylized fact that arises in environments similar to the one in our application, where manufacturers advertise new car models heavily even before they are launched. As sales pick up, and a car model moves through its life cycle, advertising expenditures decline progressively.

It is important to discuss a few caveats of Equation 18. First, it presumes that the optimal choice of advertising is interior. Second, it presumes that exit is an exogenous and deterministic decision, which is potentially problematic. For example, since we do not explicitly model $\bar{T}_j$, it would be possible to argue that because less advertised products are less likely to be incorporated in a consumer choice set, they also become less profitable, resulting in an earlier exit decision. Third, it presumes that the whole history of a product, up to the moment where it exits the market, is observed. However, in most applications the sample period is truncated; it does not comprise the whole history of all products. In the results section we discuss how important are those caveats in our application.

The equilibrium relationships Equations 15 and 18 determine a system of $J_t \times 2$ equations since they must be satisfied for all J_t products.

3 Estimation

In this section, we describe the empirical strategy we use to estimate, on the basis of the previous three equilibrium equations, the vector of parameters of the model $\theta \equiv \{\alpha, \sigma_0, \beta, \gamma, \eta, \kappa, \psi, \lambda\}$. We set the discount factor, ρ, to .99. We also discuss some identification issues.

3.1 Estimation Routine

We follow an estimation routine inspired by Berry, Levinsohn, and Pakes (1995), and described in detail by Nevo (2001). The estimation simulates the market shares for mean utility levels and uses these imputed mean utilities in a moment condition. This condition can be combined with other moment conditions arising from firms' pricing and advertising decisions, which express orthogonality between appropriate instruments and the unobservable components.

The three equilibrium relationships are estimated simultaneously using the Generalized Method of Moments (GMM), considering the objective function $\Lambda' Z A_N^{-1} Z \Lambda$, where A_N is a weighting matrix, $Z = (Z_\xi, Z_\zeta, Z_u)$ are instruments orthogonal to the composite error $\Lambda = (\xi, \zeta, u)$, and

$$Z'\Lambda = \left[\begin{array}{c} \sum_j Z_{\xi_j} \xi_j(s^n, P_{ns}, P_H; \theta) \\ \sum_j Z_{\zeta_j} \zeta_j(s^n, P_{ns}, P_H; \theta) \\ \sum_j Z_{uj} u_j(s^n, P_{ns}, P_H; \theta) \end{array} \right].$$

We have defined ξ_j, ζ_j, and u_j as vectors that aggregate time observations of ξ_{jt}, ζ_{jt}, and u_{jt}, respectively. If n individuals are sampled, s^n denotes the observed vector of market shares of all products, and P_{ns} is the empirical distribution of ns simulation draws from the assumed distribution of consumer characteristics $v_i = (v_{iy}, v_{i0})$. In addition, P_H is the empirical distribution of H simulation draws from the assumed distribution of the awareness variable ς.

Because we do not observe the realized choice set of each consumer, we must depart from the standard algorithm offered by Berry, Levinsohn, and Pakes (1995). In particular, we require a probability that each product is purchased by any consumer for all choice sets that might include it. In most markets, the number of different products is quite large – in our application, we find an average of 130 products – so considering all possible choice sets poses a significant computational burden. To solve this dimensionality problem we simulate a choice set for each individual in each period according to the awareness probabilities of all products specified in the model, and we construct an importance sampler to smooth out the simulated choice probabilities. The simulator for these probabilities results from the average over individuals. This strategy is a dynamic extension of the procedure by Goeree (2008). Rather than simulating choice sets for each consumer to choose, we simulate H complete histories of choice sets. Consumer characteristics remain constant over time to obtain the simulation estimator for market shares. Appendix B describes this procedure in detail.

The method outlined previously requires valid instruments. That is, they must be correlated with specific functions of the observed data, but they should be uncorrelated with the unobservable variables and the expectations disturbance. We choose two sets of instruments for the demand and price equations. First, as it is standard in literature, we observe that the markup equations described in the previous section show that the price of product j is correlated with the characteristics of the products offered by the same multiproduct firm, as well as the products sold by rival firms. We also assume that the supply and demand unobservables are mean independent of both observed product characteristics and cost shifters. With that assumption, we can include as instruments the observed product attributes (other than price and advertising) and cost shifters. Unfortunately, since product characteristics do not change frequently, in order to capture monthly variation in our endogenous variables we also need to rely on a second type of instruments. They consist of price differences with respect to their individual time means, $\widetilde{p}_{jt} = p_{jt} - (\frac{1}{T})\sum_{s} p_{js}$, lagged a certain number of periods. By writing prices as deviations from their within-group mean, we can eliminate the correlation with the error term arising from the individual fixed effect. This type of instruments was first proposed by Bhargava and Sargan (1983), and its moment restrictions have been studied by Arellano and Bover (1995).

For the advertising equation we use the characteristics of products as instruments, because the error term of the equation from the firm's advertising decision, which underlies the estimation, is an expectation error. According to the rational expectation assumption, this error is not correlated with the state variables.

Following standard practice, we initially set $A_N = Z'Z$ to obtain a consistent estimate of the asymptotically efficient weighting matrix. We later use this matrix to re-estimate the model and obtain the final result.

Finally, to reduce the computation burden, we restrict the non-linear search over the parameters to a subset $\{\alpha, \sigma_0, \kappa, \lambda, \psi\}$. We concentrate out the parameters $\{\beta, \gamma, \eta\}$ and minimize the GMM objective function with respect to $\{\alpha, \sigma_0, \kappa, \lambda, \psi\}$. This search relies on Nelder and Mead's (1965) non-derivative simplex search routine because the objective function is not smooth with respect to the awareness parameters $\{\kappa, \lambda, \psi\}$.

3.2 Identification

One of our research goals is to separate the effect that advertising has through the awareness process from effects due to changes in consumer utility. We can achieve this identification through a combination of the different implications that both effects of advertising have during the life cycle of a product, together with our functional form assumptions for the evolution of choice sets.

In particular, Equation 5 shows that the probability that an individual buys a certain product is a function of the probability that the product maximizes the utility among all the products included in a given choice set and the probability that such a choice set arises. An increase in advertising of a product will increase both terms. However, this increase differs depending on the awareness of the product. Our modeling assumptions (particularly in Equation 7) imply that advertising has a bigger impact on the probability that a product is included in the choice set when the awareness level is low. When the awareness level is high though, the effect of advertising tends to be low, because awareness converges to a stationary level. To the extent that consumers are more aware of products that have been in the market for a longer time, observing products at different ages allows us separate the effects. When the product is new in the market, advertising expenditures mainly affect consumer awareness, mediated in our model by a non-linear effect. The combination of these two features enables us to identify the awareness parameters (λ, ψ, κ). Later in the life of the product however, because a stationary proportion of consumers already has included the product in their choice set, changes in sales as a result of advertising can be essentially attributed to the effect that operates through the utility function, measured by γ. Ching and Ishihara (2010) use a similar identification strategy.

4 Empirical Application

4.1 The Spanish Automobile Market

We illustrate the preceding methodology with an application to the Spanish automobile market of the 1990s. In particular, we constructed a panel that covers eleven years, from January 1990 to December 2000. We have monthly observations (132 months) with the "car model" as the elementary unit of analysis. During these eleven years we observe 257 different models offered by 32 brands (multiproduct firms). The unit of observation is a model/month and, in total, we have 16,362 observations.

Our data comes from three sources.[10] The "Asociación Nacional de Fabricantes de Automóviles y Camiones" (ANFAC) provides data on new car registrations (sales). This information has been complemented with *Guía del comprador de coches*, a Spanish magazine that reports final consumer prices for each car model,[11] as well as characteristics such as brand, size (square meters), engine displacement over car weight (measured in

[10]See `http://www.anfac.com`, `http://www.infoadex.es`, and `http://www.ine.es`.

[11]In the estimation, we distinguish between final prices and prices perceived by producers, net of taxes and tariffs. At the end of the 1990s, the Spanish automobile market experienced a gradual reduction of tariff and non-tariff protections as a result of the country's integration into the European Economic Community (EEC). This process was completed in 1993 with a complete dismantling of tariffs for European foreign producers and a common EEC tariff of 10% for non-European foreign producers.

cubic centimeters per kilogram), gas mileage (kilometers covered at a constant speed of 90 kilometers per hour with one liter of gasoline), and maximum speed. The car models' attributes are taken from the most representative (sold) version of the model.

The second source of information is Infoadex, a consultancy that collects data on advertising expenditures, by monitoring firms' exposure in the media on a daily basis. The advertising data contains total advertising expenditures through main media channels: newspapers, magazines, television, radio, cinema, and billboards. They also distinguish the advertising expenditures by firms in the Spanish automobile industry into the efforts to promote the brand (on average 18.2% of the total), promote a specific model (70.1%), or advertise a group of models with similar characteristics (11.7%). Brand advertising is characterized primarily by a focus on the brand position and communication of its attributes and benefits, without referring to any car models. Because our unit of analysis is car models, we focus mainly on the advertising of specific models. We attribute the expenditures of advertising a group of models equally to all its components.

The third source of information is the Spanish Statistical Institute (INE), which provides data on the number of Spanish households that we use as a proxy of the potential market size[12] and the distribution of Spanish income per capita during the 1990s (annual mean and standard deviation).

Table 2 reports summary statistics for annual sales, average model prices, advertising expenditures, size, maximum speed, gas mileage, and engine size. We observe that sales varied considerably during the 1990s, mimicking the economic cycle. In 1993 car sales dropped around 32% (compared with 1992), and the ratio of advertising to revenue increased more than 20%. This result suggests that producers adjusted their advertising expenditures to smooth demand changes from common markets shocks, and it points to a potential simultaneity problem of advertising and sales.

In Table 3 we illustrate the advertising pattern across products in the Spanish automobile market, including annual price averages and advertising expenditures according to the percentiles of the advertising-to-revenue ratio distribution. As we discuss next, car models are heavily advertised during the first years, so these statistics only consider observations for car models that stay in the market beyond two years. The advertising-to-revenue ratio is very skewed, ranging from close to 0% in the lowest decile to almost 15% in the highest, with a median around 3%. We observe a negative relationship between advertising and price, indicating that advertising is used more intensively as a tool

[12]Model market shares are computed as unit sales of each model divided by the total market size (number of households). We convert the shares into annual values to facilitate comparisons with previous studies that used yearly data.

to differentiate car models in the lowest segments of the market. One possible reason for this regularity is that for car models that belong to luxury segments, the producers aim to achieve this differentiation through other means, such as brand recognition. This result suggests an important role of advertising as a source of differentiation.

In any given month, positive advertising expenditures are reported in about 90% of the models (95% at the annual level). The main exception are five car models that comprise less than 1% of the sales and are never advertised. Figure 1 shows that more than 40% of the models are always advertised and 80% are not advertised at most during 15 months (compared to the eight years that the average model is present in the market). These zero advertising expenditures are concentrated in the last few months the car model is in the market.[13] This the reason why, as the figure also shows, more than 70% of the models are advertised in all months in their first two years after entry. The remaining proportion of observations with zero advertising expenditures are mainly explained by a seasonal component; more car models are advertised before the summer and fewer in July and August.

The model we presented in previous sections assumes that all firms choose an interior (i.e., positive) level of advertising. In order to accommodate corner solutions in our econometric specification we estimate the dynamic term of Equation 18 only for those observations with a positive advertising expenditure and a constant dynamic term for those observations with zero advertising expenditures. This strategy together with the fact that the identification of the dynamic effect is based on the first years the model is in the market (for which advertising expenditures are mostly positive) and the presence of dummies of month mitigates the potential biases that may arise.

Table 4 shows the life cycle of a car model. Because sales are very skewed and in order to abstract from selection problems, we focus on the median model among those that stay in the market for more than six years. Sales typically increase up to the third year in the market and then tail off. Advertising, instead follows a pattern described by Horsky and Simon (1983): Firms advertise heavily when products are introduced in the market but reduce their advertising as sales increase and the product moves through its life cycle. In particular, there is a remarkable drop of 31% in advertising expenditures around the fourth year. Table 5 provides an informal explanation for this behavior. Using again car models that stay in the market for more than six years, we regress car sales with respect to contemporaneous as well as cumulative advertising expenditures. The estimation shows

[13]If we do not consider the last year in the market we observe that almost 60% of the models are always advertised and 90% have zero advertising expenditures at most during 15 months.

that the previously accumulated advertising expenditures, controlling for the effect of the current ones, only have a significant effect on sales in the first two years that a car has been in the market. This result also provides support for the identification strategy described in the previous section, since it suggests that we can isolate the static effect of advertising on consumer utility by focusing on car models that are late in their life cycle.

The Spanish automobile market is a particularly suitable application of our model, considering the intense process of model entry observed during that period. Table 6 reports the number of models in the market, as well as the entry and exit flows. From 1990 to 2000, the Spanish automobile market witnessed an important increase in the number of models, from 97 in 1990 to 169 at the end of 2000. The process that lifted tariff and non-tariff protection in the Spanish market motivated the intense entry of manufacturers and products. During the 1990s, approximately 180 models entered the market. This significant entry flow plays an important role in our model for estimating the awareness process associated with new products in the market.

The exit of 98 models before the end of 2000 further enables us to estimate the advertising equation; to compute the second term of the dynamic advertising Equation 18, we needed to observe product exits. On average, these 98 models exit after 8 years in the market, with a range that goes from 1 to 20 years. We also observe the entire market life of 46 models. We next argue that, first, the exit of these car models does not seem to be driven by the dynamic effect of advertising and thus, as our model assumes, we can treat the exit decision as exogenous. Second, we also show that by focusing on these models our estimation of the dynamic advertising equation we are unlikely to introduce significant biases due to the truncation of the sample.

In Table 7 we study whether the exit decision is driven by our state variables and, in particular, the consumer awareness of the product. We proxy the awareness using the accumulated advertising expenditures of the model and for this reason we focus on those models for which entry is observed. Our estimations suggest that this variable is not a significant determinant of the exit decision.[14] The results also indicate that the contemporaneous variables that result from our structural equations (price, advertising, and units sold) are significant in the specification with the expected sign. Although our results do not indicate causality they are consistent with the view that when a car model is about to exit the market, the manufacturer chooses to advertise it less, sets a lower price, and sells fewer units. In the last specification we instrument those variables using

[14]The decision of multinational car producers about when to manufacture a car model explains why they are introduced or discontinued from different countries at similar dates. For this reason, exit decisions are quite independent of the performance of that model in a specific market.

lags with respect to their sample mean at the product level. The results provide evidence that once we control for this simultaneity they no longer explain the exit decision.

The dynamic effect of advertising characterized by Equation 18 presumes that we observe the exit of all products during the sample period. In most applications, including ours, the sample period is truncated meaning that the exit of most products is not observed. One of the solutions that Berry and Pakes (2001) propose to solve this problem consists on using all products and estimate the continuation profits (as a function of the state variables) of those models for which truncation exists. Alternatively, one could just estimate the dynamic equation for those products for which exit is observed. Both approaches imply trade-offs. The first results in additional structure, further assumptions, and consequently, an increase in the burden of estimation. The second, to the extent that the probability of truncation is related to the profitability of a car model, could lead to biased results due to a sample selection problem. For example, it could be that less successful products tend to exit the market earlier.

In our application we use the second approach for two reasons. First, we observe the exit of a significant number of car models, allowing us to estimate the parameters quite accurately. Second, simple specifications do not approximate well future profits for products for which exit is not observed. In particular, natural candidates for the determinants of future profits such as the age of the product do not explain much.[15] Even though older products are more likely to exit the market, the estimations in Table 7 indicate that the overall predictive power of this variable is quite limited. The reason is that there is a large heterogeneity in the profitability of different car models. This heterogeneity can be seen in Figure 2 that shows the large variability in the moment of exit of different car models.

Finally, notice that the data we have collected have a high frequency (monthly observations), which help us overcome the so-called data interval bias problem. This bias was first identified by Clarke (1976), who showed that the effects of advertising are sensitive to the frequency of data used.

4.2 Preliminary Results

We start by analyzing the results delivered by a standard multinomial logit demand model. Although this model imposes unrealistic substitution patterns (Berry 1994), the ease of computation makes it a good approach to evaluate the impact of advertising and

[15] In other applications natural candidates exist. Zhao (2006) studies the market for digital cameras and derives continuation profits from Moore's Law.

the potential of the instruments to reduce the biases in the estimation.

In Table 8 we report estimation results for six different specifications. To compute the parameter estimates, we use ordinary least square (OLS) and instrumental variable (IV) regressions of transformed log market shares, $\ln(s_{jt}) - \ln(s_{0t})$, on alternative mean utility specifications. As determinants of the log market share, we include variables such as the price, size, maximum speed, gas mileage, and engine displacement over the weight of the car. Annual and month dummies control for common variations in the market over time and seasonal patterns. Finally, brand dummies control for the effect of the image of the brand/firm. The first column reports estimates for the OLS regressions. The remaining columns report specifications that control for the endogeneity of the price in the demand function using as instruments product characteristics and differences in prices with respect to their time means lagged 6 and 12 months. In the last two specifications advertising expenditures are also instrumented.

Most product attributes have a positive, consistent sign across specifications. When the price is instrumented, its negative effect increases, in this case by a factor of three. The implied price elasticity is reported at the bottom of the table (Berry 1994). When advertising expenditures are considered in the latter specifications though, the price effect decreases considerably. The reason is that advertising expenditures have a positive effect on sales and, as Table 3 shows, these expenditures are negatively correlated with the price of the product.

Although the effect of advertising is positive, the third specification shows that this effect is negative in the first three years of the product in the market, since initially a car model is heavily advertised but sales tend to build up over time. The fourth column shows that this effect reverses sign when the dynamic dimension of advertising is considered and it is not measured as current expenditure but as the cumulative expenditures up to the third year in the market.

Finally, in the last specification, we aim to identify the differentiated effects that advertising has during the first three years. The results reinforce the previous findings, showing that cumulative advertising expenditures increase sales in the first two years a car model is present the market. In the third year, however, advertising has a negative (though not significant) effect. As we will see in the next section, this result might be due to the large heterogeneity in the speed at which awareness levels evolve for different car models; the awareness process finishes in the first two years for some models but lasts more than six years for others.

These results further suggest that a model that exogenously imposes the end of the awareness process likely cannot disentangle the dynamic effect of advertising related to the awareness process of new products from other relevant effects of advertising. The model we estimate next does not suffer from this shortcoming though, because the end of the awareness process is endogenous with the evolution of the firm's advertising expenditure.

4.3 Results

Table 9 reports the results of the estimation for four different model specifications. The model in the first column closely resembles the specification by Berry, Levinsohn, and Pakes (1999) but also includes the effect of advertising as a regressor in the utility function. To deal with the endogeneity and simultaneity of price and advertising, this model jointly estimates a demand, a price, and a static advertising equation.[16] The second column enhances the specification by considering that consumers are only aware of a subset of existing products. Advertising affects current awareness of the product, but inclusion probability in the future grows deterministically as a function only of the time the product has been in the market. Thus, the effect of advertising is static and resembles Goeree's (2008). The third column includes both static and dynamic effects of advertising but assumes that firms have a discount factor 0. As a result, firms only internalize the static effect of advertising. Finally, we consider the complete specification where firms internalize the dynamic effect of advertising over the choice set of consumers.

In all models, the dependent variable is the (monthly) market share of each car model, computed as the number of units sold of that model divided by the total size of the market, measured by the number of households. Among the explanatory variables, we include monthly and brand dummies to control for time fixed effects and firm-specific factors. As a robustness test, we also considered (unreported) specifications with a more extended set of model characteristics that had little effect on the results. Finally, we include annual controls for 1995 to 1997 to capture the effects of the car scrappage plans enacted during those years, which may have advanced consumers' purchasing decisions.

The results in the first specification display the expected signs. Consumers value bigger, more powerful, and more fuel-efficient cars. The price effect has a coefficient of -5.52.[17] The coefficient associated with advertising expenditures is 1.755. In an

[16]In this approach, Equation 18 gets replaced in the three first specifications by its static counterpart,

$$(p_{jt} - mc_{jt}) \frac{\partial s_{jt}}{\partial a_{jt}} I_t - 1 = u_{jt}.$$

[17]In this specification, the price variable (in thousand euros) is divided by income. To compare the price coefficient with those of the logit specifications in Table 8, we need to divide it by 31, because

unreported regression, we estimated the same model with the assumption that advertising is chosen at the firm level. As expected, because products are substitutes, failing to account for the interaction of advertising of one product with sales of other products leads to an overestimate of the impact of advertising. When we account for this effect, the coefficient suffers a minimum change to 1.737, suggesting that the bias from our assumption that firms behave as single good producers is relatively small. On the supply side, we observe that the marginal cost of production increases with the weight of the car, as well as the power and efficiency of its engine. Most of these coefficients can be estimated quite accurately.

In the second specification, the estimated effect of advertising over consumer utility is higher. As Draganska and Klapper (2011) note, this difference arises from the ability of advertising to increase sales among those consumers who already have the product in their choice set. Thus, the second model must attribute a higher impact to advertising to compensate for the fewer consumers reached. The price coefficient decreases in absolute value because the increase in the sales over time is now attributed to the increasing awareness of the product and not on the decrease in price we observe during its life-cycle. In this specification, the effects of consumer-awareness parameters are estimated quite accurately and with the expected sign.

In the next specification, we introduce the dynamic effect of advertising on the probability of a product's inclusion in the choice set which leads to an effect of advertising closer to that anticipated by the first estimation. However, the price effect is lower. With an assumption of a 0 discount factor the producer underestimates the impact of advertising and the model interprets this mismatch as if the demand is more price inelastic. Therefore, it is more profitable for the producer to increase the price than to increase advertising and sell more.

The full specification shows that once the firm accounts for the dynamic effects of advertising, the coefficients related to consumer utility partially resemble those obtained in the first column. Furthermore, the second term in Equation 18 is a function of the parameters that govern the evolution of the consumer choice set (λ, ψ, κ). Therefore, when we compare the results with those obtained in the previous specifications, we observe that taking into account the forward-looking behavior of firms is crucial to the accurate identification of these parameters.

Table 10 reports the demand-price elasticities delivered by the consumer awareness model (specification (iv)), which range between 2.2 and 3.1, in line with the results

median household income was €31,000 during the study period.

obtained for the automobile industry by Berry, Levinsohn, and Pakes (1995) in the United States, by Verboven (1996) for Europe, and by Moral and Jaumandreu (2007) for Spain.

Finally, we emphasize the implications of one of the main contributions of this article, namely the analysis of the evolution of the choice set and its relationship with advertising expenditures. The results in Table 9 indicate that brand advertising, understood as a proxy for the presence of a brand in the market and measured by ψ, has a positive impact on the initial awareness level of a car model. Furthermore, the awareness process is highly persistent, because λ takes a value greater than 1.

In an unreported regression we also considered an enlarged model in which consumers are affected not by the advertising flow but by the *goodwill* stock of a product, understood as a (depreciated) sum of previous advertising expenditures. Such a specification can accommodate the stylized fact that the large initial investments in advertising occur together with a low level of sales. Preliminary results indicate that including this additional effect does not change the coefficients obtained in our full specification though. However, it may have an impact on the accuracy of the consumer-awareness coefficients, such that additional conditions would be necessary for their separate identification.[18]

To illustrate the importance of the awareness process for new car models, in Figure 3 we depict the estimated probability that a consumer is aware of the median car model and compare it with the simulated awareness probability, without advertising. The effect of advertising in the awareness process is significant, and it decreases the time required from almost six years to approximately two. The figure also indicates the estimated awareness probability for two extreme car models, the one with the shortest awareness process (i.e. the Fiat Punto, launched in 1994) and the one with the longest one (i.e. the Rover 214, launched in 1990). Again, the differences are substantial and show that whereas in the first case, the end of the process arrives in less than two years, in the second case, it can take more than six years.

The dynamic model implies an average and median short-run advertising elasticity, measured as the static effect of advertising through consumer utility once we abstract from its effect over the choice set, of .48 and .18, respectively. These values are in line with the results of the meta-analysis of the literature undertaken in Sethuraman, Tellis, and Briesch (2011). Table 11 reports the median elasticity for different deciles of the ratio of advertising over revenue distribution. The elasticity exhibits an inverse-U shape as a function of the ratio, such that it is highest for intermediate values. This

[18]See also Barroso (2009) for the estimation, with the same data, of a model with goodwill stock of advertising where consumer awareness is not considered.

finding is consistent with data that show that for these intermediate values the advertising expenditure that firms choose is maximal.

As pointed out earlier, our estimates of the dynamic effects of advertising could be biased due to selection of the car models for which exit is observed. Indeed, some evidence suggests that car models for which we observe exit exhibit slightly different characteristics, particularly when we focus on the oldest. To evaluate the potential bias in our results we conduct two robustness tests, reported in Table 12. For comparison, specification (i) reproduces the dynamic model in Table 9. The second specification includes the result of the same model once we restrict the estimation of the dynamic advertising equation to models that stay in the market between 6 and 10 years. For these models, that include the average incumbency in the market of 8 years, we do not observe important differences in the main co-variates with respect to the complete sample. The results using this reduced sample do not change significantly.

In specification (iii) we estimate the model for the complete sample. Following Berry and Pakes (2001) we need to estimate the continuation profits of car models for which exit is not observed. We assume that the future profits of model j when it is only observed until period $\bar{T}$, $V_{j\bar{T}}(\omega_{\bar{T}})$, can be written as

$$V_{j\bar{T}}(\omega_{\bar{T}}) = \pi_j(a_{\bar{T}}, \omega_{\bar{T}})(\iota_1 + \iota_2 \omega_{j\bar{T}}).$$

That is, future profits are a multiple of the profits in the last period the product is observed, and this multiple depends on the awareness of that product in the last period. This specification captures part of the heterogeneity in market success of a car model through last period profits and the multiplier accounts for the different decay in profits of a car model depending on the level of consumer awareness. To the extent that consumer awareness builds up from previous advertising expenditures and the age of the model, the sign of the coefficient ι_2 is undetermined; for models that have been a long time in the market a high awareness level indicates a high probability of exit. The results do not differ substantially from those of our benchmark specification. The identification of the parameters of the dynamic advertising equation, however, is less precise. This is particularly true for the coefficients that describe the continuation profits, reflecting the fact that there is great heterogeneity in the moment a product exits the market.

4.4 Model Counterfactuals

The model we have estimated also can be used to perform counterfactual analysis. We are particularly interested in studying the evolution of sales with different assumptions about the awareness process. For the median car model, in Figure 4, we include the simulated sales during the first five years in the market according to the complete specification together with three different counterfactual scenarios: (1) no awareness process and all consumers know about the model from the outset, (2) the awareness process takes place without advertising (and is driven only by the time in the market), and (3) the effect of advertising on awareness is static.

When consumers are perfectly aware of all products in the market, sales roughly decrease over time. This evolution is driven mainly by the entry of new and more modern products that steal consumers away from established car models. This decrease in sales is partially offset, as Table 4 shows, by the decrease in prices that we observe over the life cycle of the model. This effect dominates in the fifth year, when car discounts are particularly steep. The decline of initial sales in this specification is at odds with the realized evolution of sales; as the results in Table 4 shows sales of a car model reach their peak after three years in the market.

When the awareness process is introduced as an exogenous component driven by the time the product has been in the market, the previous decreasing pattern of sales becomes diluted. The longer a product has been in the market, the more likely it belongs to a consumer's consideration set. As a result, sales become erratic, and we do not observe a peak in sales. A similar pattern arises when advertising is assumed to have a static effect on the awareness process. This result suggests that the dynamic component of advertising is essential for explaining the evolution of sales over time.

This simulation also enables us to compute how much of the total impact of advertising on sales is due to its dynamic component. To do it, we compare predicted sales under the complete specification with sales that emerge when advertising has an impact only among consumers currently aware of the product. On average, 50% of the effect of advertising on sales can be attributed to this dynamic component. As expected, Figure 4 demonstrates that the difference is particularly remarkable at the beginning, when the dynamic component allows the firm to increase the proportion of consumers that includes that particular car model in their choice set.

5 Conclusion

We have presented a structural model that explicitly considers advertising as part of a firm's strategy. Advertising not only has an effect on consumer utility but also can affect which products they are aware of. To capture this dynamic effect of advertising, we explicitly modeled the evolution of product choice sets that consumers are likely to face.

Using the market for automobiles in Spain as an illustration, we show that the great disparity in the level of advertising expenditures chosen by different manufacturers leads to a significant dispersion in the awareness process that marks different car models. Although on average the awareness process finishes around the third year, it ranges from two to six years. Our model also helps us disentangle the positive effect of advertising on the awareness level of a new car model from the negative effect that stems from the actions of competitors and particularly from the introduction of newer products. Incorporating both effects is important for explaining the evolution of sales over the life cycle of a car model. In particular, low levels of advertising imply a slow awareness process and could result in a flat (or even decreasing) evolution of sales in very competitive markets. We also estimate that on average, 50% of the effect of advertising on sales that stems from the awareness process can be attributed to this dynamic component.

Our analysis suggests that in markets with frequent new product entry, advertising is an important tool that firms use to accelerate initial sales. This conclusion is consistent with the common observation that in markets such as those for cars, digital cameras, or cell phones, advertising represents a large component of a firm's costs.

In turn, our findings open several avenues for further research. Most of our analysis focused on the impact of product advertising. In our application, brand advertising is used as a proxy for the presence of the firm in the market, to approximate initial awareness of a product. However, we also abstract from the determinants of this initial awareness. As Krishnan and Jain (2006) argue, the initial awareness level is a fundamental piece to explain how consumers learn about new products. Further research should address this question.

The lack of micro data also prevented us from studying some effects of advertising that might be important in some applications. For example, consumers do not forget about a product, even if it is not publicized during a long period of time. Similarly, these data limitations keep us from distinguishing the different effects of advertising for mature products, as Draganska and Klapper (2011) do, and estimate the stationary level to which the level of awareness converges. Access to this kind of information could complement our analysis.

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Appendix

A Dynamic Equation

From Equation 16, the profit function that a given firm maximizes for each product j at time t can be expressed as the following Bellman equation,

$$V_j(\omega_t) = sup_{a_{jt}} \left\{ \pi_j(a_t, \omega_t) + \rho E_\omega \left[V_j(\omega_{t+1}) | \omega_t, a_t \right] \right\},$$

where the expectation term considers the optimal actions that will be taken in each future period. Using the Equation 8 which determines the evolution of the consumers' choice sets, this term can be rewritten as

$$E_\omega \left[V_j(\omega_{t+1}) | \omega_t, a_t \right] = \sum_{\omega_{-jt+1}} \sum_{\omega_{jt+1}} V_j(\omega_{jt+1}, \omega_{-jt+1}) K(\omega_{jt+1} | \omega_{jt}, a_{jt}) K(\omega_{-jt+1} | \omega_{-jt}, a_{-jt}),$$

where $-j$ represents products other than j, and $K(\omega_{j\ t+1} | \omega_{jt}, a_{jt})$ denotes the Markov transition kernel for the awareness level

$$K(\omega_{j\ t+1} | \omega_{j\ t}, a_{j\ t}) = \begin{cases} \omega_{jt+1} = \lambda \omega_{jt} + 1 & \text{with prob } \frac{\kappa a_{jt}}{1 + \kappa a_{jt}}, \\ \omega_{jt+1} = \lambda \omega_{jt} & \text{otherwise.} \end{cases} \tag{19}$$

With our assumptions, the Markov transition kernels for the awareness levels are independent across products.

If the solution to the following problem, that determines the optimal advertising expenditure of product j at time t, is interior, it must satisfy the first-order condition

$$\frac{\partial \pi_j(a_t, \omega_t)}{\partial a_{jt}} + \rho \sum_{\omega_{-jt+1}} \sum_{\omega_{jt+1}} V_j(\omega_{jt+1}, \omega_{-jt+1}) \frac{\partial K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} K(\omega_{-jt+1} | \omega_{-jt}, a_{-jt}) = 0.$$

Replacing $\frac{\partial K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}}$ with $\frac{\partial \ln K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} K(\omega_{jt+1} | \omega_{jt}, a_{jt})$ transforms the second term into

$$\begin{aligned} \sum_{\omega_{-jt+1}} \sum_{\omega_{jt+1}} & V_j(\omega_{jt+1}, \omega_{-jt+1}) \frac{\partial \ln K(\omega_{j\ t+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} K(\omega_{jt+1} | \omega_{jt}, a_{jt}) K(\omega_{-jt+1} | \omega_{-jt}, a_{-jt}) \\ = & \ E_w \left[V_{jt+1}(\omega_{t+1}) \frac{\partial \ln K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} \right]. \end{aligned}$$

Thus, the first-order condition can be rewritten as

$$\frac{\partial \pi_j(a_t, \omega_t)}{\partial a_{jt}} + \sum_{\tau=1}^{\bar{T}_j} \rho^\tau \pi_j(a_{t+\tau}, \omega_{t+\tau}) \frac{\partial \ln K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} + u_{jt} = 0,$$

where $\bar{T}_j$ is the time when product j exits the market, and u_{jt} is the expectations error,

$$u_{jt} \equiv \rho E \left[V_{jt+1}(\omega_{t+1}) \frac{\partial \ln K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}} | \omega_t \right] - \sum_{\tau=1}^{\bar{T}_j} \rho^\tau \pi_j(a_{t+\tau}, \omega_{t+\tau}) \frac{\partial \ln K(\omega_{jt+1} | \omega_{jt}, a_{jt})}{\partial a_{jt}}.$$

The standard Rational Expectations assumption, $\sum_{\tau=0}^{\infty} \rho^{\tau}\pi_{t+\tau} = V(\omega_t) + u_t$ with, $E[u_t|\omega_t] = 0$, describes the equation underlying the estimation,

$$E\left[\left((p_{jt} - mc_{jt})\frac{\partial s_{jt}(\omega_t, a_t, p_t)}{\partial a_{jt}} I_t - 1\right) + \sum_{\tau=1}^{\bar{T}_j} \rho^{\tau}\pi_j(a_{t+\tau}, \omega_{t+\tau})\frac{\partial \ln K(\omega_{jt+1}|\omega_{jt}, a_{jt})}{\partial a_{jt}}\right|\omega_t\Bigg] = 0.$$

Using Equation 19 we obtain the advertising Equation 18,

$$\left((p_{jt} - mc_{jt})\frac{\partial s_{jt}(\omega_t, a_t, p_t)}{\partial a_{jt}} I_t - 1\right) + \sum_{\tau=1}^{\bar{T}_j} \rho^{\tau}\pi_j(a_{t+\tau}, \omega_{t+\tau})\frac{1}{a_{jt}(1+\kappa a_{jt})} + u_{jt} = 0.$$

The presence of the term $\bar{T}_j$ means that to compute this equation, we must observe the time each model exits the market. Alternatively, we can model the continuation profits of that model. Furthermore, to consider the advertising decision as the result of a multiproduct dynamic decision, we would need, in addition, to address the exit of the firm. To the extent that the advertising expenditures on one product do not affect significantly the market share of other products offered by the same firm, assuming that it firm sells a single product should lead to similar results.

B Estimation Algorithm

We introduce new notation to describe the estimation algorithm. First, we present Equations 15 and 18, which specify the price and advertising decision rules, respectively, in matrix notation:

$$\begin{aligned} (p_t - mc_t)\left[\Gamma_t \circ \Delta_t^p\right] &= s_t, \\ (p_t - mc_t)\left[I_t \circ \Delta_t^a\right] - I + \left(\sum_{\tau=1}^{\bar{T}_j} \rho^{\tau}\pi_{t+\tau} \circ \frac{1}{(I+\kappa a_t)\circ a_t}\right) &= u_t. \end{aligned}$$

The symbol $\circ$ denotes the Hadamard product. The vectors p_t, mc_t, s_t, and a_t collect the price, marginal cost, market share, and advertising, respectively, of all the J products in the market. The $J \times J$ matrix Γ_t collects the brand relations between products, so the element (j, j') takes a value of 1 if products j and j' are produced by the same firm and 0 otherwise. The vector $\pi_{t+\tau}$ collects the cash flow of the J products and, therefore,

$$\pi_{t+\tau} = (p_{t+\tau} - mc_{t+\tau})\, I_{t+\tau} \circ s_{t+\tau} - a_{t+\tau}.$$

The $J \times J$ matrix Δ_t^p collects the price cross-demand effects, so that its (j, j') element is $\Delta_{jj'}^p = \frac{\partial s_{j't}}{\partial p_{jt}}$. The vector Δ_t^a collects the own-demand effects of advertising on consumer utility (the static effect). Therefore, its j element is $\Delta^a_{jt} = \frac{\partial s_{jt}}{\partial a_{jt}}$. Finally, I is a vector of ones of size J.

With the previous notation, we can describe the estimation algorithm. For each element of $\theta = \{\alpha, \sigma_0, \beta, \gamma, \eta, \kappa, \psi, \lambda\}$, the unobservable components are obtained using the following the steps:

1. Estimation, by simulation, of the market shares implied by the model:

   (a) For each product j, simulate H complete awareness histories $\{\varsigma_{jt}\}_{t=1}^{T}$ from draws of a Bernoulli variable of the form

   $$\varsigma_{jth} = \begin{cases} 1 & \text{if} \quad \frac{\kappa a_{jt}}{1+\kappa a_{jt}} \geq \bar{\varsigma}_{jh}, \\ 0 & \quad\text{otherwise,} \end{cases}$$

   where $\bar{\varsigma}_{jh}$ is the h^{th} draw from a uniform random variable $[0,1]$ for product j. With this draw, we can compute the vector of awareness probabilities for all products $\phi_{jt}(\theta)$ according to Equations 6, 7, and 8.

   For new models, initial awareness is set according to Equation 10, whereas for models already in the market in 1990, the pre-sample awareness probability is

   $$\omega_{j1/1990} = \psi \overline{a}_f^b \lambda^{Age_{j1990}} + \frac{\kappa \overline{A}_j}{1+\kappa \overline{A}_j} \sum_{s=0}^{Age_{j\ 1990}-1} \lambda^s,$$

   where $\overline{A}_j$ and $\overline{a}_f^b$ are the average (monthly) advertising expenditures in 1990 for model j and brand f, respectively.

   (b) For each period t, simulate ns consumer choice sets by generating ns Bernoulli variables for each product b_{jit} with mean $\phi_{jt}(\theta)$,

   $$b_{jit} \equiv \begin{cases} 1 & \text{if} \quad \phi_{jt}(\theta) \geq \bar{b}_{ji}, \\ 0 & \quad\text{otherwise,} \end{cases}$$

   for $i = 1, ..., ns$, where $\bar{b}_{ji}$ are realizations from a uniform random variable [0,1]. For each choice set, S_{it}, product j is included if and only if $b_{jit} = 1$.

   (c) Draw ns vectors (v_{iy}, v_{i0}) from a multivariate normal distribution with mean 0 and an identity covariance matrix.

For each period t, ns consumers are simulated, $(v_{iy}, v_{i0}, b_{1it}, ., b_{jit}, ., b_{Jit})$, with the same characteristics but different choice sets over time.

As opposed to the static model of Goeree (2008), the procedure is repeated for the H complete awareness histories to compute the simulation estimator of market shares

$$s_{jt}(P_{ns}, P_H, \delta_t, X_t; \theta) = \frac{1}{H} \sum_{h=1}^{H} \left(\frac{1}{ns} \sum_{i=1}^{ns} f_{ijt|S_{it}}(v_i, \varsigma_h, \delta_t, X_t; \theta) \right),$$

where ς_h is the awareness history h of all products.

2. Solve for the demand unobservable implied by the simulated and observed market share, which can be computed as

$$\xi_{jt}(s_t^n, P_{ns}, P_H; \theta) = \delta_{jt}(s_t^n, P_{ns}, P_H; \theta) - \left[\sum_k \beta_k x_{jkt} + \gamma a_{jt} \right],$$

where the mean utility and advertising effects $\delta_j(s^n, P_{ns}, P_H; \theta)$ are solved recursively using the contraction mapping suggested by Berry, Levinsohn, and Pakes (1995), which matches the model-predicted vector of market shares s_t and the observed market shares s_t^n for all products in period t. We define

$$\delta_t^{k+1} = \delta_t^k + \ln(s_t^n) - \ln(s_t),$$

so that δ_t^{k+1} is the vector of mean utilities computed in the step $k+1$.

3. Calculate the vector of cost unobservables from the difference between the price and the markup computed from the market shares. According to Equation 14, the cost unobservables can be written as

$$\zeta(s^n, P_{ns}, P_H; \theta) = [p - b\,(s^n, P_{ns}, P_H; \theta)] - \ln(w)\,\eta$$

where $pmc\,(s^n, P_{ns}, P_H; \theta)$ is the markup obtained from Equation 15, that is,

$$pmc\,(s^n, P_{ns}, P_H; \theta) = [\Gamma \circ \Delta^p(s^n, P_{ns}, P_H; \theta)]^{-1}\, s^n.$$

4. Calculate the rational expectations disturbance u from Equation 18

$$\begin{aligned} u(s^n, P_{ns}, P_H; \theta) \;&=\; b\,(s^n, P_{ns}, P_H; \theta)\, I_t \circ \Delta_t^a\,(s^n, P_{ns}, P_H; \theta) - I \\ &\quad + \left(\sum_{\tau=1}^{\bar{T}_j} \rho^\tau \pi_{t+\tau}\,(s^n, P_{ns}, P_H; \theta) \circ \frac{1}{(I + \kappa a_t) \circ a_t} \right). \end{aligned}$$

Once the standard errors are computed, we can use the algorithm from Nelder and Mead (1965) to minimize the objective function and determine the parameters to be used in the next iteration. The same draws are used in all iterations to guarantee that the estimation is unbiased.

Figure 1: Cumulative Percentage of Car Models that are not Advertised a given Number of Months.

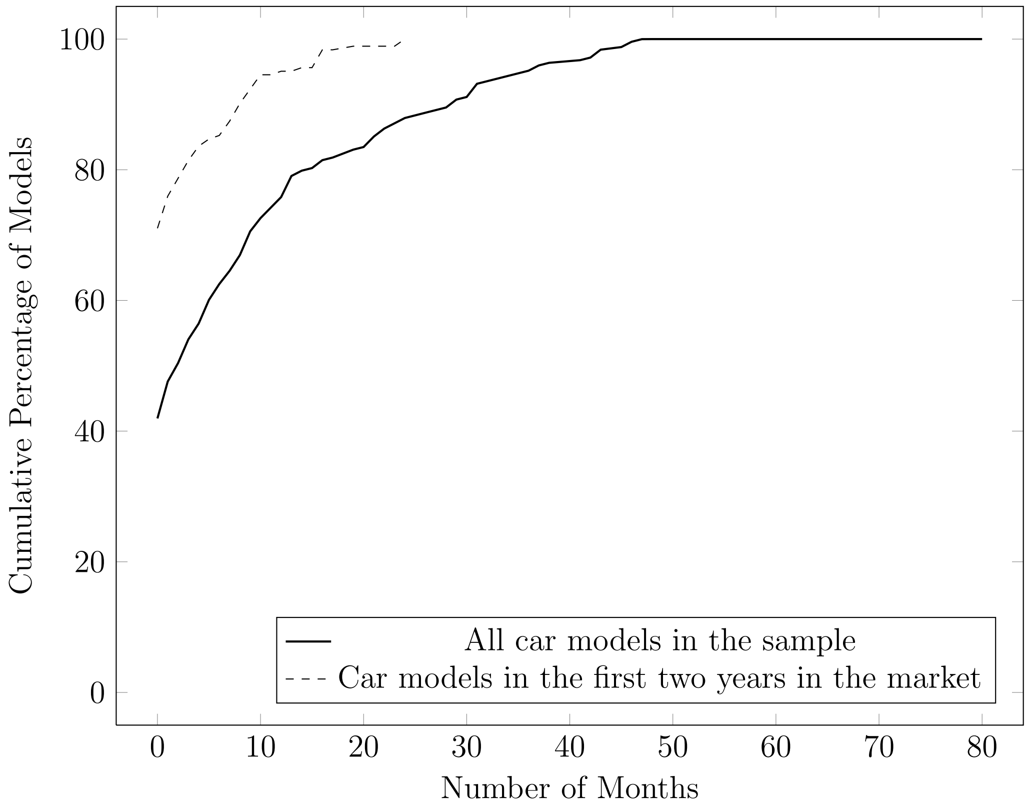

Figure 2: Distribution of Car Model Age at Exit

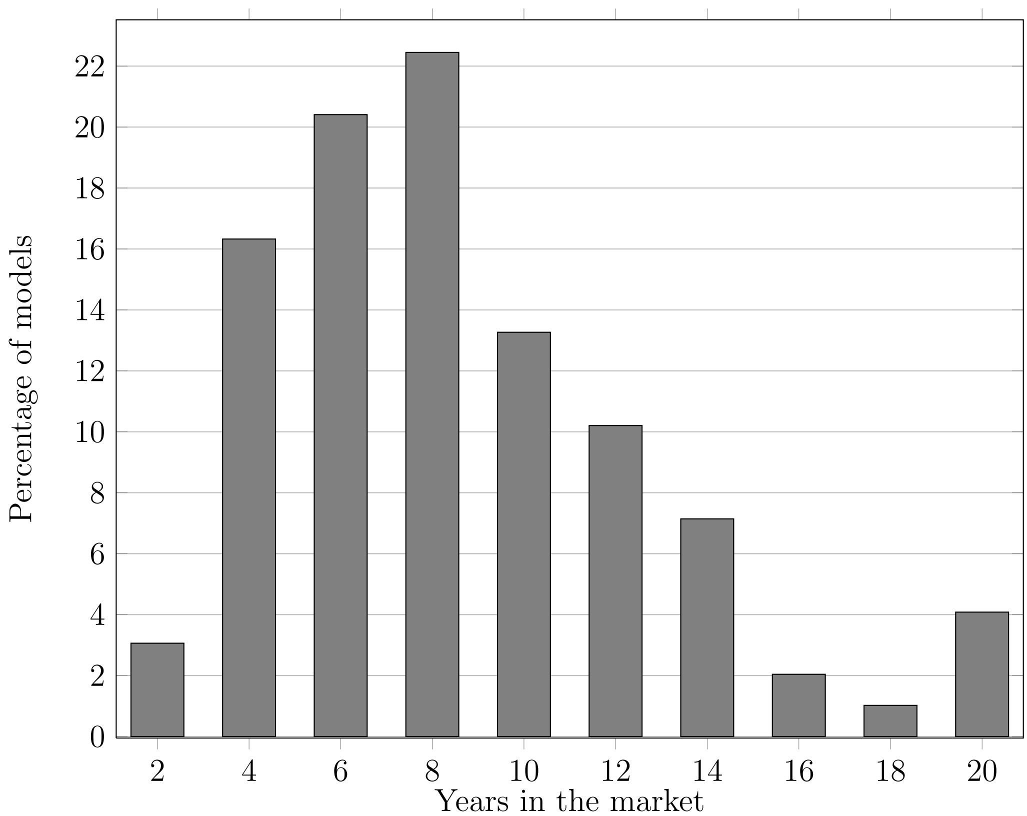

Figure 3: Simulated Consumer Awareness Probabilities.

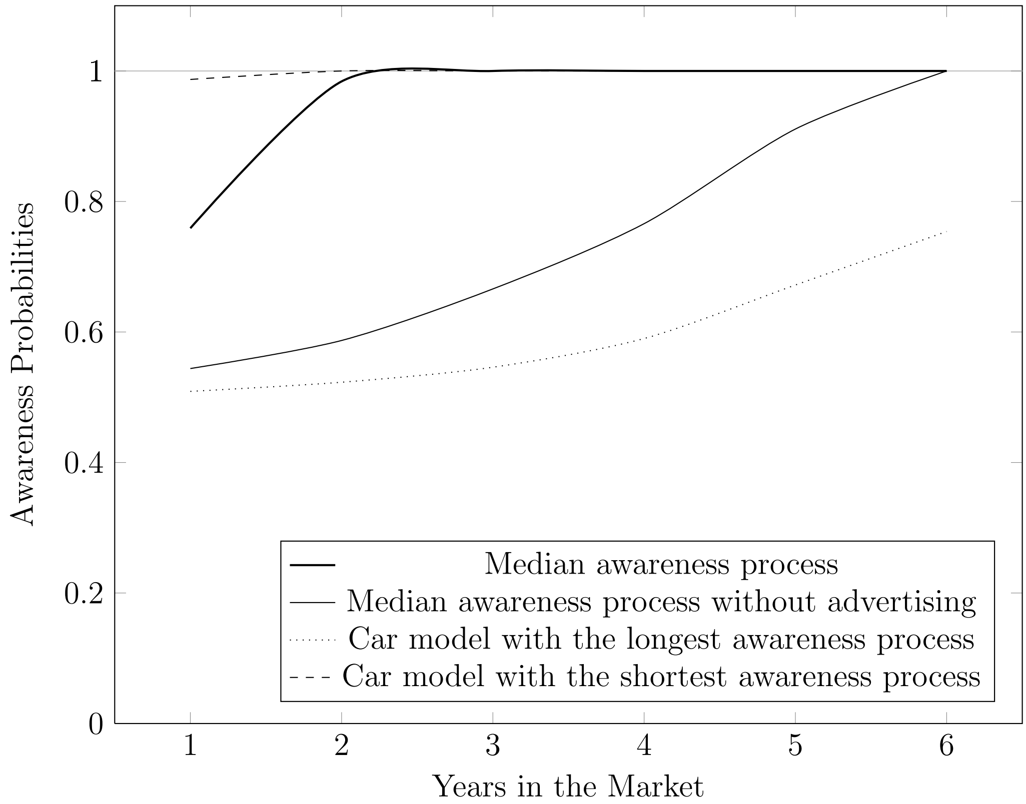

Figure 4: Counterfactural Sales under Different Specifications of the Awareness Process.

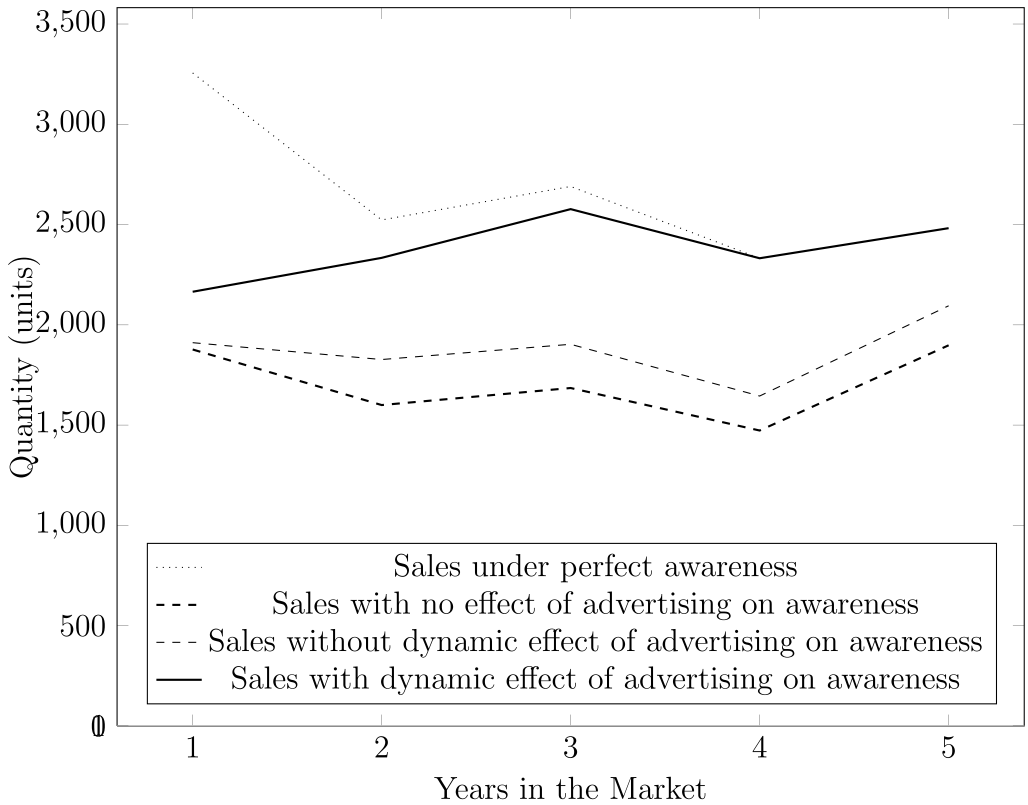

Table 1: Description of the Main Variables.

Variable	Explanation
a_{jt}	Advertising expenditure on product j at time t. See Equation 1.
a^b_{jt}	Average annual brand advertising of firm f at time t. See Equation 10.
α_i	Effect of the price on utility of agent i. See Equation 1.
β_k	Mean taste of attribute k across consumers. See Equation 2.
C_{it}	Choice set of consumer i at time t. See Equation 4.
δ_{jt}	Mean utility of product j in period t. See Equation 2.
η_k	Effect of attribute k on marginal cost. See Equation 14
ε_{ijt}	Unobserved consumer i's taste for product j at time t. See Equation 1.
ϕ_{jt}	Probability that product j is included in a choice set at time t. See Equations 6 and 7.
γ	Effect of advertising expenditure on utility of agent i. See Equation 1.
I_t	Size of the market at time t.
κ	Curvature of the effect of advertising on awareness. See Equation 9.
λ	Carryover coefficient of the awareness level. See Equation 8
mc_{jt}	Marginal cost of product j at time t. See Equation 14.
p_{jt}	Price of product j at time t. See Equation 1.
ψ	Effect of brand advertising in initial awareness. See Equation 10.
s_{ijt}	Unconditional probability that product j is preferred by consumer i at time t. See Equation 5.
σ_0	Standard deviation from the mean taste of the outside option, good 0. See Equation 3.
ς_{jt}	Changes in awareness of product j at time t due to advertising. See Equations 8 and 9.
u_{jt}	Expectations error of product j at time t in the dynamic advertising equation. See Equation 18.
w_{jkt}	Observable attribute k in product j at time t relevant for costs. See Equation 14.
x_{jkt}	Observable attribute k in product j at time t relevant for demand. See Equation 2.
ξ_{jt}	Unobservable attributes of product j at time t relevant for demand. See Equation 2.
ω_{jt}	Awareness level of product j at time t. See Equations 7 and 8.
$\bar{\omega}_{jt}$	Initial awareness level of product j if introduced at time t. See Equation 10.
y_i	Income of consumer i
ζ_{jt}	Unobservable attributes of product j at time t relevant for costs. See Equation 14.

Table 2: Descriptive Statistics, Time Variation.

Year	Quantity (units)	Price (in 10^3 Eur)	Advertising Expenditure (in 10^6 Eur)	Size (in m^2)	Maximum Speed (in km/h)	Gas Mileage (in l/100km)	Engine Displacement (in cc/Kg)
1990	10,979	11.870	3.27	6.61	171.7	5.29	1.62
1991	8,731	11.740	2.64	6.66	173.1	5.32	1.61
1992	9,687	11.286	3.89	6.71	174.9	5.34	1.64
1993	6,616	11.557	4.72	6.74	175.9	5.34	1.63
1994	8,283	11.469	4.91	6.69	174.3	5.39	1.69
1995	7,314	11.844	4.19	6.70	175.1	5.49	1.56
1996	7,660	11.941	4.20	6.76	176.4	5.44	1.51
1997	7,902	11.907	4.13	6.84	178.3	5.54	1.48
1998	8,642	11.918	3.97	6.91	180.3	5.76	1.46
1999	9,317	11.741	3.90	6.97	182.3	5.81	1.44
2000	9,351	11.783	3.45	7.01	183.8	5.85	1.43

Notes: Price and car model attributes are (annual) sale weighted means. Quantity and advertising are annual means for the car models that remain in the market during the considered year. Prices are measured in 1995 euros.

Table 3: Advertising Pattern across Car Models.

Percentile	Number of Models	Average Advertising/Revenue Ratio	Average Price (in 10^3 Eur)
0	18	.0259	22.298
10	18	.3553	23.041
20	19	1.0064	24.857
30	18	1.7486	18.380
40	18	2.4561	17.404
50	19	3.4185	14.236
60	18	4.4536	14.098
70	19	5.5907	13.201
80	18	7.4468	11.827
90	18	14.6057	12.120

Notes: Prices in 1995 euros. Annual means. Percentiles refer to the Advertising-to-Revenue distribution. Only car models in the market for more than three years are considered. Five models were never advertised.

Table 4: Price, Advertising Expenditure, and Quantities Sold by Car Model Age.

Model Age	Number of Models	Price (in 10^3 Eur)	Advertising Expenditure (in 10^6 Eur)	Quantity (units)
1st Year	74	14.015 (7.805)	3.077 (6.879)	2,165 (10,343)
1st-2nd Year	77	13.568 (7.627)	2.641 (7.777)	2,363 (14,235)
2nd-3rd Year	83	13.087 (7.889)	2.289 (7.583)	2,719 (15,235)
3rd-4th Year	99	13.099 (8.153)	1.579 (7.241)	2,414 (15,626)
4th-5th Year	101	12.876 (8.289)	1.300 (6.979)	2,486 (14,980)

Notes: Standard deviations in brackets. The data corresponds to the median of the product's average price, total quantity, and advertising expenditures during the year. To avoid selection problems, only models in the market for (at least) six years are considered.

Table 5: Dynamic Effect of Advertising Expenditures on Car Model Sales.

	Quantity	Quantity
Constant	-452.2164	-305.1985
	(440.7087)	(419.8453)
Advertising	$1,330.812^{***}$	$1,406.915^{***}$
	(117.5556)	(151.3677)
Accumulated Advertising	183.4763^{***}	
	(54.7757)	
Accumulated Advertising $\times d_2$		438.8205^{***}
		(201.6663)
Accumulated Advertising $\times d_3$		199.2157
		(136.0584)
Accumulated Advertising $\times d_4$		154.1857^{*}
		(92.8823)
Observations	368	368
Adjusted R^2	.751	.737

Notes: d_s is a dummy variable that takes value 1 if and only if the age of the car model is s. *Acc Advertising* adds all prior advertising expenditures. The sample is selected as in Table 4. Standard deviations in brackets.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 6: Entry and Exit of Car Models by Year.

	Number of Models	Model Entries	Model Exits
1990	97	20	2
1991	105	10	5
1992	116	16	10
1993	117	11	8
1994	122	13	12
1995	127	17	11
1996	134	18	11
1997	152	29	11
1998	160	19	11
1999	160	11	7
2000	169	16	10
Total		180	98

Table 7: Determinants of the Exit of a Car Model.

	(i) Probit Exit	(ii) Probit Exit	(iii) IV Probit Exit
Constant	-3.2268^{***}	-3.7089^{***}	-3.379^{***}
	(.3279)	(.4885)	(1.146)
Accumulated Advertising	.00165	.0027	$-.00152$
	(.00170)	(.0031)	(.0102)
Age		$.0239^{***}$	$.0244^{*}$
		(.0047)	(.0126)
Age^2		$-.00012^{***}$	$-.00012$
		(.00004)	(.0001)
Price		$-.0171^{*}$	.0265
		(.0090)	(.140)
Advertising		$-.1748^{*}$	-1.722
		(.1033)	(1.512)
Quantity		$-.00029^{**}$	.000617
		(.00013)	(.000671)
Observations	8,090	8,090	6,595
Pseudo R^2	.5044	.5404	.4995

Notes: The specifications include year, month, brand, and market segment dummies. In the last column prices, advertising expenditures, and quantities sold are instrumented using lags with respect to their model average. Robust standard errors in brackets.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 8: Demand Parameter Estimates using a Multinomial Logit Model.

	(i) OLS	(ii) IV for Price	(iii) IV for Price	(iv) IV for Price	(v) IV for Price Adv	(vi) IV for Price Adv
Constant	−13.8700***	−18.5552***	−17.3831***	−17.4433***	−16.4900***	−16.5561***
	(.2495)	(.4092)	(.3748)	(.3746)	(.4183)	(.4265)
Size	−.2116	4.4150***	3.9834***	4.1345***	3.8184***	3.8519***
	(.2258)	(.3892)	(.3535)	(.3525)	(.3676)	(.3723)
Maximum Speed	.6137***	1.7004***	1.4215***	1.4125***	1.1947***	1.2121***
	(.0930)	(.1243)	(.1134)	(.1136)	(.1227)	(.1242)
Gas Mileage	1.0767***	.3635***	.1994**	.1519**	−.0077	−.0077
	(.0623)	(.0827)	(.0746)	(.0744)	(.0813)	(.0814)
CC per Kg	.9358***	2.7038***	2.2515***	2.3058***	1.9384***	1.9612***
	(.0683)	(.1369)	(.1255)	(.1255)	(.1433)	(.1466)
Price	−.0884***	−.2357***	−.2074***	−.2113***	−.1889***	−.1903***
	(.0283)	(.01003)	(.0092)	(.0092)	(.0102)	(.0104)
Advertising			.7139***	.6500***	1.3067***	1.3130***
			(.0188)	(.01701)	(.1112)	(.1093)
Advertising $\times d_2$			−.0826***			
			(.0304)			
Accumulated Advertising $\times d_{2,3}$				.0100***	.0048***	
				(.0008)	(.0012)	
Accumulated Advertising $\times d_2$						.0075***
						(.0022)
Accumulated Advertising $\times d_3$						−.00129
						(.0021)
Median Price Elasticity	1.26	3.28	2.88	2.99	2.64	2.66
Observations	12,928	12,928	12,928	12,928	12,928	12,928
Adjusted R^2	.4552	.3388	.4556	.4506	.4163	.4153

Notes: The dependent variable is $ln(s_{jt}) - ln(s_{j0})$. Standard deviations in brackets. The specification includes year, month, and brand dummies. The dummy variable d_s that takes value 1 if and only if the age of the car model is s. The dummy $d_{2,3}$ takes value 1 if and only if the age of the car model is 2 or 3 years. Accumulated advertising expenditures are in billion euros.

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 9: Parameter Estimates under Different Specifications of the Proposed Model.

		(i) Static Model	(ii) Static Choice-Set Effect of Adv	(iii) Myopic adv decisions	(iv) Dynamic Model
Demand Side Parameters					
Effect on Consumer Utility					
Mean β_k	Constant	-8.291^{***}	-7.849^{***}	-8.339^{***}	-8.180^{***}
		(.027)	(.166)	(.390)	(.662)
	Size	3.883^{***}	3.361^{***}	3.447^{***}	3.705^{***}
		(.026)	(.283)	(.203)	(.026)
	Max. Speed	1.357^{***}	1.297^{***}	1.300^{***}	1.285^{***}
		(.009)	(.063)	(.090)	(.133)
	Gas Mileage	$.098^{***}$	.039	$.102^{**}$	$.114^{**}$
		(.013)	(.044)	(.049)	(.047)
	CC per Kg	$.036^{***}$	$.176^{***}$	.025	.046
		(.005)	(.031)	(.049)	(.034)
Outside Good	σ_0	2.724^{***}	3.038^{***}	2.968^{***}	2.558^{***}
		(.277)	(.332)	(.318)	(.345)
Price	α	-5.517^{***}	-4.809^{***}	-4.900^{***}	-5.311^{***}
		(.430)	(.386)	(.414)	(.556)
Advertising	γ	1.755^{***}	2.007^{***}	1.754^{***}	1.764^{***}
		(.017)	(.053)	(.077)	(.051)
Effect on Consumer Awareness					
Carryover	λ		1.055^{***}	1.277	1.058^{***}
			(.049)	(9.007)	(.221)
Initial Awareness	ψ		2.859^{**}	2.807	4.657^{***}
			(1.374)	(1.765)	(1.894)
Advertising	κ		$.756^{***}$	$.688^{***}$	$.907^{***}$
			(.094)	(.092)	(.193)
Supply Side Parameters					
Log Attributes η_k	Constant	4.001^{***}	3.814^{***}	3.841^{***}	3.926^{***}
		(.578)	(.561)	(.564)	(.587)
	Size	.085	.020	.029	.093
		(.091)	(.131)	(.135)	(.131)
	Max. Speed	$.861^{***}$	$.892^{***}$	$.887^{***}$	$.872^{***}$
		(.108)	(.086)	(.081)	(.112)
	Gas Mileage	$.208^{***}$	$.186^{***}$	$.189^{***}$	$.209^{***}$
		(.036)	(.063)	(.063)	(.063)
	CC per Kg	$.587^{***}$	$.606^{***}$	$.604^{***}$	$.591^{***}$
		(.044)	(.043)	(.060)	(.055)
	Weight	1.026^{***}	1.059^{***}	1.055^{***}	1.037^{***}
		(.058)	(.086)	(.081)	(.078)
	Time Trend	$-.002^{***}$	$-.003^{***}$	$-.003^{***}$	$-.003^{***}$
		(.001)	(.000)	(.000)	(.001)

Note: Standard deviations in brackets. Advertising expenditures in million euros.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 10: Price Elasticities in the Dynamic Model.

Percentile	Number of Models	Average Price-Elasticity	Average Price (in 10^3 Eur)
0	18	-3.1430	6.4695
10	18	-2.8435	8.2835
20	19	-2.6303	10.2220
30	18	-2.5586	11.6907
40	19	-2.3595	13.5800
50	18	-2.2926	15.6781
60	18	-2.3019	18.0188
70	19	-2.2299	20.9865
80	18	-2.3680	24.0134
90	18	-2.4199	39.3753

Notes: Elasticities are computed from specification (iv) in Table 9. Percentiles refer to the price distribution.

Table 11: Short-run Advertising Elasticities in the Dynamic Model.

Percentile	Number of Models	Average Adv-Elasticity	Average Monthly Adv. Expend. (in 10^6 Eur)	Average Adv/Revenue
0	18	.0006	.0003412	.0259
10	18	.0294	.0169091	.3552
20	19	.0881	.0510582	1.0064
30	18	.2417	.1413775	1.7486
40	18	.6666	.3934695	2.4561
50	19	.8690	.5088904	3.4185
60	18	1.2011	.7055156	4.4535
70	19	.3858	.2218887	5.5907
80	18	.7394	.4280157	7.4468
90	18	.5628	.3227788	14.6057

Notes: Elasticities are computed from specification (iv) in Table 9. Only car models observed in the market for more than three years are included. Percentiles refer to the Advertising-to-sales distribution.

Table 12: Robustness Tests to Assess the Potential Truncation Problem.

		(i) Benchmark Model	(ii) Reduced Sample	(iii) Whole Sample
Demand Side Parameters				
Effect on Consumer Utility				
Mean β_k	Constant	-8.180^{***}	-8.383^{***}	-8.552^{***}
		(.662)	(.285)	(.187)
	Size	3.705^{***}	4.043^{***}	4.492^{***}
		(.026)	(.107)	(.059)
	Max. Speed	1.285^{***}	1.435^{***}	1.603^{***}
		(.133)	(.079)	(.012)
	Gas Mileage	$.114^{**}$	$.078^{**}$	.044
		(.047)	(.037)	(.053)
	CC per Kg	.046	.030	.045
		(.034)	(.024)	(.046)
Outside Good	σ_0	2.558^{***}	2.876^{***}	3.084^{***}
		(.345)	(.338)	(.374)
Price	α	-5.311^{***}	-5.738^{***}	-6.375^{***}
		(.556)	(.609)	(.762)
Advertising	γ	1.764^{***}	1.753^{***}	1.743^{***}
		(.051)	(.053)	(.054)
Effect on Consumer Awareness				
Carryover	λ	1.058^{***}	1.061^{**}	1.037^{***}
		(.221)	(.336)	(.019)
Initial Awareness	ψ	4.657^{***}	3.821^{*}	4.102^{**}
		(1.894)	(1.574)	(1.972)
Advertising	κ	$.907^{***}$	1.445^{***}	$.801^{*}$
		(.193)	(.230)	(.484)
	ι_1			34.35
				(151.17)
	ι_2			-1.503
				(2.446)
Supply Side Parameters				
Log Attributes η_k	Constant	3.926^{***}	4.065^{***}	4.190^{***}
		(.587)	(.581)	(.580)
	Size	.093	.082	.097
		(.131)	(.137)	(.128)
	Max. Speed	$.872^{***}$	$.852^{***}$	$.835^{***}$
		(.112)	(.111)	(.111)
	Gas Mileage	$.209^{***}$	$.207^{***}$	$.210^{***}$
		(.063)	(.064)	(.063)
	CC per Kg	$.591^{***}$	$.582^{***}$	$.569^{***}$
		(.055)	(.058)	(.056)
	Weight	1.037^{***}	1.017^{***}	$.996^{***}$
		(.078)	(.077)	(.071)
	Time Trend	$-.003^{***}$	$-.003^{***}$	$-.003^{***}$
		(.001)	(.001)	(.001)

Note: Standard deviations in brackets. Advertising expenditures in million euros.
* Significant at 10%; ** Significant at 5%; *** Significant at 1%.