Age effects, unobserved characteristics and hedonic price indexes: The Spanish car market in the 1990's

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Abstract

This paper computes and compares alternative quality-adjusted price indexes for new cars in Spain in the period 1990-2000. The proposed hedonic approach simultaneously controls for time-invariant unobserved product effects and age effects, that can be interpreted as a proxy for time-variant unobservables. The results show that the non-adjusted price index largely overstates the increase in the cost of living induced by changes in car prices and that the previous evidence for this market have not measured the real extent of that bias, probably due to the omission of controls for unobservables. It is also shown that omitting age effects can lead to misleading conclusions. In particular, their omission would imply that the year-on-year Spanish Consumer Price Index would have been overestimated by around 0.1% on average during the sample period. Excluding both the controls for age effects and time-invariant unobservables would have risen this bias up to a 0.2%. The estimated price indexes give also some insights on what could have been the determinants of price evolution in the Spanish car market.

Keywords: Hedonic price indexes, Spanish car market, car prices, IPC, CPI, cost of living **JEL codes**: C43, E31, L11, L13

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1 Introduction

The consumer price index (CPI) is an economic magnitude of major interest in economic policy. From a microeconomic point of view inflation increases consumer's cost of living. One immediate macroeconomic implication is the pressure to increase wages, which in turn has a direct impact on competitiveness. The CPI is also the basis for measuring growth and productivity in real terms, not to mention its influence in the evolution of interest rates and other financial variables governing for instance investment decisions at the micro and macro levels, which also influence growth rates. In this context, the correct measurement of consumer price's changes is a fundamental issue (Boskin *et al.*, 1998).

The CPI is usually measured as a weighted average of the prices of a fixed basket of goods representing consumer expenditure. However, the report of the Boskin Commission has established that one of the major drawbacks of this methodology is the inability to cope with the quality change and new product biases (Boskin, 1996), therefore overstating the increase in the cost of living (Boskin *et al.*, 1998). The recommendations of the Boskin report have influenced statistical agencies to take the steps toward making the CPI a better approximation of a true cost of living index. They have also served to renew the interest on hedonic regressions and hedonic price indexes as a potential way of controlling for those biases.

Hedonic price indexes are constructed based on a hedonic regression where the price of the good is explained by its characteristics. The coefficients of this regression are a sort of prices for characteristics that may be used to construct an index of quality change. The price change of the good is then adjusted by this quality change to build a price index free of quality or new product biases. Most of the literature considers hedonic regressions with observed product characteristics, while the impact of omitted unobserved product characteristics have received very little attention. Most authors rely on brand or make dummies hoping that this will be enough to control for product unobservables. However, Benkard & Bajari (2005) and Requena-Silvente & Walker (2006) show, using different methodologies, that not including specific controls for unobserved effects can induce a significant bias in hedonic price indexes. Benkard & Bajari (2005) propose a method based on factor analysis to correct for these biases and they apply it to the US personal computer market finding that not taking into account unobserved effects induces an upward bias in the hedonic index of about 1.4% per year. The alternative approach proposed by Requena-Silvente & Walker (2006) controls for product unobservables by introducing model dummies in the hedonic regressions. In their application to the UK car market they find that the contribution of car-model effects to the value of cars has fallen since the 1970's, suggesting a downward bias in the hedonic index.

In this paper, following Requena-Silvente & Walker (2006) I construct a hedonic price index for cars in Spain in the 1990's controlling for time-invariant product unobservables. I extend their approach to control also for time-variant unobserved factors by including controls for age. Age effects have already been used in the literature (see for example the application to the Dutch car market of Dalen & Bode, 2004, and the references therein) but the simultaneous inclusion of age and car-model effects has not been tried before.¹ As usual in this literature I find that price indexes are larger than quality-adjusted prices, but also that car-model effects play an important role that will be misleading unless we control for age effects. In particular, it is shown that in the absence of age effects just controlling for time-invariant unobservables tends to overstate the hedonic price index by a large amount. As a consequence, the year-on-year Spanish CPI would have been overestimated by around 0.1% on average during the sample period. Excluding both the controls for age effects and time-invariant unobservables would have risen this bias up to a 0.2%.

The recent literature has mainly focused on durable goods where quality upgrading is frequent and product replacement is high. These types of goods usually have a large weight in the CPI (specially in the case of cars) and therefore any adjustment in price indexes for those categories may have a relevant impact on the CPI. Examples include

¹Erickson & Pakes (2011) propose a rather different approach to account for the problems of product selection bias and unobserved characteristics. They show that under certain assumptions it is possible to explain changes in the value of unobserved effects as a non-parametric function of the observed characteristics and the initial unobserved effects. These estimated changes in unobservables are then used to adjust the quality-corrected price changes.

computers (Pakes, 2003; Brown, 2000), domestic appliances (Ioannidis & Silver, 2003; Silver & Heravi, 2004), electronic devices (Chwelos *et al.*, 2008) and specially cars.

The automobile sector has been widely studied in the hedonic price index literature, probably as a consequence of the important weight that automobiles have in consumer price indexes. Among the papers that have computed hedonic prices indexes for cars for different countries and periods of time we have: i) For the US: Court (1939), Griliches (1961) between 1954-1960, Triplett (1969) between 1960-1965 and Ohta (1987) for used cars between 1970-1983. ii) For the UK: Cowling & Cubbin (1972) between 1956-1968, Murray & Sarantis (1999) between 1977-1991 and Requena-Silvente & Walker (2006) between 1971-1998. iii) For the Netherlands: Kroonenberg & Cramer (1974) between 1964-1971 and Dalen & Bode (2004) between 1990-1999. iv) For Portugal Reis & Silva (2006) between 1997-2001. v) For Italy Tomat (2002) between 1988-1998.

Regarding the Spanish market Izquierdo *et al.* (2001) have computed hedonic prices for new cars using monthly data for the period 1997-2000. Their hedonic regressions explain prices as a function of quality indexes, constructed from a comprehensive set of 35 observed characteristics, in order to avoid the collinearity problems common to this methodology (Pakes, 2003). The main finding is that quality corrected prices are 3.1% lower per year as compared to the price index computed by the Spanish National Statistics Office. Matas & Raymond (2009) offer estimates for the period 1981-2005 but using yearly, instead of monthly, data. They perform standard hedonic regressions but they also propose two different smoothing techniques to deal with the parameter instability caused by collinearity. They do not address directly the problem of product unobservables, assuming that they may be captured by brand dummies. Their results show that not controlling for quality improvements overestimates nominal price increases at an average rate of 8.8% per year for this 25 years. For the period 1997-2001 they estimate a gap of around 2.85% per year, in line with the results of Izquierdo *et al.* (2001), although a bit smaller.

The rest of the paper is organized as follows: Section 2 describes de data and the quality improvement process of cars in Spain. Section 3 explains the methodology followed

in the hedonic regressions. Section 4 presents the price indexes to be computed. Section 5 shows and discuss the results. Finally, section 6 concludes.

2 Quality improvement patterns for cars in Spain during the 1990's

2.1 Data Description

I use a unique data set of monthly registrations of new cars in Spain from January 1990 to December 2000. These data were initially collected by Moral & Jaumandreu (2007),² who also provide a thorough description of the data base. It includes information on listed nominal and real prices and characteristics such as car size (length, width, luggage capacity), power, maximum speed, fuel consumption, and equipment (dummies for air conditioner, anti-lock braking system, power steering, central door locking and electric windows). It also has information on model age and on the geographical origin of the brand producing the model. Table 1 describes the set of characteristics.

The unit of observation is the car model. Car models often have several variants or subvariants. In the data, a given model denomination is associated with the characteristics of its most popular variant in the month of observation. Therefore, the variation in characteristics over time is due to the variation of the characteristics of the representative variant (and not due to a change on the variant chosen). The number of registrations for a model are, however, the sum of registrations of all variants.

Some filters were introduced to exclude super luxury models, e.g., Ferrari or Rolls Royce. Models with fewer than 10 registrations per month are also excluded. Nevertheless, the data set accounts for more than 99.9% of car registrations during the sample period.

Models are classified in segments following industry sources³. In particular, I consider

 $^{^2{\}rm The}$ data base there, which runs from January 1990 to December 1996, has later been extended up to December 2000.

³National Association of Automobile and Truck Manufacturers (ANFAC) Annual Report (2006), page 57. Accessible online at http://www.anfac.es . During the 1990's the Minivan segment was still marginal in Spain, for that reason it was grouped in a unique category that nowadays has split into two, following the consolidation of the segment.

the following classification in eight segments: Small-Mini, Small, Compact, Intermediate, High Intermediate, Luxury, Sport, and Minivan. The segments from Small-Mini to Luxury correspond to vertical product differentiation, while Sport and Minivan can be identified with the horizontal one. These two segments include cars of different levels of quality, all of them having in common that they are designed to serve a more specific purpose.

2.2 The evolution of automobile characteristics and prices

One of the most salient features of the Spanish car market in the 1990's is the intense process of product entry and replacement. The number of products increases steadily over the period due to the entry of new firms (mainly from Asia) and the expansion of the product range of incumbents. We can therefore say that the market is characterized by an scenario of increased competition, specially from Asian manufacturers (Jaumandreu & Moral, 2008). The evolution of prices and car characteristics suggests that non-price competition is the strategy followed by the majority of firms. The average price of cars in real terms increases all over the period, except for Asian models (Figure 1), which may be due to the fact that at the beginning of the sample period Asian producers were concentrating mainly on models of the upper-class segments. As they expanded their range of products to cover segments of lower quality it is natural that the global average price decreases. The initial decline in prices (Figure 2) can be attributed to the context of economic crisis at the beginning of the decade in Spain. The quality of cars, measured by the amount of each characteristic, clearly increases all over the period, perhaps more in the case of non-Asian models.^{4,5} The general trend in the period goes toward larger, faster and more powerful cars but with smaller luggage capacity and higher consumption rates. This is particularly marked in the case of European models, probably as a response to the increased competition from Asian models in the second half of the decade. The average Asian car seems to follow the opposite pattern, but as mentioned before, this is mainly

 $^{^{4}}$ These figures are omitted here for the sake of brevity. All the tables, figures and results (including estimates and standard errors for all econometric specifications) mentioned throughout the paper are available as supplementary material downloadable from http://works.bepress.com/xose-luis_varela-irimia/6/

⁵All the figures presented here are weighted by unit sales.

a consequence of the fact that the earlier Asian cars were concentrated in the upperquality segments. After 1995 the Spanish market witnesses an intense wave of entries by Asian makers, mainly in the medium and lower quality segments. Nevertheless, Spanish, European and American manufacturers contribute also very actively to the enlargement of the number of models offered in Spain.

The evolution of car amenities such as air conditioning, power steering, etc. follows a similar pattern, although in this case it is very clear that improvements in these characteristics are always introduced in the upper-class segments and they eventually spread over the rest. It is important to clarify that the Minivan and Small-Mini segments became popular during this period so that the variety and number of models increased significantly. As a consequence the average characteristics varied a lot due to the intense entry process, specially at the beginning of the sample period.

In summary, it seems clear that the automobile sector in Spain experienced a remarkable improvement in quality which a simple price index would ignore, thus overstating the increase in the cost of living attributed to car purchases. Therefore, the application of hedonic regression techniques to the computation of price indexes seems to be clearly justified.

3 Hedonic regressions

The hedonic regression methodology is aimed at explaining price variations by the change in product characteristics. Its practical implementation requires choosing and justifying assumptions regarding model specification, functional form of the hedonic function, parameter constancy or weighting. The next subsections address each of these issues.

3.1 Model specification

The most basic hedonic specification relates price to a number of characteristics (C):

$$p_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \varepsilon_{it}$$
(1)

where β_0 is an intercept, x_{ijt} denotes characteristic j of product i at time t. The age of the car model can be one of these characteristics. β_{jt} denotes the implicit price of characteristic j at time t and ε_i is some *iid* error term. In some cases the researcher may have access to a thorough set of product characteristics, comprehensive enough to justify the assumption that there remains no unobserved characteristic and the model is well specified. However, in most cases the set of characteristics is much more limited and observability becomes an issue. And even if we had such an exhaustive set of characteristics we could always think of factors like reliability, consumer's perception of quality or reputation that have an effect on prices but are not specifically captured by any combination of technical characteristics. If these factors are also correlated with the observed characteristics then their omission would make the estimation of $\beta's$ inconsistent. One approach that has become common to address this problem consists on adding brand or make dummies, hoping that reputation or reliability will be adequately captured:

$$p_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \sum_{b=1}^{B-1} \gamma_{bt} Brand_b + \varepsilon_{it}$$

$$\tag{2}$$

where $Brand_b = 1$ if product *i* belongs to firm *b* and zero otherwise. As usual, one of the *B* brands must be excluded to avoid collinearity problems. γ_{bt} captures the brand effect. This set of dummies may be augmented in some cases, like the automobile sector, with the addition of segment dummies:

$$p_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \sum_{b=1}^{B-1} \gamma_{bt} Brand_b + \sum_{l=1}^{L-1} \delta_{lt} Seg_l + \varepsilon_{it}$$
(3)

where $Seg_l = 1$ if product *i* belongs to segment *l* and zero otherwise. δ_{lt} captures the corresponding segment effect. Unfortunately, even with brand or segment dummies there may remain unobserved factors specific to model *i*. One possible solution would be to introduce M - 1 product specific dummies to capture such effects:

$$p_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \sum_{m=1}^{M-1} \eta_{mt} Model_m + \varepsilon_{it}$$

$$\tag{4}$$

where $Model_m = 1$ if m = i and zero otherwise, and η_{mt} is the associated model effect. This effect would capture all the unobserved factors related to the particular car model as well as the effect associated to belonging to a given firm and segment.

However, if the number of products is large this approach could be problematic due to the lack of degrees of freedom. An alternative solution would specify a model with a time-invariant product fixed effect (ζ_i) :

$$p_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \zeta_i + \varepsilon_{it} = \beta_{0t} + \sum_{j=1}^{C} \beta_{jt} x_{ijt} + \nu_{it}$$

$$(5)$$

In this specification the time-invariant car-model effect is an omitted variable affecting prices through the compounded error term ν_{it} . Assuming that this effect is time-invariant permits the consistent estimation of β 's using panel data fixed effects estimators. For instance, using first differencing or a within transformation would remove ζ_i , but also all other time-invariant regressors, so their coefficients would not be separately indentified from ζ_i .⁶ The estimated prices for characteristics, β , would be the same in approaches 4 and 5 (see Cameron & Trivedi, 2005, section 21.6.4, p.732). Approaches 1-3 are common in the literature and approach 4 has been proposed by Requena-Silvente & Walker (2006). In this paper I will compare the results from all of them, but using the specification 5 instead of 4.

Regarding the choice of characteristics in X the common approach has been using as many as there are available. However, the potential collinearity between many of these characteristics can induce some problems in the estimation of β 's, notably the appearance of "wrong" signs or parameter instability. Nevertheless, following Pakes (2003), these problems have not been a particular source of worry in the literature. Therefore, in my empirical specification I will be using all characteristics listed in Table 1.⁷ Among them, the role of model age deserves particular attention.

⁶For this reason this specification does not include brand or segment dummies.

⁷A few more characteristics were originally available, but they were either almost perfectly collinear with or just simple redefinitions of other variables like horse power, fuel consumption or car size, so they were not considered. The hedonic indexes, however, are quite robust to variations in the contents of X, except in what concerns the variable *age* (see section 5).

The variable age, measures the age of the product, i.e., the period of time elapsed since it was firstly introduced in the market. So, age informs about the degree of obsolescence of the product (older products could be seen as more successful). For instance, Dalen & Bode (2004) find evidence of positive age effects, which they interpret as a gradual improvement of the quality of car models "after introduction without inmediately adjusting the basic technical description of the model" (p.1177). Moreover, according to Oliner (1993), hedonic equations should include the age as an explicit argument because if omitted characteristics are correlated with model age, this would be an adequate proxy for them. Therefore, the age can be informative about product specific (quality) characteristics that cannot be inferred from the observed technical specifications and that can also be time-variant. In consequence, introducing age as an explanatory variable (i.e., as an additional x_{ijt}) can help in controlling for unobserved effects in combination with ζ_i in expression 5. The latter would control for time-invariant product specific unobserved effects, while the former would capture the time-variant ones that are common to the products of the same age. After these controls are introduced it does not seem implausible to assume that most of all relevant sources of (time-variant or -invariant) unobserved product heterogeneity are being accounted for.

If product unobservables are really an issue then the estimation of expressions 1-3 should yield biased estimates of β . The introduction or not of age would just affect the size of the bias. In specification 5 however, the omission of age could introduce some bias and its inclusion should remove it. If the time-variant unobserved effects are correlated with X then omitting them would induce correlation between X and the error term. The size and direction of these biases are empirical questions that depend on the correspondent estimates of the effects.

3.2 Functional form of the hedonic function

In the previous subsections linear expressions of the hedonic regression have been used for simplicity in the exposition. However, the relation between prices and characteristics could follow any general functional form: $p_{it} = f(X_{it})$. Nevertheless, the literature has focused on linear relations but allowing for the possibility of transforming the data to have a more flexible specification. The usual approach has consisted on applying a Box-Cox transformation to the dependent and/or the right hand side variables and estimating the transformation parameters consistent with the data. It turns out that in most cases the Box-Cox parameters are close enough to 0 or 1 to safely assume semi-log, log-log or simple linear specifications. Therefore, most of the work of functional form selection reduces to determining the best suitable transformation of the data.

Regarding the automobile industry previous studies have found that a semi-log specification (taking logs on the price and leaving the right hand side variables unchanged) is the one that best fits the data, it is the case of Dalen & Bode (2004) or Requena-Silvente & Walker (2006). For the Spanish market, Matas & Raymond (2009) also find the semi-log the most adequate choice. That will also be the one I will use in this paper. This choice is sustained by the fact that the maximum likelihood estimates for the parameters of the Box-Cox transform on a regression of price on characteristics for the whole sample yield a parameter of 0.013 (*p*-value 0.116) for price and 1.14 for the right hand side variables (the dummies are excluded from the transformation). Therefore the assumption of linearity for right hand side variables and logs for price does not seem unreasonable.⁸

3.3 Parameter constancy and the use of weights in hedonic regressions

The hedonic price index methods can be applied following different estimation strategies that are basically differentiated by the sample size they use:

1. The time dummy variable (TDV) method fits the hedonic regression to the whole sample, adding to the model specification a set of time dummies. The idea is that the coefficient of the dummy of say, period t, will represent the growth in the price index from the initial period to time t net of quality changes, which are controlled

⁸Similar results were obtained for per-period regressions, although in this case the Box-Cox coefficient on the right hand side variables was estimated less precisely in some periods, but it was in general significantly different from zero.

for through the variation of characteristics. The main drawback of this method is that it restricts the coefficients (prices) of characteristics to be constant over the whole sample period. Even if one could consider that this assumption would be reasonable for short sample periods or in contexts where consumer perception and valuation of quality remain constant over time, the truth is that in the literature parameter constancy is most often rejected by Chow tests of structural break. The case of the automobile industry is not an exception.

- 2. The adjacent period (AP) method can be seen as a refinement of the TDV where parameter constancy is assumed to hold only for two consecutive periods and a dummy is added to capture the quality-adjusted price increase of the second period with respect to the first one. A whole index series can then be constructed by chaining the time dummies coefficients.
- 3. The single period equation (SP) method allows the prices of characteristics to vary from period to period. Its parameter estimates can then be used to construct indexes of quality change which serve to correct the quality bias of the non-adjusted price index. One potential drawback of this approach is, as mentioned before, the parameter instability on the estimated prices of characteristics. However, the quality-adjusted price indexes constructed from them seem to be quite robust in general (Pakes, 2003).

In this study I will follow the single period equation approach, that has gained in popularity precisely because it avoids the assumption of parameter constancy, which is not recommended unless it is sustained by the data (Triplett, 2004, p.61). This is generally not a problem in the AP method, however this paper is aimed at assessing the impact of unobservables on price indexes, rather than comparing the results of SP and AP methods⁹ (see again for examples Triplett, 2004, p.61-63).

Another point of debate in the hedonic literature is whether the hedonic regressions should be weighted or not. In this respect, and following the recommendations in Triplett

 $^{^9\}mathrm{For}$ the same reason I will not consider here the matched model approach.

(2004) I will make use of weights to avoid an excessive impact of prices of products whose market share is low because they are viewed as less satisfactory by consumers. The price variation of these type of goods should have less importance than other more successful models.¹⁰

3.4 Estimation issues

Taking into account all considerations of the previous subsections, the final hedonic specifications to be taken to the data are:

$$\ln p_{it} = \beta_{0t} + \beta_{1t}C90_{it} + \beta_{2t}CarSize_{it} + \beta_{3t}LGC_{it} + \beta_{4t}HP_{it} + \beta_{5t}maxSp_{it} + (6) + \beta_{6t}Age_{it} + \beta_{7t}AC_{it} + \beta_{8t}ABS_{it} + \beta_{9t}PST_{it} + \beta_{10t}CDL_{it} + \beta_{11t}EW_{it} + \varepsilon_{it}$$

where β_{6t} captures the age effects.

$$\ln p_{it} = \beta_{0t} + \beta_{1t}C90_{it} + \beta_{2t}CarSize_{it} + \beta_{3t}LGC_{it} + \beta_{4t}HP_{it} + \beta_{5t}maxSp_{it} +$$
(7)
+ $\beta_{6t}Age_{it} + \beta_{7t}AC_{it} + \beta_{8t}ABS_{it} + \beta_{9t}PST_{it} + \beta_{10t}CDL_{it} + \beta_{11t}EW_{it} +$
+ $\sum_{b=1}^{B-1} \gamma_{bt}Brand_b + \varepsilon_{it}$

where the γ 's capture brand effects.

$$\ln p_{it} = \beta_{0t} + \beta_{1t}C90_{it} + \beta_{2t}CarSize_{it} + \beta_{3t}LGC_{it} + \beta_{4t}HP_{it} + \beta_{5t}maxSp_{it} + (8)$$
$$+\beta_{6t}Age_{it} + \beta_{7t}AC_{it} + \beta_{8t}ABS_{it} + \beta_{9t}PST_{it} + \beta_{10t}CDL_{it} + \beta_{11t}EW_{it} + \sum_{b=1}^{B-1}\gamma_{bt}Brand_b + \sum_{l=1}^{L-1}\delta_{lt}SEG_l + \varepsilon_{it}$$

¹⁰I have check however the results using no weights and the impact over the hedonic price indexes turns out to be not substantial.

where the δ 's capture segment effects.

$$\ln p_{it} = \beta_{0t} + \beta_{1t}C90_{it} + \beta_{2t}CarSize_{it} + \beta_{3t}LGC_{it} + \beta_{4t}HP_{it} + \beta_{5t}maxSp_{it} +$$
(9)
+ $\beta_{6t}Age_{it} + \beta_{7t}AC_{it} + \beta_{8t}ABS_{it} + \beta_{9t}PST_{it} + \beta_{10t}CDL_{it} + \beta_{11t}EW_{it} +$
+ $\zeta_i + \varepsilon_{it}$

where ζ_i denotes the time-invariant car-model effects. Assuming that observed characteristics are exogenous, expressions 6 - 8 can be estimated period to period by ordinary least squares. Expression 9 requires at least two periods to control for the unobserved component ζ . Therefore, in the estimation of 9 I follow the approach proposed in Matas & Raymond (2009) of taking moving samples of order h. They suggest this procedure as a way to smooth the estimated coefficients of single period hedonic regressions, that tend to be erratic from period to period. This method has the added advantage of providing enough time observations for the application of the within $estimator^{11}$ in equation 9. It should be clarified that this approach allows different prices for characteristics every period, except for the first h-1 periods. What is assumed is that the coefficients of period t can be satisfactorily estimated by pooling all periods from t-h+1 to t. In this subsample the prices for characteristics from t - h + 1 to t - 1 are held equal to those in period t. Next, for the estimation of period t + 1 the coefficients of t + 1 will be assumed to hold for the previous t - h + 2 to t periods, and so on. So, contrary to what happens in the AP or TDV approaches, holding the coefficients constant is a manner of improving the estimation of the per-period coefficients. It is assumed that for the estimation of β_t the previous t - h + 1 periods contain useful information, and that we can take advantage of it even if we "temporarily" impose the coefficients of period t over the previous t - h + 1periods. In the AP or TDV methods the sample remains constant and so do the coefficients within the sample. The order of the moving sample, h, should be of a size just

¹¹The within estimator for a fixed effects model is an ordinary least squares estimator of a model where the original variables are substituted by their within transformation, which consists on subtracting to each variable its time mean, i.e., for a variable y_{it} its within transformation is: $y_{it}^w = y_{it} - \frac{1}{T} \sum_{t=1}^{T} y_{it}$, where T is the number of time periods for the cross-section unit *i*. The within transformation is therefore a way of removing the car-model effect ζ_i from the data.

enough to control for the fixed effect, and not too large to avoid an excessive smoothing. For the empirical application I have chosen h = 12 because for shorter samples many of the characteristics are usually constant and therefore their coefficients could not be separately identified from the fixed effect. Recall that we are using here monthly data and that even if there is a significant rate of product change and improvement, many models do not experience changes in their technical specifications from one month to the next one.¹² By fixing h = 12 we are assuming a one-year moving sample¹³, which may be seen as a bit *ad hoc* but which is also consistent with all studies using yearly data to estimate hedonic prices for characteristics.¹⁴ To make the results more comparable I will estimate specifications 6 - 8 using the moving sample of order 12 ¹⁵

4 Quality-adjusted price indexes

I use a unit sales weighted Laspeyres geometric index¹⁶, as proposed in Feenstra (1995), to measure the price increase of automobiles. The quality-adjusted index for model i is therefore defined as:

$$\ln I_{it} = \ln p_{it} - \ln p_{it-1} - (X_{it} - X_{it-1}) \beta_t$$
(10)

where $Q_{it} = (X_{it} - X_{it-1}) \beta_t$ represents the quality correction and can be interpreted as a characteristics quantity index (Triplett, 2004, p.60). Notice that all time-invariant characteristics, the brand and segment dummies or the car-model effects, would cancel out if they were introduced in Q_{it} . Thus, the differences between the alternative quality-adjusted

¹²This is also the main reason for not computing price indexes using the AP hedonic approach.

¹³The hedonic indexes are quite robust to the choice of h. For instance, there is not much difference between those computed for values of h = 6, 12, 24. However, for h = 6 still many characteristics remained constant preventing the estimation of their hedonic prices, and h = 24 seems perhaps a too long period to impose the equality of parameters to the moving sample.

¹⁴Although it is true that in these cases there is no alternative choice given the data constraints.

¹⁵The hedonic indexes from 6 - 8 computed using single period hedonic regressions are virtually identical to those using the moving sample.

¹⁶One advantage of using characteristics price indexes is that the functional form of the hedonic specification is not linked to the index number formula (Triplett, 2004, p.60). If we were following the TDV or AP approaches the use of semi-log hedonic specifications would imply that a geometric index would be a must rather than a choice.

price indexes proposed come from the different estimates of β 's in each specification. In order to mitigate the potential impact of coefficient instability in the single period hedonic regressions over the indexes I smooth the β 's using a weighted moving average of coefficients or order k = 3 as proposed in Matas & Raymond (2009).¹⁷ Therefore, the smoothed coefficient for characteristic j in period t is:

$$\hat{\beta}_{jt}^{smooth} = \lambda_{t-1}\hat{\beta}_{jt-1} + \lambda_t\hat{\beta}_{jt} + \lambda_{t+1}\hat{\beta}_{jt+1}$$

where $\hat{\beta}_{jt}$ denotes the estimate of β_{jt} and $\lambda_t = \frac{\left[var(\hat{\beta}_{jt})\right]^{-1}}{\sum\limits_{s=t-1}^{t+1} \left[var(\hat{\beta}_{js})\right]^{-1}}$. The aggregated index is the weighted sum:

$$I_t = \exp\left(\sum_{i=1}^{n_t} s_{it-1} \times \ln I_{it}\right) \tag{11}$$

where n_t is the number of models in period t and s_{it} is the market share of model i in period t, such that $\sum_{i=1}^{n_t} s_{it} = 1$. This is the kind of approach followed by the Spanish National Statistics Office (see for example Izquierdo *et al.*, 2001). The indexes (11) are then chained to construct a whole series.

I use as reference the non-quality-adjusted index, comparing it to adjusted indexes from each of the four specifications (6 - 9).

5 Results

The hedonic specifications 6-9 were estimated for each period.¹⁸ Tables 2-5 show abridged versions of the hedonic parameter estimates, reporting the results for the month of May of each year.^{19,20} The estimated coefficients have in general the right sign, although a

¹⁷It must be said, however, that smoothing does not have any significative impact over the hedonic price indexes because the results were essentially identical for orders of smoothing of 3, 7, 13 and 1 (no smoothing).

¹⁸Given the choice of h and k, the final number of periods available for hedonic regressions is T =132 - h + 1 = 121 and for the computation of indexes is T = 132 - h - k + 2 = 119. The figures take as base period the first one available, i.e., t = h + k - 1 = 14 (February 1991).

¹⁹The choice of May does not obey any particular reason, the results for other months provide qualitatively similar insights.

²⁰The full set of results is available at http://works.bepress.com/xose-luis varela-irimia/6/

few variables show reversed signs for certain periods, a fact frequently reported in the literature (Pakes, 2003). The size of coefficients (in absolute value) also varies over time, but changes tend to be smooth from period to period. This may be a consequence of having monthly regressions, because even if we can expect parameter instability (as usually found in the literature), it should be smaller between two consecutive months than between two consecutive years. It is not unreasonable to expect that consumers' valuation of characteristics do not change much within a year, and that would be consistent with obtaining very similar results for price indexes using different orders of smoothing of the hedonic parameters.

The quality-adjusted hedonic price indexes resulting from the estimation of specifications 6-9 are presented in Figure 3, the non-adjusted index is also included for comparison.²¹ We can see that correcting for quality using dummies for brand or segment has a strong impact, in line with the results generally reported in the literature and similar to those reported by Izquierdo et al. (2001) or Matas & Raymond (2009) for the Spanish market. One important finding is however that not taking into account car-model effects largely overestimates the dummy-corrected indexes that stem from expressions 7 and 8. Indeed, the index coming from specification 9 shows that quality-adjusted prices remained basically constant for the whole period. By the end of 2000 the difference between the car-model-effects- and the brand-dummies-corrected indexes is about 18% and the difference with respect to the non-adjusted index is around 35%. This represents an average year-on-year difference of 1.8% and 3.5%, respectively. Taking into account that the purchase price of new cars had at that time a weight of 5.27% in the Spanish Consumer Price $Index^{22}$ (IPC) we can say that omitting observed and unobserved quality improvements in automobiles would have led to an overestimation of the IPC of almost a 0.2% per year during the 1990's.

Interestingly, the omission of age effects has a striking influence over the hedonic

²¹These are all nominal indexes.

²²This is the weight for the index with base in 1992 computed until 2001. It has been obtained from the website of the Spanish National Statistics Office, accessed 4 August 2011 at: http://www.ine.es/jaxi/tabla.do?path=/t25/p138/pond/l1/&file=02003.px&type=pcaxis by selecting the class "610.Purchase of vehicles for personal transport" and the period "weighting CPI-92".

index when adjusting for car-model effects, leading to opposite conclusions. Omitting age effects seems to be an important source of bias, which would be more relevant in the case of the car-model effects specification than in the dummy variables ones. As discussed in subsection 3.1 we can expect that not introducing age in specifications 6-8 would just affect the size of the bias of hedonic coefficients. The bias would already exist due to the omission of part or all of the time invariant car-model effects. However, in specification 9 there should not be any significant bias due to the omission of unobserved effects, so by omitting age we could be inducing some bias that would have not existed previously. The results without age effects show a similar pattern than those reported for the UK by Requena-Silvente & Walker (2006). They find that car-model effects push-up the hedonic index with respect to the brand dummies case and they attribute the result to the fact that the value of unobserved components is decreasing over time. In our case it seems that age effects are in general positive,²³ suggesting that the quality of cars perceived by the consumers is improving even if this is not reflected in the characteristics observed by the econometrician. Therefore, the omission of age effects would tend to underestimate quality improvement thus overestimating quality-adjusted prices. The estimated age coefficients in the fixed effects specification are much $larger^{24}$ than the corresponding coefficients in the dummy specifications, so their omission also induces a much larger upward bias in the quality-adjusted index in the fixed effects case than in the brand and brand-segment dummies cases. In particular, the hedonic coefficients of age under fixed effects take their largest values between January 1993 and April 1996. Their omission determines the strikingly different pattern of the hedonic price index between figures 3 and 4 in that period.

I have used the coefficient estimates of the hedonic specifications to construct price

 $^{^{23}}$ The coefficient of age is positive for most of the per-period regressions. It is negative for periods 18 to 47 (June 1991 to November 1993) and 131-132 (November to December 2000) in the brand dummies specification; for periods 18 to 65 (June 1991 to May 1995), 97 to 107 (January to November 1998) and 131-132 in the brand and segment dummies specification; for periods 28 to 35 (April 1992 to November 1992) and 95 to 120 (November 1997 to December 1999) in the fixed effects specification. Therefore, we can say that the pattern of signs for age effects is similar across specifications. It is also consistent with previous evidence: Dalen & Bode (2004) also find positive age effects that change to negative between 1990 and 1994 for the Dutch car market.

²⁴Around ten times larger.

indexes by car model geographic origin and segment.^{25,26} The objective is to determine whether the behavior of prices is determined by the evolution of any particular type of models. Figures 5-8 report the results for car models from Spain, Europe (excluding Spain), Asia and America. Asian cars are clearly leaders in (car-model and age effects) quality-adjusted price reductions with a 20% drop in the whole sample period. American cars also reduced their quality-adjusted price while the Spanish and European ones increased between 3% and 8%. However, for making comparisons we must take into account that the average price at the initial period was different across geographic origins. Asian cars where on average most expensive at the beginning of the sample (Figure 1) and we could expect that as more models were introduced in lower-class segments the average price would fall even if the quality improvement was not too high. In order to make a balanced comparison, we can look for example at the beginning of 1995, where the average real price of Asian and European cars was roughly the same, around 12 000 Euro. The real price of Asian cars remained roughly constant afterwards, while European cars increased around a 10%. In the same period, car-model and age effects quality-adjusted prices for Asian cars fell by a 7% while European ones fell by less than 4% Therefore, even starting from similar price ranges, Asian cars seem to have improved in quality faster than the rest. The increasing competitive pressure from these models may have served to discipline the European makers towards better products to retain their market shares. Figure 6 shows that between mid-1995 and the end of 1997 the fixed effects qualityadjusted price of European cars fell down sharply after three years of increase (the brand and segment dummies approaches also show that pattern, although it spreads over two more years, until the end of 1999), probably as a response to the wave of entry of models from Asian manufacturers that took place after 1995. Spanish and American models kept

²⁵This means that no segment- or origin-specific hedonic regressions were run to construct these indexes. The scarcity of observations in several classes prevents the implementation of this approach. This is also the reason for some volatile patterns displayed for example in segments like Minivan or Small-Mini, or for car models original from Spain. In these cases and for some periods, due to the relatively small number of products, the entry or exit of just one product can have an big impact on the index.

 $^{^{26}}$ These are all weighted indexes. The weights sum to 1 within each class considered. For example, in the figure for European cars (Figure 6) the weights assigned to each model are per period market shares conditional on being a European car.

their car-model and age effects quality-adjusted prices more or less constant (Figures 5 and 8). These indexes show however some jumps that can be attributed to the smaller number of models in these categories, specially for Spanish cars, that make the indexes more sensitive to product entry or exit.

The indexes for each segment shown in figures 9 to 11 have been computed following the same approach than for the by-origin figures. To make the exposition more concise, I present only the results for the most popular segments, the Small, Compact and High-Intermediate, that account for around 70% of the market. However, their examination does not suggest that there is a specific segment leading price reductions. Quality-adjusted prices tend to increase in the first half of the sample and then start to decrease around 1995. The intensity of price increases and decreases is obviously different across segments but the general impression is that both trends are roughly uniformly distributed across segments.

6 Concluding remarks

The use of hedonic regressions to compute quality-adjusted price indexes is nowadays a common practice in the economics literature. Nevertheless, the impact of unobserved product characteristics in that analysis has been largely neglected. Building on Requena-Silvente & Walker (2006) I propose an approach that serves to compute such indexes taking into account the existence of both time-variant and time-invariant unobserved effects and I apply it to the Spanish car market. The former are controlled by introducing model age as an additional characteristic, the latter are accounted for by using fixed effects panel data estimators. Although these two approaches have been separately proposed in the literature they have not been used simultaneously. The results show that the estimated indexes for the Spanish automobile market can be even lower than what had already been reported, suggesting that the consumer price index could have been overestimated by a 0.2% per year, which constitutes an important bias considering its importance in measuring productivity changes or in determining wage increases. Controlling for age effects turns out to be crucial for obtaining these results, implying that time-variant

unobserved effects are as important as the time-invariant ones, at least in what concerns the Spanish car market.

Extending the analysis to the segment and geographical origin level leads to two additional conclusions: First, that the patterns of price evolution are similar across segments, such that price increases or decreases seem to be distributed uniformly across segments, i.e., price increases or decreases do not seem to be concentrated on a particular segment. Second, the price decrease of both the non-adjusted and the adjusted price indexes in the second half of the decade seems to be motivated by the strength of competition after an intense wave of new entries of Asian models. Asian cars show by far the largest quality-adjusted price reductions, specially due to their strong quality improvements. It seems plausible to interpret the price reductions of Spanish and European incumbents as a response to that pressure, although a more formal analysis would be needed to clearly determine to what extent this is the case.

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Tables

Mean	Std. Dev.	Unit of measure
19.99	12.84	Thousand euros
7.37	1.00	Length \times width (m ²)
119.28	48.67	Horse power
6.23	1.13	Liters per 100 Km
430.55	358.68	Liters
189.90	25.37	Km per hour
76.86	69.45	Months after introduction
0.49	0.50	Dummy
0.39	0.49	Dummy
0.79	0.41	Dummy
0.82	0.39	Dummy
0.80	0.40	Dummy
	Mean 19.99 7.37 119.28 6.23 430.55 189.90 76.86 0.49 0.39 0.79 0.82 0.80	MeanStd. Dev.19.9912.847.371.00119.2848.676.231.13430.55358.68189.9025.3776.8669.450.490.500.390.490.790.410.820.390.800.40

Table 1. Characteristics and descriptive statistics

$\operatorname{Ln}(p)$	May 1991	May 1992	May 1993	May 1994	May 1995	May 1996	May 1997	May 1998	May 1999	May 2000
C90	-0.00279 (0.00778)	-0.0299 (0.00807)	-0.0168 (0.00703)	-0.0277 (0.00698)	-0.0524 (0.0106)	-0.0153 (0.00907)	$\begin{array}{c} 0.0125 \\ (0.00813) \end{array}$	$\begin{array}{c} 0.0334 \\ (0.00612) \end{array}$	$\begin{array}{c} 0.00756 \\ (0.00586) \end{array}$	$\begin{array}{c} 0.0192 \\ (0.00594) \end{array}$
CarSize	$\underset{(0.0198)}{0.194}$	$\begin{array}{c} 0.223 \\ (0.0107) \end{array}$	$\begin{array}{c} 0.189 \\ (0.00820) \end{array}$	$\underset{(0.00904)}{0.196}$	$\underset{(0.00949)}{\textbf{0.204}}$	$\begin{array}{c} 0.212 \\ (0.00762) \end{array}$	$\begin{array}{c} 0.184 \\ (0.0141) \end{array}$	$\underset{(0.0202)}{0.131}$	$\begin{array}{c} 0.134 \\ (0.00699) \end{array}$	$\begin{array}{c} 0.145 \\ (0.00499) \end{array}$
LGC	-0.000243 (4.40 e -05)	-0.000237 (3.05 e -05)	$2.81e-06 \ (2.13e-05)$	-1.59e - 05 (2.17 $e - 05$)	$2.39e-05 \ (2.72e-05)$	$\begin{array}{c} 0.000185 \ (1.52e-05) \end{array}$	$\begin{array}{c} 8.68e-05 \\ (1.21e-05) \end{array}$	$5.29e-05 \ (1.66e-05)$	${3.00e-05 \atop (8.15e-06)}$	$2.74e-05 \ (7.59e-06)$
HP	$\begin{array}{c} 0.00456 \\ (0.000393) \end{array}$	$\begin{array}{c} 0.00526 \\ (0.000359) \end{array}$	$\underset{(0.000407)}{0.0027}$	$\begin{array}{c} 0.00495 \\ (0.000484) \end{array}$	$\begin{array}{c} 0.00332 \\ (0.000714) \end{array}$	$\begin{array}{c} 0.00179 \\ (0.000637) \end{array}$	$\begin{array}{c} 0.00415 \\ (0.000623) \end{array}$	$\begin{array}{c} 0.00455 \\ (0.000555) \end{array}$	$\begin{array}{c} 0.00612 \\ (0.000235) \end{array}$	$\begin{array}{c} 0.00594 \\ (0.000238) \end{array}$
maxSp	$\begin{array}{c} 0.00159 \\ (0.000682) \end{array}$	$\begin{array}{c} 0.00012 \\ (0.000605) \end{array}$	$\begin{array}{c} 0.00347 \\ (0.000572) \end{array}$	$\begin{array}{c} 0.00174 \\ (0.000623) \end{array}$	$\begin{array}{c} 0.00421 \\ (0.000994) \end{array}$	$\begin{array}{c} 0.00411 \\ (0.000881) \end{array}$	$\begin{array}{c} 0.000305 \\ (0.000891) \end{array}$	$\begin{array}{c} 0.0017 \\ (0.000684) \end{array}$	-0.00162 (0.000352)	-0.00239 $_{(0.000380)}$
Age	$\begin{array}{c} 6.44e-05 \ (8.39e-05) \end{array}$	-0.000183 (7.50 e -05)	-0.000151 (7.21 e -05)	$\begin{array}{c} 6.77e-05 \ (7.12e-05) \end{array}$	$7.54e - 05 \\ (7.72e - 05)$	$\begin{array}{c} 9.36e-05 \ (5.55e-05) \end{array}$	$\begin{array}{c} 0.000224 \ (5.93e-05) \end{array}$	$\begin{array}{c} 0.000225 \ (5.01e-05) \end{array}$	$\begin{array}{c} 0.000108 \\ (4.34e-05) \end{array}$	$2.10e-05 \ (4.51e-05)$
AC	$\begin{array}{c} 0.0243 \\ (0.0126) \end{array}$	$\begin{array}{c} 0.0166 \\ (0.00985) \end{array}$	$\underset{(0.00996)}{0.125}$	$\begin{array}{c} 0.0405 \\ (0.0131) \end{array}$	$\begin{array}{c} 0.0419 \\ (0.0132) \end{array}$	$\begin{array}{c} 0.0619 \\ (0.00772) \end{array}$	$\begin{array}{c} 0.0552 \\ (0.00973) \end{array}$	$\begin{array}{c} 0.0408 \\ (0.00925) \end{array}$	$\begin{array}{c} 0.0762 \\ (0.0103) \end{array}$	$\begin{array}{c} 0.0975 \\ (0.00757) \end{array}$
ABS	$\begin{array}{c} 0.0461 \\ (0.0139) \end{array}$	$\begin{array}{c} 0.0696 \\ (0.0103) \end{array}$	$\begin{array}{c} 0.0564 \\ (0.00962) \end{array}$	$\begin{array}{c} 0.0206 \\ (0.0123) \end{array}$	$\begin{array}{c} -0.00915 \\ \scriptstyle (0.0128) \end{array}$	-0.0156 (0.0137)	$\begin{array}{c} 0.0146 \\ (0.0138) \end{array}$	$\begin{array}{c} 0.0092 \\ (0.0130) \end{array}$	$\begin{array}{c} 0.0115 \\ (0.00951) \end{array}$	$\underset{(0.00768)}{0.0121}$
STP	-0.00444 $_{(0.0130)}$	$\begin{array}{c} 0.0342 \\ (0.0119) \end{array}$	$-0.0353 \\ \scriptscriptstyle (0.0123)$	-0.0282 (0.0122)	-0.0331 (0.0133)	-0.0595 $_{(0.0104)}$	$\begin{array}{c} 0.011 \\ (0.0133) \end{array}$	$\begin{array}{c} 0.0422 \\ (0.00939) \end{array}$	$\underset{(0.00769)}{0.00769)}$	$\begin{array}{c} 0.0807 \\ (0.0152) \end{array}$
CDL	$\begin{array}{c} 0.048 \\ (0.0159) \end{array}$	$\begin{array}{c} 0.0188 \\ (0.0190) \end{array}$	$\begin{array}{c} 0.0482 \\ (0.0105) \end{array}$	$\begin{array}{c} 0.00171 \\ (0.0148) \end{array}$	-0.0187 (0.0185)	-0.0485 (0.0195)	$\begin{array}{c} 0.144 \\ (0.0149) \end{array}$	$\begin{array}{c} 0.105 \\ (0.0110) \end{array}$	$\underset{(0.0130)}{0.0241}$	$\begin{array}{c} 0.0715 \\ (0.0121) \end{array}$
EW	$\begin{array}{c} 0.0411 \\ (0.0160) \end{array}$	$\begin{array}{c} 0.0207 \\ (0.0166) \end{array}$	$\begin{array}{c} -0.0103 \\ (0.0105) \end{array}$	$\begin{array}{c} 0.00405 \\ (0.0130) \end{array}$	$\begin{array}{c} 0.0468 \\ (0.0182) \end{array}$	$\begin{array}{c} 0.117 \\ (0.0189) \end{array}$	-0.0801 (0.0145)	-0.0931 $_{(0.0150)}$	$\begin{array}{c} 0.00291 \\ (0.0136) \end{array}$	$\begin{array}{c} -0.0776 \\ \scriptstyle (0.0162) \end{array}$
Constant	$\underset{\left(0.0719\right)}{0.414}$	$\underset{(0.0812)}{0.617}$	$\begin{array}{c} 0.285 \\ (0.0868) \end{array}$	$\underset{(0.107)}{0.511}$	$\underset{(0.154)}{0.34}$	$\underset{(0.146)}{0.231}$	$\underset{(0.158)}{0.738}$	$\underset{(0.142)}{0.729}$	$\underset{(0.0652)}{1.305}$	$\underset{(0.0599)}{1.281}$
N. obs.	1151	1259	1322	1355	1384	1428	1545	1702	1795	1866
R^2	0.968	0.97	0.967	0.95	0.946	0.957	0.957	0.966	0.972	0.979
	(Standard	errors in pare	intheses)							

Table 2. Hedonic coefficients for characteristics: Brand dummies specification (abridged table)

$\operatorname{Ln}(p)$	May 1991	May 1992	May 1993	May 1994	May 1995	May 1996	May 1997	May 1998	May 1999	May 2000
C90	-0.00083 (0.00536)	-0.025 (0.00534)	-0.0116 (0.00572)	-0.013 (0.00634)	-0.039 (0.00829)	-0.0146 (0.00662)	$\begin{array}{c} 0.00141 \\ (0.00637) \end{array}$	$\begin{array}{c} 0.00635 \\ (0.00495) \end{array}$	-0.013 (0.00509)	-0.00487 (0.00604)
CarSize	$\underset{(0.0139)}{0.167}$	$\begin{array}{c} 0.227 \\ (0.0118) \end{array}$	$\begin{array}{c} 0.209 \\ (0.0212) \end{array}$	$\begin{array}{c} 0.0898 \\ (0.0200) \end{array}$	$\begin{array}{c} 0.087 \\ (0.0207) \end{array}$	$\begin{array}{c} 0.158 \\ (0.0139) \end{array}$	$\begin{array}{c} 0.0914 \\ (0.0185) \end{array}$	$\begin{array}{c} 0.0759 \\ (0.0268) \end{array}$	$\begin{array}{c} 0.0861 \\ (0.0110) \end{array}$	$\begin{array}{c} 0.103 \\ (0.00713) \end{array}$
LGC	-0.00021 (4.30 e -05)	-0.000237 (3.07 $e-05$)	-1.24e - 05 (2.07 $e - 05$)	$\begin{array}{c} -2.38e-05 \\ (2.14e-05) \end{array}$	$-0.000146 \\ (2.63e - 05)$	$\begin{array}{c} 0.00013 \ (1.10e-05) \end{array}$	$7.70e-05 \ (1.02e-05)$	$\begin{array}{c} 4.38e-05 \ (1.89e-05) \end{array}$	$\begin{array}{c} 4.05e-05 \\ \scriptstyle (7.90e-06) \end{array}$	$5.28e-05 \ (7.91e-06)$
НР	$\begin{array}{c} 0.00428 \\ (0.000393) \end{array}$	$\begin{array}{c} 0.00577 \\ (0.000309) \end{array}$	$\begin{array}{c} 0.00258 \\ (0.000412) \end{array}$	$\begin{array}{c} 0.00462 \\ (0.000311) \end{array}$	$\begin{array}{c} 0.00427 \\ (0.000502) \end{array}$	$\begin{array}{c} 0.00256 \\ (0.000387) \end{array}$	$\begin{array}{c} 0.00483 \\ (0.000390) \end{array}$	$\begin{array}{c} 0.00545 \\ (0.000445) \end{array}$	$\begin{array}{c} 0.00665 \\ (0.000253) \end{array}$	$\begin{array}{c} 0.00633\\ (0.000259) \end{array}$
maxSp	$\begin{array}{c} 0.00214 \\ (0.000587) \end{array}$	-0.000422 (0.000518)	0.00414 (0.000606)	$\begin{array}{c} 0.000668 \\ (0.000310) \end{array}$	$\begin{array}{c} 0.00143 \\ (0.000662) \end{array}$	$\begin{array}{c} 0.00203 \\ (0.000545) \end{array}$	-0.00196 (0.000593)	-0.000711 (0.000665)	-0.00282 (0.000438)	-0.00302 $_{(0.000430)}$
Age	${3.67e-05\atop (8.37e-05)}$	-0.000306 (6.68 $e-05$)	-0.000228 (7.07 e -05)	$\begin{array}{c} -8.54e-05 \\ \scriptstyle (7.21e-05) \end{array}$	-1.95e - 05 (6.89 $e - 05$)	7.57e - 05 (5.12 $e - 05$)	$\substack{0.000166 \\ (7.04e-05)}$	$-5.59e-05 \\ (6.20e-05)$	$\substack{0.000104\\(4.75e-05)}$	$2.69e-05 \ (5.36e-05)$
AC	-0.0184 (0.0133)	-0.0261 (0.0126)	$\begin{array}{c} 0.0922 \\ (0.00981) \end{array}$	$\begin{array}{c} 0.0782 \\ (0.0119) \end{array}$	$\begin{array}{c} 0.11 \\ (0.0117) \end{array}$	$\begin{array}{c} 0.109 \\ (0.00732) \end{array}$	$\underset{(0.00794)}{0.07294}$	$\begin{array}{c} 0.0622 \\ (0.00772) \end{array}$	$\begin{array}{c} 0.0892 \\ (0.0113) \end{array}$	$\begin{array}{c} 0.0912 \\ (0.00764) \end{array}$
ABS	$\begin{array}{c} 0.0193 \\ (0.00902) \end{array}$	$\begin{array}{c} 0.0107 \\ (0.0110) \end{array}$	$\underset{(0.0146)}{0.0279}$	$\begin{array}{c} 0.0357 \\ (0.0125) \end{array}$	$\begin{array}{c} 0.025 \\ (0.0113) \end{array}$	$\begin{array}{c} 0.0188 \\ (0.0139) \end{array}$	$\begin{array}{c} 0.0597 \\ (0.0112) \end{array}$	$\begin{array}{c} 0.0428 \\ (0.0110) \end{array}$	$\begin{array}{c} 0.0094 \\ (0.00969) \end{array}$	$\begin{array}{c} 0.0251 \\ (0.00688) \end{array}$
STP	$-0.0902 \\ (0.0212)$	-0.00948 (0.0116)	-0.0611 (0.0120)	-0.0235 $_{(0.0145)}$	-0.0575 (0.0154)	-0.0373 (0.00875)	$\begin{array}{c} -0.00825 \\ \scriptstyle (0.0114) \end{array}$	$\begin{array}{c} 0.031 \\ (0.00832) \end{array}$	$\begin{array}{c} 0.0409 \\ (0.00836) \end{array}$	$\begin{array}{c} 0.0865 \\ (0.0179) \end{array}$
CDL	$\underset{(0.0147)}{0.0336}$	$\begin{array}{c} 0.0215 \\ (0.0175) \end{array}$	$\begin{array}{c} 0.0603 \\ (0.0111) \end{array}$	$\begin{array}{c} 0.00122 \\ (0.0167) \end{array}$	-0.089 (0.0199)	-0.116 (0.0178)	$\underset{(0.0130)}{0.101}$	$\underset{(0.0117)}{0.119}$	$\begin{array}{c} 0.0283 \\ (0.0141) \end{array}$	$\begin{array}{c} 0.0837 \\ (0.0113) \end{array}$
EW	$\begin{array}{c} 0.0546 \\ (0.0143) \end{array}$	$\begin{array}{c} 0.0327 \\ (0.0162) \end{array}$	-0.0123 (0.0112)	$\begin{array}{c} 0.0125 \\ (0.0158) \end{array}$	$\begin{array}{c} 0.102 \\ (0.0212) \end{array}$	$\begin{array}{c} 0.142 \\ (0.0173) \end{array}$	-0.0649 (0.0135)	-0.118 (0.0123)	-0.0297 $_{(0.0149)}$	-0.111 (0.0161)
Constant	$\underset{(0.119)}{1.136}$	$\underset{(0.0891)}{0.568}$	$\underset{(0.137)}{0.109}$	$\underset{(0.155)}{\textbf{1.566}}$	$\underset{(0.159)}{1.195}$	$\underset{(0.130)}{0.632}$	$\underset{(0.158)}{1.454}$	$\underset{(0.257)}{1.742}$	$\begin{array}{c} 1.759 \\ (0.0973) \end{array}$	$\underset{(0.0921)}{1.913}$
N. obs.	1151	1259	1322	1355	1384	1428	1545	1702	1795	1866
R^2	0.978	0.979	0.971	0.962	0.957	0.97	0.97	0.977	0.976	0.982
	(Standard	errors in pare	intheses)							

Table 3. Hedonic coefficients for characteristics: Brand and segment dummies specification (abridged table)

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$\operatorname{Ln}(p)$	May 1991	May 1992	May 1993	May 1994	May 1995	May 1996	May 1997	May 1998	May 1999	May 2000
C90	-0.0675 (0.0551)	-0.0262 (0.0548)	$\begin{array}{c} 0.0531 \\ (0.0232) \end{array}$	-0.0197 (0.0151)	-0.0673 $_{(0.0291)}$	$\begin{array}{c} 0.0169 \\ (0.0323) \end{array}$	$\begin{array}{c} 0.00623 \\ (0.0144) \end{array}$	-0.0359 $_{(0.0141)}$	$\begin{array}{c} 0.0266 \\ (0.0127) \end{array}$	$\begin{array}{c} 0.0124 \\ (0.0144) \end{array}$
CarSize	$\underset{(0.0430)}{0.0430}$	$\underset{(0.241)}{0.137}$	(6060.0)	$\begin{array}{c} 0.222 \ (0.121) \end{array}$	-0.029 (0.0101)	-0.0578 (0.0548)	$\begin{array}{c} 0.00458 \\ (0.00751) \end{array}$	$\begin{array}{c} 0.00104 \\ (0.000849) \end{array}$	-0.0733 (0.0425)	-0.0622 $_{(0.0333)}$
LGC	$\begin{array}{c} 0.0024 \\ (0.000756) \end{array}$	-0.00136 (0.000522)	$\begin{array}{c} 0.00015 \\ (0.000126) \end{array}$	$\begin{array}{c} 0.000333\\ (0.000252) \end{array}$	-6.36e - 05 (8.20 $e - 06$)	-0.00039 (0.000322)	$\begin{array}{c} 6.86e-05 \\ \scriptstyle (7.31e-05) \end{array}$	-0.000114 (0.000193)	$\begin{array}{c} 0.000104 \\ (0.000153) \end{array}$	$4.02e - 05 \\ (0.000122)$
НР	-0.00277 (0.00302)	$\begin{array}{c} 0.00943 \\ (0.00333) \end{array}$	-0.00625 $_{(0.00320)}$	$\begin{array}{c} 0.00242 \\ (0.00117) \end{array}$	$\begin{array}{c} 0.00694 \\ (0.00301) \end{array}$	$\begin{array}{c} 0.00435 \\ (0.00255) \end{array}$	$\begin{array}{c} 0.00463 \\ (0.000942) \end{array}$	$\begin{array}{c} 0.0019 \\ (0.00145) \end{array}$	$7.92e - 05 \\ (0.00229)$	$\begin{array}{c} 0.00411 \\ (0.00125) \end{array}$
maxSp	$\begin{array}{c} 0.0187 \\ (0.00318) \end{array}$	$\begin{array}{c} -0.01 \\ (0.00440) \end{array}$	$\underset{(0.00402)}{0.012}$	$-9.21e-0.5 \ ^{(5.05e-05)}$	$\begin{array}{c} -0.00363 \\ \scriptscriptstyle (0.00316) \end{array}$	$\begin{array}{c} -0.00352 \\ \scriptstyle (0.00438) \end{array}$	-0.00548 (0.00131)	$\begin{array}{c} 0.00665 \\ (0.00245) \end{array}$	$\begin{array}{c} 0.00568 \\ (0.00456) \end{array}$	-0.00198 (0.00220)
Age	$\begin{array}{c} 0.00254 \\ (0.00126) \end{array}$	-0.00127 (0.000679)	$\begin{array}{c} 0.00491 \\ (0.000988) \end{array}$	$\begin{array}{c} 0.00614 \\ (0.000724) \end{array}$	$\begin{array}{c} 0.00584 \\ (0.000425) \end{array}$	$\begin{array}{c} 0.00254 \\ (0.000379) \end{array}$	$\begin{array}{c} 0.00119 \\ (0.000515) \end{array}$	-0.00105 (0.000699)	-0.00214 (0.000971)	$\begin{array}{c} 0.00179 \\ (0.000474) \end{array}$
\mathbf{AC}	$\begin{array}{c} 0.0443 \\ (0.0130) \end{array}$	$\begin{array}{c} 0.0147 \\ (0.0364) \end{array}$	$\begin{array}{c} 0.0359 \\ (0.0510) \end{array}$	-0.0416 (0.0623)	$\begin{array}{c} 0.0317 \\ (0.0216) \end{array}$	$\begin{array}{c} 0.0531 \\ (0.0338) \end{array}$	$\underset{(0.0190)}{0.0276}$	$\begin{array}{c} 0.0679 \\ (0.0203) \end{array}$	$\underset{(0.0557)}{0.115}$	$\underset{(0.0276)}{0.0321}$
ABS	-0.109 (0.0393)	-0.0416 (0.0790)	$\begin{array}{c} 0.0958 \\ (0.0360) \end{array}$	$\begin{array}{c} 0.0555 \\ (0.0497) \end{array}$	$\begin{array}{c} 0.0551 \\ (0.0250) \end{array}$	$\begin{array}{c} 0.00112 \\ (0.0548) \end{array}$	$\underset{(0.0234)}{0.0351}$	$\underset{(0.0170)}{0.0245}$	-0.0124 (0.0216)	$\begin{array}{c} 0.0308 \\ (0.0119) \end{array}$
STP	$\begin{array}{c}-0.162\\(0.0431)\end{array}$	$\begin{array}{c} 0.0528 \\ (0.0549) \end{array}$	(-)	$\begin{array}{c} 0.0109 \\ (0.0575) \end{array}$	(-) (-)	-0.0607 (0.0468)	$\begin{array}{c} 0.00326 \\ (0.0243) \end{array}$	$\underset{(0.0114)}{0.0156}$	$\begin{array}{c} 0.0398 \\ (0.0457) \end{array}$	$\underset{(0.0250)}{0.0250}$
CDL	$\underset{(0.0356)}{0.247}$	-0.0399 (0.0335)	$\begin{array}{c} 0.00852 \\ (0.0173) \end{array}$	$\begin{array}{c} 0.0404 \\ (0.0352) \end{array}$	-0.0198 (0.0103)	$\underset{(0.0341)}{0.0691}$	$\underset{(0.0135)}{0.06}$	$\begin{array}{c} 0.00157 \\ (0.00105) \end{array}$	-0.014 (0.0263)	$\begin{array}{c} 0.0572 \\ (0.0199) \end{array}$
EW	-0.218 (0.0357)	$\underset{(0.0435)}{0.106}$	$\underset{(0.0663)}{0.134}$	$\begin{array}{c} 0.0292 \\ (0.0396) \end{array}$	$\begin{array}{c} 0.00253 \\ (0.0302) \end{array}$	$\begin{array}{c} -0.00872 \\ \scriptstyle (0.0293) \end{array}$	-0.0565 $_{(0.0174)}$	-0.0198 (0.0156)	$\begin{array}{c} 0.0183 \\ (0.0288) \end{array}$	-0.0629 $_{(0.0432)}$
Constant	$\begin{array}{c} -1.636 \\ \scriptstyle (0.837) \end{array}$	$\underset{(1.172)}{3.08}$	$-0.0559 \\ \scriptscriptstyle (0.921)$	$\underset{(0.772)}{0.206}$	$\begin{array}{c} \textbf{2.605} \\ \textbf{(0.462)} \end{array}$	$3.006 \\ (0.705)$	$\underset{(0.210)}{2.939}$	$\underset{(0.336)}{1.556}$	$\underset{\left(0.613\right)}{2.037}$	$\begin{array}{c} 2.745 \\ \scriptstyle (0.416) \end{array}$
N. obs.	1151	1259	1322	1355	1384	1428	1545	1702	1795	1866
R^{2} b	0.547	0.524	0.589	0.48	0.63	0.407	0.347	0.348	0.311	0.392
	(Standard	errors in pa	rentheses)							
	^a In very spe	cific months sol vith other reare	me characteristi	ics did not show (mough variation	to have their he	edonic coefficien	ts for those per	iods properly id	entified due to

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 b This is the R^{2} of the within-transformed equation and thus the effect of the time-invariant effects (that would be equivalent to the effect of product dummies) is not accounted for. If we take it into account we would obtain values for the R^2 around 0.9, as in tables 2, 3 or 5.

Ln(p)	May 1991	May 1992	May 1993	May 1994	May 1995	May 1996	May 1997	May 1998	May 1999	May 2000
C90	-0.0152 (0.00844)	-0.0263 $_{(0.00572)}$	-0.0334 (0.00614)	-0.0444 (0.00672)	-0.0827 (0.00938)	-0.0316 (0.00988)	$\begin{array}{c} 0.00125 \\ (0.0116) \end{array}$	$\begin{array}{c} 0.0358 \\ (0.00823) \end{array}$	$\begin{array}{c} 0.017 \\ (0.00825) \end{array}$	0.00706 (0.00981)
CarSize	$\begin{array}{c} 0.191 \\ (0.0165) \end{array}$	$\begin{array}{c} 0.215 \\ (0.0118) \end{array}$	$\underset{(0.00896)}{0.179}$	$\underset{(0.00901)}{0.183}$	$\underset{(0.00900)}{0.191}$	$\underset{(0.0106)}{0.186}$	$\begin{array}{c} 0.171 \\ (0.0152) \end{array}$	$\underset{(0.0197)}{0.13}$	$\begin{array}{c} 0.113 \\ (0.00864) \end{array}$	$\underset{(0.00954)}{0.112}$
LGC	-0.000284 (3.90 e -05)	-0.000265 (2.84 e -05)	$\frac{1.57e-05}{(1.75e-05)}$	$4.19e - 05 \\ (1.33e - 05)$	$5.00e - 05 \ (1.52e - 05)$	$\begin{array}{c} 9.12e-05 \ (1.66e-05) \end{array}$	$\begin{array}{c} 8.30e-06 \\ (1.42e-05) \end{array}$	$\begin{array}{c} -2.05e-05 \\ (1.32e-05) \end{array}$	$egin{array}{c} -9.15e-06\ (1.03e-05) \end{array}$	$-5.39e - 06 \\ (1.16e - 05)$
HP	$\begin{array}{c} 0.00759 \\ (0.000489) \end{array}$	$\begin{array}{c} 0.0066 \\ (0.000377) \end{array}$	$\begin{array}{c} 0.00474 \\ (0.000406) \end{array}$	$\begin{array}{c} 0.00566 \\ (0.000428) \end{array}$	$\begin{array}{c} 0.00612 \\ (0.000544) \end{array}$	$\begin{array}{c} 0.00433 \\ (0.000530) \end{array}$	$\begin{array}{c} 0.00414 \\ (0.000505) \end{array}$	$\begin{array}{c} 0.00415 \\ (0.000436) \end{array}$	$\begin{array}{c} 0.00605 \\ (0.000323) \end{array}$	$\begin{array}{c} 0.00692 \\ (0.000348) \end{array}$
maxSp	-0.000695 (0.000744)	$\begin{array}{c} -0.000183 \\ \scriptstyle (0.000641) \end{array}$	$\begin{array}{c} 0.00316 \\ (0.000625) \end{array}$	$\begin{array}{c} 0.00262 \\ (0.000557) \end{array}$	$\begin{array}{c} 0.0026 \\ (0.000817) \end{array}$	$\begin{array}{c} 0.00399 \\ (0.000815) \end{array}$	$\begin{array}{c} 0.00236 \\ (0.000777) \end{array}$	$\begin{array}{c} 0.00298 \\ (0.000527) \end{array}$	$\begin{array}{c} 0.000519 \\ (0.000518) \end{array}$	-0.000449 (0.000607)
Age	-7.88e - 05 (8.83 $e - 05$)	-0.000118 (5.38 $e-05$)	$\underset{(6.42e-05)}{0.000219}$	$\begin{array}{c} 0.000302 \\ (5.30e-05) \end{array}$	$\substack{0.00041\\(6.47e-05)}$	$\begin{array}{c} 0.000342 \ (6.18e-05) \end{array}$	$\begin{array}{c} 0.000288 \\ (4.70e-05) \end{array}$	$\begin{array}{c} 0.000237 \\ (4.95e-05) \end{array}$	$\begin{array}{c} 0.000221 \ (5.33e-05) \end{array}$	$\begin{array}{c} 0.000354 \\ (5.01e-05) \end{array}$
AC	-0.0335 (0.0151)	-0.0242 (0.00987)	$\begin{array}{c} 0.0301 \\ (0.0105) \end{array}$	$\begin{array}{c} 0.0221 \\ (0.0131) \end{array}$	-0.0305 (0.0128)	$\begin{array}{c} 0.0114 \\ (0.0122) \end{array}$	0.0598 (0.0109)	$\begin{array}{c} 0.0621 \\ (0.0115) \end{array}$	$\begin{array}{c} 0.111\\ (0.0104) \end{array}$	$\begin{array}{c} 0.148 \\ (0.0129) \end{array}$
ABS	$\begin{array}{c} 0.0941 \\ (0.0168) \end{array}$	$\begin{array}{c} 0.145 \\ (0.0129) \end{array}$	$\begin{array}{c} 0.175 \\ (0.0158) \end{array}$	$\begin{array}{c} 0.174 \\ (0.0157) \end{array}$	$\underset{\left(0.0153\right)}{0.128}$	$\underset{(0.0138)}{0.0776}$	$\begin{array}{c} 0.0739 \\ (0.0143) \end{array}$	$\begin{array}{c} 0.0921 \\ (0.0131) \end{array}$	$\begin{array}{c} 0.052 \\ (0.0117) \end{array}$	$\begin{array}{c} 0.00345 \\ (0.0134) \end{array}$
STP	$\begin{array}{c} 0.0317 \\ (0.0193) \end{array}$	$\begin{array}{c} 0.0458 \\ (0.0121) \end{array}$	$\begin{array}{c} 0.0253 \\ (0.0113) \end{array}$	$\begin{array}{c} 0.000349 \\ \scriptstyle (0.0120) \end{array}$	$\begin{array}{c} 0.00506 \\ (0.0158) \end{array}$	-0.0871 (0.0172)	-0.0182 (0.0155)	$\begin{array}{c} 0.0128\\ (0.0115) \end{array}$	-0.0244 (0.0116)	$\begin{array}{c} 0.0227 \\ (0.0153) \end{array}$
CDL	$\underset{(0.0228)}{0.194}$	$\underset{(0.0280)}{0.138}$	$\underset{\left(0.0227\right)}{0.105}$	$\underset{(0.0154)}{0.0293}$	$\begin{array}{c} 0.0582 \\ (0.0207) \end{array}$	$\underset{(0.0234)}{0.0234}$	$\underset{\left(0.0178\right)}{0.213}$	$\underset{(0.0121)}{0.139}$	$\begin{array}{c} 0.107 \\ (0.0133) \end{array}$	$\begin{array}{c} 0.147 \\ (0.0156) \end{array}$
EW	-0.134 (0.0201)	$\begin{array}{c} -0.097 \\ \scriptstyle (0.0257) \end{array}$	$\begin{array}{c} -0.0706 \\ (0.0211) \end{array}$	-0.0483 (0.0156)	$egin{array}{c} -0.0337 \ (0.0213) \end{array}$	$\begin{array}{c} 0.0333\\ (0.0267) \end{array}$	-0.151 (0.0176)	-0.139 (0.0146)	-0.0904 (0.0183)	-0.198 (0.0187)
Constant	$\underset{(0.101)}{0.686}$	$\underset{(0.0838)}{0.593}$	$\underset{(0.0838)}{0.326}$	$\underset{(0.0868)}{0.46}$	$\underset{(0.115)}{0.607}$	$\underset{(0.127)}{0.351}$	$\begin{array}{c} 0.558 \\ (0.133) \end{array}$	$\underset{(0.117)}{0.548}$	$\underset{(0.0887)}{1.01}$	$\underset{(0.102)}{1.164}$
N. obs.	1151	1259	1322	1355	1384	1428	1545	1702	1795	1866
R^2	0.936	0.949	0.934	0.918	0.903	0.898	0.905	0.929	0.913	0.912
	(Standard er	rrors in paren	theses)							

Figures



Figure 1. Average real price by origin (deflated by the Spanish Consumer Price Index)



Figure 2. Average real price by segment (deflated by the Spanish Consumer Price Index)



Figure 3. Hedonic price indexes



Figure 4. Hedonic price indexes (not controlling for age effects)



Figure 5. Hedonic price indexes by origin of car model: Spain



Figure 6. Hedonic price indexes by origin of car model: Europe



Figure 7. Hedonic price indexes by origin of car model: Asia



Figure 8. Hedonic price indexes by origin of car model: America



Figure 9. Hedonic price indexes for the Small segment



Figure 10. Hedonic price indexes for the Compact segment



Figure 11. Hedonic price indexes for the High-Intermediate segment