MEASURING QUALITY-ADJUSTED INFLATION RATES FOR A HETEROGENEOUS OLIGOPOLY*

David Prentice
and
Xiangkang Yin
La Trobe University

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Abstract: Both the theory and practice of using hedonic regressions to quality adjust inflation estimates are implicitly developed for monopolistic competitive markets. We demonstrate conditions required for consistent OLS estimation of hedonic regression for an oligopoly. To reflect firm heterogeneity, we make two recommendations on empirical practice. The first is to use quantity weights in constructing the index rather than the unsatisfactory equal weighting system implicit in the standard pooled regression. Second, to test for instability across product type, as well as over time. Implementing these recommendations results in higher estimates of inflation, similar to official quality-adjusted inflation rate.

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Correspondence to: Dr Xiangkang Yin, Department of Economics and Finance, La Trobe University, Bundoora, Victoria 3083, Australia. Tel: 61-3-9479 2312. Fax: 61-3-9479 1654. Email: x.yin@latrobe.edu.au
Accurately measuring prices and their rate of change, inflation, is central to almost every economic issue. There is virtually no other issue that is so endemic to every field of economics. (Boskin et al., 1998)

I. Introduction

A central problem in economic measurement is to accurately measure inflation. Where there is a rapid technological change, traditional methods are often strained, as the commodities in a basket of goods are discontinued and replaced by new products, face new competition or simply change substantially in nature. For a price index accurately measuring increases in the cost of living, price changes due to quality changes must be removed. The hedonic regression method is suggested to extract quality changes from prices, leaving pure inflationary changes to be measured.

In this paper, we focus on the methods of using hedonic regressions to adjust price indices for quality changes. The first hedonic price study was emerged in Court (1939) when he was requested by the General Motors to assess the effects of auto price changes on the total volume of auto sales. After the seminal contribution of Griliches (1961), there have been many studies estimating quality-adjusted inflation rates. Early contributions include Chow’s (1967) empirical study of the United States computer market and Triplett’s (1969) work on the US automobile industry. Raff and Trajtenberg (1997) together with Gordon (1990, Ch. 8) covers seventy years of hedonic price index for United States automobiles (1906-40 and 1947-1983). Studies outside the United States include Shiratsuka (1995b) in Japan, Thompson (1987) in Ireland, Cowling and Cubbin (1972) in the UK. Because of the bias of conventional Consumer Price Index (CPI) in the quality effects and because of the advance of hedonic analysis in accounting these effects, the U.S. Bureau of Labor Statistics has been making greater use of hedonic statistical techniques in their calculation of CPI. “Starting in January 1998, the hedonic model developed and used in the Producer Price Index for adjusting
personal computer prices will be employed in the Personal Computers and Peripheral Equipment category of the CPI. New research is underway on estimation of hedonic models using the CPI television sample (Moulton et al., 1997). New funding is expected to support collection of product price and characteristic data for samples of approximately 2,500 individual items each year, focused in the consumer durables categories.” (Abraham et al., 1998)

However, much of the theoretical work on hedonics is done with effectively competitive markets, featuring numerous relatively small producers, in mind. Practices in empirical work seem most suitable for this case. So we recast Rosen (1974)’s theory for the oligopoly case, yielding a reduced form of hedonic regression specification used in previous work. We also note that implementation requires that the characteristics of products be determined before price competition; otherwise endogeneity will create econometric problems. We then implement the features of previous empirical practice to best control for the oligopoly we analyze – the passenger vehicles market. While the automobile has been criticized as overly complex such that performing hedonic regressions are problematic (Triplet (1990)) it remains a product experiencing substantial quality changes. So attempts to improve the analysis seem worthwhile.

Our analysis has three features. First, following Shiratsuka (1995b) we consider instability across broad types of vehicles as opposed to over time as is standard in the literature. Second, as oligopolists not infrequently vary in size, we focus on the problem of measuring quality-adjusted inflation rates where weights are important. The standard method of extracting quality-adjusted inflation rates from the coefficients of hedonic regressions is more appropriate for industries characterized as monopolistically competitive rather than oligopolistic where economies of scale and heterogeneity in size have more significant roles in competition. When we make these changes we demonstrate that hedonic regressions based
on the type of motor vehicles (small, medium and sports/luxury) can increase the explanatory power in our application, relative to the standard pooled methods, and even the yearly regressions. Furthermore, making these changes and constructing quality-adjusted indices based on the weights of car registration lead to a higher estimated rate of inflation. Using estimate coefficients based on types yields estimated inflation rates similar to the quality-adjusted official inflation rates.

The paper is proceed as follows. In section two the theory of hedonic pricing is extended to deal with an oligopoly. In section three, the data of the particular case - the Australian passenger vehicle market - are introduced and their suitability discussed. In section four the methodology is implemented and in section five the indexes calculated and discussed.

II. The Theory and Practice of Hedonic Price Analysis

In this section we first discuss the standard case. Then we describe how the standard case is extended to oligopoly. The third subsection constructs a quality-adjusted price index. In the final subsection, we discuss the implications of our approach on previous empirical practices.

A. Competitive and Monopolistic Competitive Markets

Hedonic theory, as specified by Rosen (1974), begins with the view of each product being a unique bundle of characteristics. Consumers of the product receive utility from the embodied quantities of characteristics.¹ Let the vector \( q \) indicate all characteristics and \( p \) the price of the product containing these characteristics. Consumer \( i \)'s utility is represented by indifference curves \( U_i(p, q) = u \) as shown by \( U_i(p, q, u_i) \) curves \( (i = 1, 2) \) in Figure 1.² Assuming all characteristics are goods, consumers effectively have to trade-off quality and the purchase price. The indifference curves are assumed to be well behaved, featuring second derivatives, and being concave.
Each firm produces one product, is atomic and is a price taker. The products are distributed continuously across the characteristics space. Technology results in high quality products being produced at higher costs. Each firm chooses their product location and price to maximize profit, supplying the quantity demanded. The firm’s problem is summarized in an offer curve for each level of profit as depicted by the \( F_i(p, q, \pi_i) \) curves \( (i = 1, 2) \) in Figure 1. With certain plausible conditions, these offer curves are smooth and convex. In equilibrium, there is a set of price-quality combinations such that the indifference curves and offer curves are tangential at each point. There is likely to be a locus of equilibrium points as tastes differ widely across consumers and technologies differ widely across firms. In Figure 1, two equilibrium points \( E_1 \) and \( E_2 \) are illustrated. The equilibrium locus is described by the relationship between the product price and its quality.\(^3\)

\[
p = p(q). \tag{1}
\]

The partial derivative \( \partial p / \partial q_k \) along the equilibrium locus (1) provides the marginal price of one unit extra characteristic \( k \) when the characteristic level is \( q \).

This description seems most applicable to markets where there are large number of small firms, without opportunities for strategic pricing or strategic choices of location such as those described as perfectly or monopolistically competitive. Furthermore, as free entry results in all profitable opportunities for differentiation being exploited, the continuous distribution of products is compatible with the continuous relationship embodied in the functional forms, and ordinary least squares estimation methods used in practice.

### B. Oligopoly

In this subsection we outline an argument for a reduced form relationship between a products price and its characteristics if the market is an oligopoly (see Feenstra (1995) for a structural account of an extension to oligopoly). Two problems immediately suggest
themselves if the market is an oligopoly. First, is the assumption of a continuous distribution of products across the characteristics space reasonable? Oligopoly theory does not provide an unambiguous answer to this question as there are two offsetting effects. First, the efficiency effect, formalized by Tirole (1992), suggests a general tendency towards the incumbent filing the characteristics space with products. Such an entry is always more profitable for the incumbent as the gains from coordinating prices and locations with its existing products are internalized, unlike for new entrants (See Schmalansee (1978) for the product differentiation case, and Judd (1985) for conditions under which this case holds). Offsetting this effect is that quality competition can result, if there is relatively little price competition, in minimum differentiation between products.

The second problem is whether there is a relationship between the product price and its characteristics as for the competitive case, with given qualities. Solving this problem requires modeling the choice of quality as well as price determination.

As suitable for the passenger vehicle market, highlighted by its use as a foundation for recent empirical work, the oligopoly model is a discrete choice differentiated products model (see Anderson et al (1992)). Consumers are described by a characteristics vector, $a$, making a discrete choice from a finite $J$ product variant available in the market. Product $j$ is chosen if and only if

$$U(a, p_j, q_j) \geq U(a, p_r, q_r), \quad r = 0, 1, 2, \ldots, J$$

where alternative zero, the outside alternative, represents the option of not purchasing any of the goods. Let $A_j = \{a : U(a, p_j, q_j) \geq U(a, p_r, q_r), \text{for } r = 0, 1, \ldots, J\}$ and $f(a)$ the probability density function of consumer distribution, the demand for each model is given by

$$D_j(p, q) = D \int_{a \in A_j} f(a) da,$$

where $D$ is the total population.
To simplify notation, the firms are single product firms, but this can be easily relaxed. Firm $j$ in the industry has a profit function

$$\Pi_j = (p_j - mc_j)D_j - fc_j,$$  \hspace{1cm} (4)

where it is assumed that marginal cost $mc_j$ is independent of output level but which is a function of product characteristics and $fc_j$ is the fixed cost for a firm to produce a specific good. Firms in an industry play a two-stage game. They simultaneously choose the product characteristics in the first stage and then in the second stage determine their price strategies. The first-order condition for the price subgame is

$$D_j + (p_j - mc_j) \frac{\partial D_j}{\partial p_j} = 0.$$  \hspace{1cm} (5)

Caplin and Nalebuff (1991) provide a set of conditions for the existence of equilibrium for a family of models including (5). Assuming the model satisfies the conditions, the solution of (5) provides each firm’s price strategy given their product characteristics choices in the first stage; i.e.,

$$p_j = p_j(q_1, q_2, ..., q_J).$$  \hspace{1cm} (6)

Substituting it into the firm’s profit function (4) to eliminate price variables, it turns out that the profits in the first stage are completely determined by the characteristics of products. Assuming the first $k_1$ characteristics are continuous and the remaining characteristics are discrete, the profit maximization in the characteristics subgame can be carried out as follows. Given a profile of discrete characteristics, firm $j$ chooses a set of continuous characteristics for its product to satisfy the first order condition,

$$D_j \nabla mc_j / \nabla q_j + (p_j - mc_j) \nabla D_j / \nabla q_j - \nabla fc_j / \nabla q_j = 0,$$  \hspace{1cm} (7)

where $\nabla$ is the operator of vector derivative with respect to the continuous characteristics vector of variant $j$, $q_j$. Solving (7) yields

$$q_j = q_j(q_1, q_2, ..., q_n).$$  \hspace{1cm} (8)
where \( q_j^2 \) indexes the discrete characteristics vector of variant \( j \). Substituting (8) and (6) into (4), the profit function can be written as a function of the profile of discrete characteristics; i.e., \( \Pi_j = \Pi_j(q_i^2, q_j^2, ..., q_j^2) \). So, the Nash-equilibrium discrete characteristics, \( q_j^2^* \) is determined by

\[
\Pi_j(q_i^2^*, ..., q_{j-1}^2^*, q_j^2^*, q_{j+1}^2^*, ..., q_j^2^*) \geq \Pi_j(q_i^2, ..., q_{j-1}^2, q_j^2, q_{j+1}^2, ..., q_j^2), \quad \forall j. \tag{9}
\]

Substituting \( q_j^2^* \) into (8) and in turn (6) yields an equilibrium pair of price and characteristics for firm \( j \), \( (p_j^*, q_j^*) \).

Not much changes if we now consider a small number of firms that produce multiple variants. When the number of variant is sufficiently large, there are many such pairs in the \((p, q)\)-space so that there is an equilibrium locus of the form of (1) linking all these pairs as illustrated as \( p(q) \) in Figure 1. Hence, in the oligopoly case, that a descriptive relationship between the price and characteristics can be estimated, with the qualities taken as exogenous, if they are specified before the pricing game begins. Note that unlike Feenstra (1995) we have placed less structure on the role of the characteristics. Rather than assigning them the roles as cost determinants, the characteristics in this formulation capture both costs and the mark-up. In other words, we are focusing on obtaining a reduced form relationship.

C. Empirical Application: Constructing a Quality-Adjusted Price Index

In this subsection, we review constructing a quality-adjusted price index using hedonic regressions. After presenting the decomposition of a price change into that due to quality changes and that due to other changes, we discuss the direct and imputation methods for constructing quality-adjusted price indexes using hedonic regressions. We conclude by comparing the appropriate methodology for an oligopoly.

Figure 2 illustrates that a price change for a single product can be decomposed into that due to quality change, and that due to other factors, where \( p_i(q) \) and \( p_s(q) \) are, as
determined in equation (1), in time periods \( s \) and \( t \). In period \( t \), we observe a price of variant \( j \), \( p_{jt} \), with quality specification \( q_{jt} \). Their counterparts in period \( s \) are \( p_{js} \) and \( q_{js} \). The observed nominal price increase is \( p_{js} - p_{jt} \) while the quality has also improved by \( q_{js} - q_{jt} \) in the two periods. Denote \( \bar{p}_{js} \) as the price after allowing for quality changes. The de facto market value of quality improvement for characteristic \( k \), is given by the slope of the quality-price locus: \( \Delta p_s / \Delta q_{ks} \). This market value of quality change enables us to separate quality change from gross price change of a variant to obtain “pure” price change in two different time periods. If there are \( K \) characteristics, the market value of the quality improvement is equal to

\[
p_{js} - \bar{p}_{js} = \sum_{k=1}^{K} (q_{ks} - q_{ks}) \Delta p_s / \Delta q_{ks},
\]

which implies the pure or quality-adjusted price change between periods \( t \) and \( s \) is \( \Delta_{js} = \bar{p}_{js} - p_{jt} = p_{js} - p_{jt} - \sum_{k=1}^{K} (q_{ks} - q_{ks}) \Delta p_s / \Delta q_{ks} \). In other words, taking away the quality change, \( \sum_{k=1}^{K} (q_{ks} - q_{ks}) \Delta p_s / \Delta q_{ks} \), from nominal price change, \( p_{js} - p_{jt} \), generates the pure price variation, \( \Delta_{js} \).

\textbf{FIGURE TWO IS ABOUT HERE}

The discussion so far has been in terms of decomposing a price change for an individual variant. An estimate of the inflation rate requires aggregation of the quality-adjusted price changes of a set of variants. Two methods of constructing the quality-adjusted price index are the regression method and the imputation methods.

With the regression method, a regression of price on a set of characteristics is performed on either a cross section or a pool of cross-sections over at least two periods. A popular functional form in practice is that of the semi-log:

\[
\log p_{jt} = \alpha_0 + \sum_{k=1}^{K} \alpha_k q_{ks} + \sum_{t+1}^{t+N} \beta_s D_s + \epsilon_{jt}. \quad \tau = t, \ldots, t+N; \quad j = 1, 2, \ldots, J (10)
\]

where \( N \) is the number of periods in the pool, \( \alpha_k \) (\( k = 1, \ldots, K \)) are the coefficients on the characteristics and \( \beta_s \) (\( s = t+1, \ldots, N \), where \( t \) is the first period in pool) are the coefficients on
the set of time dummies. The aggregate index of quality-adjusted prices in period \( s \) is equal to 
\[
\exp(b_s), \text{ where } b_s \text{ is the estimator of } \beta_s. 
\]

The imputation method more closely resembles the traditional methods of constructing a price index (see Dulberger (1989) or Triplett (1989) for more details). First, it requires to run a hedonic regression of the form of (10) on samples of single, with the time dummies excluded, or multiple periods. The estimated equation is then used to impute quality-adjusted prices – either as predicted values of the regressions – or through adjusting actual prices (see an earlier use in Triplett and McDonald (1977)). In particular the quality-adjusted price index is constructed as a weighted average of each variant’s change, 
\[
\sum_{j=1}^{J} w_{jst} \Delta p_{jst}, \text{ where } w_{jst} \text{ is the weight.}
\]
Examples of weights include the market share of product \( j \) in period \( t \) or \( s \) or their weighted average. If the price index for the commodity in period \( t \) is 100, the quality-adjusted price index in period \( s \) is 
\[
P_{st} = \sum_{j=1}^{K} w_{jst} \bar{p}_{jst} / p_{jst},
\]
where
\[
\bar{p}_{jst} = p_{jst} - \sum_{k=1}^{K} (q_{stk} - q_{tjk}) \Delta p_{st} / \Delta q_{stk},
\]
\[
w_{jst} = v_{jt} / \sum_{r=1}^{J} v_{rt},
\]
where \( v_{jt} \) is the output volume of product \( j \) in period \( t \). The role of the hedonic regression in this method is to provide estimates of the derivative, \( \Delta p_{st} / \Delta q_{stk} \), to enable quality adjustment, i.e., to estimate \( \bar{p}_{jst} \) which is then applied to (11). If there are no quality improvements for all products in the question, then \( \bar{p}_{jst} = p_{jst} \) and (11) collapses to a conventional weighted average of relative prices.

Each of these methods has advantages and disadvantages. The direct method is simple to run and uses all information. Its disadvantage is that the implicit weighting scheme is
unappealing. In particular, when the log price change \((\log p_{jt} - \log p_{jt})\) is decomposed into quality adjustment \((\log p_{jt} - \log p_{jt})\) and pure price variation \((\log p_{jt} - \log p_{jt})\) for the two period pool, the estimator \(b\) yields:

\[
\exp(b) = \exp\left(\sum_{j=1}^{J} \left(\frac{\log p_{jt} - \log p_{jt}}{J}\right) \right) = \left(\prod_{j=1}^{J} \frac{p_{jt}}{p_{jt}}\right)^{1/J},
\]

which is an unweighted geometric average of quality-adjusted relative price in two periods. Even if there are minimal quality changes going on, the CPI and Hedonic Price Index are not guaranteed to move in a similar fashion. Griliches (1971), Raff and Trajtenberg (1997) have recognized this equal weight problem in the multi-period cross-sectional regression. One solution that has been suggested is to use weighted least squares for estimation. This is problematic in an oligopoly as if product market shares are used as weights then these are likely to be correlated with the error term yielding inconsistent estimates of the coefficients.

However, the imputation methods enable weighting of the different prices – which is a considerable advantage. But these methods have two types of disadvantages. First, if a fixed weight form of index is used, there is some loss of information – either the prices and characteristics of new models or discontinued models depending on whether a Paasche or Laspeyres type index is calculated. Second, the practice of imputing prices is troubling in an oligopoly. The impact of a missing variety is not considered in the perfect competitive models but in an oligopoly, the observed prices would unlikely to have been observed if the prices that are imputed had been actual prices (see, Triplett (1989)).

III. The Data

The dataset that we work with is a set of price and characteristics for all cars sold as new in the Australian passenger vehicle market from 1987 – 1998, as collected by an industry data-collection firm Glasses Guide. This dataset has three features making it particularly suitable for this problem, and an improvement over existing datasets.
First the industry is an oligopoly. Ford, General Motors, Mitsubishi and Toyota are the main local manufacturers with a four firm market share ranging from 80% to 63%. The only other sizeable firms (achieving shares of over 10% at some point) are Nissan, a local manufacturer in the first half of the period, and Hyundai, an importer.

Second, major choices of characteristics are not made locally. Nearly all small and luxury cars are imported as are the majority of medium sized cars. Furthermore, to a varying degree, locally manufactured cars are based on international designs with changes for local driving conditions.

Third, this period features relative technological and regulatory stability. The last major change in environmental regulation occurred in 1987 and petrol prices have been stable. The main change is that tariffs fell over the period according to a timetable known in advance.

This dataset is particularly complete, including all variants of each model. For example, over the period there are up to 30 different variants of the Toyota Camry offered in each year. Some variants are identical in characteristics and price, and thus are deleted from the dataset. A few observations with incomplete information are also deleted, leaving 9849 active observations. The dataset also includes information on a wide set of characteristics. We work with six continuously defined characteristics – Size, Highway and City Fuel Consumption, Kerb Weight, Maximum Torque and Maximum Power – and 37 characteristics defined as dummy or ranked variables e.g. number of speakers on a compact disc system. The summary statistics of the data are presented below in Table 1.

The summary statistics of the data are presented below in Table 1.

**Table 1 is about here.**

Column two of Table 1 demonstrates for each year there is a substantial number of observations. Columns three and four demonstrate that the number of makes and characteristics increase over the period, particularly from 1990 on. Column five confirms the
industry is an oligopoly. While typically over twenty-five makes are sold each year, the top four makes account for over 63% of registrations (Top 8 account for over 84%). In addition, there is a wide variety of market shares, typically between 3 to 24%. The last column demonstrates the most popular makes are under-represented in the sample. In particular, while the four largest makes account for between 63 and 80% of registrations, they account for only 31 – 48% of observations in each year.

Before constructing a quality-adjusted price index, we present a raw price index constructed from the sample data (hereafter referred to as the sample index), and the official Motor Vehicle CPI calculated by the Australian Bureau of Statistics (ABS). The sample index is constructed using the same time pattern of weights as for the ABS index. The weights are constructed from domestic registrations reported in the Black and White Data book (Glass’s Guide, 1990 – 1998) and the details are illustrated in Appendix II. The two indices differ for two reasons. First, the official CPI is calculated from a small sample of transaction prices, instead of a large sample of list prices (hence the weights will also be different). Second, the CPI is also quality adjusted - using information from producers and distributors. In Table 2, the sample index and the ABS Motor Vehicle CPI for the sample period are presented. Estimates of average inflation for the whole period, and for a sub-period over which prices rose are also presented.

**TABLE 2 IS ABOUT HERE**

Compositional differences aside, quality adjustment by the ABS appears to knock about two percentage points off the CPI. The two indices move together until 1990, from which the sample index reveals more rapid price increases. Interestingly, this is when the number of characteristics begins to increase. Both indices peak in 1995 – 1996, after which prices tend to fall.
Before beginning the analysis, it is worthwhile discussing how the dataset used for this paper differs from earlier work. In Table 3 below, previous papers that have calculated quality-adjusted price indices for cars are summarized.

TABLE 3 IS ABOUT HERE

Our sample differs from previous work in three respects. First, we have a much larger set of characteristics and models. Most studies in Table 3 work with between 30 and 100 observations each year. Only Shiratsuka (1995b) with 470 – 500 annual observations, and Raff and Tratjenberg (1997) with up to 1000 annual observations (though usually much less) have similar sample sizes. It is important to have both a large number of observations and a large set of characteristics to reinforce each other. Second, we perform the study in a more recent period. Only three of previous studies use data after 1971, and only two use data from the 1990s. Using recent data can check whether previous results overly depend on unobservable features of the periods in which these studies cover. Finally, this is the first published study using Australian data – which as we have argued above has certain characteristics making it most suitable for such an analysis.

IV. Estimation of Quality-Adjusted Inflation Rates

In this section we conduct three tasks required before constructing quality-adjusted price indexes. First, a functional form is chosen for the hedonic regression. Second, the selection of variables is checked for degrading multicollinearity. Third, we analyze the stability of the hedonic regression in three directions – over time, over three types of cars, and by make.

A. Functional Form

We adopt the log-linear functional form (10) for the hedonic regression for two reasons. First, it is relatively easy to interpret and extract a quality-adjusted price index from
this form. Second, it is the most popular form and using it enables us to focus on the main difference between our methodology and previous work.

Two alternatives have been suggested in the literature. First, Cropper et al. (1988) suggests allowing the data to select the functional form through estimating a generalized Box-Cox functional form. This is used by other authors such as Shiratsuka (1995b), but extracting a price index is less straightforward.

Second, the linear function form has been suggested based on theoretical arguments (Arguea and Hsaio (1993), Feenstra (1995)) but these arguments do not seem applicable for our case. First, the conditions required for Feenstra’s arguments to hold have been rejected for cars in demand system work (Berry, Levinsohn and Pakes, 1995). Second, the arbitrage arguments of Arguea and Hsaio seem more appropriate in competitive environments.

Finally, Shiratsuka (1995a, 1995b) compares all three approaches and concludes that they do not make a great difference. Thus, following Shiratsuka, we also continue with the log-linear form. In particular, we estimate the following empirical version of equation (10):

$$
\log p_{jt} = a_0 + \sum_{k=1}^{K} a_k q_{kjs} + \sum_{s=t+1}^{t+N} b_s D_s \quad \tau = t, \ldots, t+N; \quad j = 1, 2, \ldots, J, \quad (15)
$$

where $a_k (k = 1, \ldots, K)$ are the estimates of $\alpha_k$, and $b_s (s = t+1, \ldots, t+N)$ are the estimates of the $\beta_s$. To construct the quality-adjusted price index, estimates of the implicit prices of the characteristics are needed. For the discrete characteristics variables, subscripted ($k = K_1 + 1, \ldots, K$), the jump in the price if quality $q_{ks}$ is present ($q_{ks}$ equal to one), is given by

$$
\Delta p_s / \Delta q_{ks} = \exp a_k .
$$

If a set of single period cross-sections are estimated, equation (12) is converted to

$$
\bar{p}_{js} = p_{js} - \sum_{k=1}^{K_1} (q_{kjs} - q_{kjs}) a_k p_{js} - \sum_{k=K_1+1}^{K} (q_{kjs} - q_{kjs}) \exp a_k . \quad (16)
$$

Substituting estimates from (16) and (13) into (11) yields quality-adjusted inflation rates.
B. Multicollinearity.

Both intuition and the principle of minimum differentiation suggest that sets of characteristics may be similar across cars, resulting in multicollinearity. Arguea and Hsaio (1993) and Shiratsuka (1995b) emphasize this problem and delete a considerable portion of their set of explanatory variables to eliminate it. Following them, we also adopt the methodology presented in Belsley (1991, 137-147) to detect and deal with multicollinearity. It is true that adding collinear variables reduces efficiency and may create instability in estimates. But on the other hand omitting relevant explanatory variables certainly causes omitted variable bias. This suggests some caution in following Belsley’s approach and we casually check for omitting explanatory variables.

Selecting the set of explanatory variables requires three steps. Beginning with the matrix of the complete set of explanatory variables – all characteristics, make and time dummies – we calculate a set of condition indices and perform a variance decomposition on the cross-product matrix. Belsley (1991) suggests a condition index exceeding 30 is associated with potentially harmful multicollinearity. We find only seven indexes over 30 and three of them over 100 with the highest being 346.9. The variance decomposition matrix suggests many possible linear dependencies. In attempting to separate out two groups of linearly dependent and independent variables we are unable to obtain the clean separation between the two groups as demonstrated by Belsley, finding any of seventeen different explanatory variables associated with a condition index of just over 30. Thus, we construct three sets of explanatory variables – Clean, Semi-Clean and Complete (where Complete omits only Fuel Consumption – City) as summarized in Table 4.

TABLE 4 IS ABOUT HERE

We note that even the Clean set of explanatory variables includes more than is included in the set of explanatory variables used by Arguea and Hsaio (1993) and Shiratsuka
(1995b). This could be due to either the size and breadth of the dataset or that relatively less vehicle design is done in Australia. Instead, vehicles (or designs for manufacturers) from three substantially different markets in North America, Japan and Europe are marketed in Australia, resulting in greater differentiation than in the domestic markets where they are designed.

Some of the explanatory variables that are eliminated from the clean group include likely characteristics that are of interest to consumers. So, we introduced some of them back into the set of variables and examined their contribution to explanatory variables. Because of the large sample size, a formal nested hypothesis test will almost always reject the restricted form. For this sake, we examine their effects more casually, as done by Ohta and Griliches (1975), considering their statistical significance, the change in the sum of squared residuals (RSS), and changes in other estimates upon addition.

Examining the Semi-Clean and Complete specifications, adding each set of variables appears to improve the explanatory power of the regression. With a relatively complete set of characteristics and Torque, we do not expect adding Weight and Power will improve explanatory power. However, the RSS falls by nearly one third with Weight and Power. Some degrading multicollinearity may have been introduced at this point as size became insignificant, the number of characteristics dummies significantly different from zero falls from 29 to 27 and the coefficients on some variables changing signs. Nevertheless because we would rather lose a bit of efficiency than introduce bias so we use the complete set of explanatory variables.

C. Structural Stability.

As the coefficients on the hedonic regression have been interpreted as implicit prices, determined by demand and supply of characteristics, previous work, summarized in Table 3, assumes these prices and coefficients are unstable over short periods. Therefore, rather than running one multiple cross-section regression for the whole sample period, a set of
regressions on adjacent periods (overlapping or separate) of multiple years, single years or
even quarters. However, where cross-sections are pooled a maintained assumption is that
there is a common pure price component. For example, consider Figure 2, the assumption
implies that the equilibrium locus $p_s(q)$ is a derived from a parallel shift of $p_t(q)$. With the
same vertical distance between two loci at all quality levels, all products have the same pure
price change between two periods. In other words, distinct nominal price variations cross
variants occur only if there are different quality improvements for the second period.

In a competitive market, common pure price variation could arise due to common
input price shocks or changes in tastes. In a differentiated oligopoly, with strategic pricing,
more significant variation in coefficients may occur across makes (as first raised by Dhrymes
(1971)) or types of car (as first raised by Shiratsuka (1995b)) than over time. So, common
pure price variation is unlikely (see Silver (1999) for a similar point). In practice, rather than
dividing the sample by periods, greater explanatory power is achieved by dividing by make or
by type.

In particular, the motivation for dividing by make is that a car producer typically
produces multiple models and coordinate their prices (Bresnahan (1988) and Chandler
(1962)). The greater the coordination across models by producers, the more significant
variation in coefficients will be by make relative to that by time.

The motivation for dividing the sample by type of car is that the studies on demand
system work by Bresnahan (1987) and Berry, Levinsohn and Pakes (1995) highlight how
prices and margins on products are determined substantially by the extent of competition from
similar products. Hence, the effects of strategy changes for particular models (or even demand
or cost changes) are likely to be most strongly felt by the set of the most similar models. The
more segmented the car market, the more significant variation in coefficients will be by type
relative to that by time.
To determine if the relationship between characteristics and price is stable, we compare the results of a hedonic regression on the full sample with the results of sets of hedonic regressions where the sample has been divided by year, by type and by make. These regressions are hereafter referred to as the Full Sample, By Year, By Type and By Make regressions. Chow tests are performed in each case, and the total residual sum of squares of the set of regressions noted. While a formal test cannot be performed comparing the three breakdowns of the sample, an informal comparison of results suggests diving the sample by year and by type is superior than by make or using the full sample.

Before presenting the results, the divisions by make and by type need to be discussed in more detail. For the By Make regressions, separate regressions are performed for cars produced by each of the four local manufacturers. In addition, one regression is performed for all imported cars. In the By Type regressions, type assignment follows Glass’s Guide’s categories: small, medium and sports/luxury and from which the weights are calculated.

The significant Chow test statistics for all cases demonstrate dividing the sample by year, make or type represents a significant improvement over the single multiperiod regression. These results are similar to those of Shiratsuka (1995b) who also found breaking the sample by type an improvement. Though a direct statistical comparison across breaks cannot be made, the By Year and By Type specifications achieve a lower RSS, suggesting greater explanatory power, than By Make. Hence, in the next section, both the By Year and By Make categorizations will be used.

Before proceeding, it is worthwhile returning to Table 3 to compare our approach with previous work. Three features stand out. First, we continue with the Semi-log functional form. Second, we work with single year and multiple year samples but also work with subsamples.
by make and by type of car. Third, even after checking for multicollinearity, we continue to work with a relatively large set of characteristics.

V. Quality Changes and Inflation Rates in an Oligopoly

In this section, based on the theoretical analysis of section two and the empirical analysis of section four, we construct and analyze a set of quality-adjusted price indices. After presenting the hedonic regressions, the indices constructed using each set of hedonic regressions are presented.

A. Results of the Hedonic Regressions.

We summarize the results of each of three sets of hedonic regressions in Table 6. The second column presents the coefficients for the Full Sample regression. The third column presents the average and standard deviation of the estimated coefficients for the set of twelve By Year regressions. In the last three columns, the coefficients for the By Type regressions on samples of small, medium and sports/luxury cars are presented. In the first set of rows, results for the coefficients on the continuous characteristics, which are also those most commonly reported in other work, are reported. In the second half of the table, results for the dummy variable and scaled variable characteristics are summarized.

Table 6 is about here

Table 6 demonstrates that the results are quite satisfactory. Each equation has high explanatory power, as measured by the $\bar{R}^2$. All variables except for size are consistently significantly different from zero. The signs are as expected or interpretable. Larger cars or cars with greater torque tend to be relatively under-priced. It is suggested that Australians tend to prefer cars with a lot of torque so they tend to be over-torqued for their price. With the large number of characteristics controlled for, the significantly positive coefficient on weight is interpreted as reflecting safety. The last three columns demonstrate that there are distinct
differences across types of cars. In particular, for small cars, both size and torque come in as positive and significantly different from zero. The different result compared with the other classes could be because there are no small cars manufactured in Australia. As the sports/luxury class includes both Bentleys and Porsches it is perhaps not surprising that size is insignificant. Fuel consumption is also insignificant for Sports/Luxury group. This is also not surprising: one does not quibble over fuel bills when driving a Lamborghini. However, the positive and significant coefficients on fuel consumption suggest that this variable may be picking up some unobservables i.e. individuals are willing to trade off higher fuel consumption for larger quantities of other attributes.

As the hedonic equations appear reasonable, the next step is to construct the quality-adjusted price indices. These are presented in Table 7. In the second column, an index constructed from the Full Sample regression is presented. In the third column, an index constructed using the twelve By Year regressions is presented. In the fourth column, an index using the By Year regressions, but using the weights (described in Section III) is presented. Finally, in the fifth column, an index using the By Type results and weights is calculated. At the foot of the table, average annual inflation rates are calculated for both the sample period, and for (1987 – 1995), when prices consistently rose.

Table 7 is about here

Comparing the results in columns two and three demonstrates that allowing for one-period instability, without weights, makes little difference to the full sample results. The fourth column demonstrates, surprisingly, that adding weights to the one-period regressions only makes limited differences. The results in the final column are strikingly different, with an estimated inflation rate double that estimated in the first two columns. Adding some weighting, with allowing for different coefficients across types apparently makes considerable difference. Comparing the price index series in the final column with the sample index and
the official CPI index in Table 2 reveals two observations. First, the index calculated above predicts an average inflation rate about 2% per annum lower than that from the raw data. Second, the estimated rate of inflation is similar to the official quality-adjusted rate, calculated by the ABS. However, noting that effect of quality adjustment is to reduce the rate at which prices rise, the amount of decline is similar across indices. Indeed, in general prices reveal the same pattern overtime, peaking in 1995 before declining again.

To examine the cause behind the substantially different results for the By Type regressions we need to examine the implied price indices for each of the three types, calculated from the coefficients on the time dummies in each regression. In particular, column one features the price index for small cars calculated from the coefficients on the time dummies from the By Type regression using the sample of small cars. Columns two and three are calculated similarly from the By Type regressions of the samples of medium and sports/luxury cars. These are summarized in Table 8.

**TABLE 8 IS ABOUT HERE**

There are several striking features about these results. First, the time pattern of prices for sports/luxury cars is quite distinct from the pattern for the rest of the sample, with a slow growth in prices. Second, the prices of small and medium cars increase in a similar pattern when prices fall, small cars’ prices fall more rapidly for medium cars’ prices. These results indicate that part of the reason for the striking differences across types. Because sports/luxury cars are over-represented in the sample, they drag down the estimated average inflation rate.

While a definite conclusion cannot be reached these results are suggestive, that changes in market structure may be an important influence. In particular, Nissan, the fifth large manufacturer making mainly medium and some smaller cars, exited manufacturing in Australia in 1992 and became an import specialist. On the other hand, from 1992 to 1996 Hyundai nearly triples its share of small car sales from 8.4% to 24.2%. The pattern of prices is
consistent with the story that in the medium car market, increased concentration led to prices remaining higher, while the aggressive entry of Hyundai led to a more rapid decline in prices. Prices in the sports/luxury segment appear unaffected by these changes. More work is needed to properly untangle the role of strategy in determining price movements.

VI. Concluding Remarks.

In this paper we focus on the question of constructing quality-adjusted price indices and take a reasonably stable oligopoly– Australian motor vehicle industry as example. We recast the theory of hedonic pricing to generate a reduced form specification for estimation and present the conditions under which the standard hedonic regression can be performed. We then construct quality-adjusted price indices, emphasizing two features. First, using market share weights in the construction of the index (not in the regression where inconsistency would result) and using separate regressions for three types of cars: small, medium and sports/luxury. These changes result in estimates of inflation that are considerably higher than those obtained by standard methods - indeed being close to the official estimates.

Appendix I - List of characteristics included.

Airbag (driver), Airbag (passenger), Anti-lock brakes, Air conditioning, Automatic climate control, Alarm system, Alloy wheels, Cruise control, Compact disc player, Number of compact disc stacker, Number of speakers for compact disc player, Central locking, Central locking remote control, Cloth trim, Fog lights, Independent rear suspension, Limited slip differential, Leather steering wheel, Leather trim, Leather upholstery, Metallic paint, Power front seat (driver) Power front seat (passenger), Power mirror, Power steering, Power sunroof, Power windows, Power windows (front), Radio cassette, Number of speakers for radio
cassette, Remote control boot release, Roof rack, Rear spoiler, Side airbags, Sports seat, Trip computer, Traction control system.

Appendix II - Construction of weights

For 1987 – 1992, registration weights from 1984 are used. For 1993 – 1997, average registration weights for 1988 – 1989 are used and for 1998, average registration weights for 1993 – 1994 are used. The index is designed to be as complete as possible. However, the limitations of the source for our weights mean that the weights are compiled by make-type. The number of makes and types and some highlights for each set of weights are presented in Table A.1. Even with this fairly aggregated level of weights there are problems with missing observations, mainly for luxury makes. The following types are omitted from the weights - the "other" groups in the original source and any group for which there is not a complete set of prices for the whole period. The weights are then rescaled to ignore the missing observations. Table A.1 reports the aggregate weights for the missing observations in the original set of weights.

Table A.1 Here

References


Figure 1. – Equilibrium Locus of Price-Quality Combinations
Figure 2.— Decomposition of Price Change into Quality Driven and Inflationary Components
Footnotes.

* We would like to thank Kevin Fox, Steven Kennedy Darcy McCormack and participants at seminars at the Australian Bureau of Statistics, the 1999 Conference of Economists, La Trobe University, RSSS at the ANU, and UNSW for their constructive comments. This project is funded in part from a Small ARC Grant and a Grant from the Faculty of Law and Management. Some work was done by D. Prentice at RSSS in January 2000 and he is most appreciative for their hospitality.

1. The theory is equally applicable to markets for inputs. Indifference curves are re-interpreted as isoprofit curves of purchasers.

2. Most commodities have more than one quality characteristic so that $U(p, q) = u$ actually defines an indifference surface in a $(p, q)$-space. This is referred to as an indifference curve for convenience. It is also applicable to the offer curves and equilibrium loci below.

3. For more detailed discussion, see Rosen (1974) which is an excellent reference laying concrete theoretical base for the indifference curves, offer curves and equilibrium.

4. Subscript $j$ indexes the firm or variant while subscript $k$ indexes the $k$’s element of characteristics vector $q$. So, $q_j$ is a vector but $q_k$ is a number and $q_{kj}$ is the $k$th element of vector $q_j$.

5. In case of discrete characteristics variables, $\Delta p_s/\Delta q_{ks}$ should be understood as a price jump on $p_s(q)$.

6. The third method is the characteristics price method; see Dulberger (1989) and Triplett (1989).

7. For the single period regression, quality-adjusted prices are estimated and directly placed in an index.

8. Without demonstration of method, Griliches indicates that “we should use a weighted regression approach, since we are interested in an estimate of a weighted average of the pure-
price change, rather than just an unweighted average over all possible models, no matter how peculiar or rare.” Raff and Trajtenberg admit that they have not considered weights because of the lack of quantity data.

9. The number of characteristics is reduced from 126 by eliminating characteristics that are (1) bundles of other characteristics (2) exclusive to one make (3) Creating Size by multiplying Length by Width. Prices are list rather than transaction prices – though reporting transaction prices for a product featuring haggling would have to be done carefully to avoid introducing other biases.
<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Observations</th>
<th>Number of Makes</th>
<th>Number of Characteristics</th>
<th>4 Firm (8 firm) Concentration Ratio</th>
<th>4 Firm Share of Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>668</td>
<td>25</td>
<td>32</td>
<td>80 (94)</td>
<td>48</td>
</tr>
<tr>
<td>1988</td>
<td>643</td>
<td>25</td>
<td>32</td>
<td>77 (94)</td>
<td>47</td>
</tr>
<tr>
<td>1989</td>
<td>710</td>
<td>27</td>
<td>32</td>
<td>74 (92)</td>
<td>48</td>
</tr>
<tr>
<td>1990</td>
<td>659</td>
<td>29</td>
<td>35</td>
<td>73 (93)</td>
<td>38</td>
</tr>
<tr>
<td>1991</td>
<td>783</td>
<td>32</td>
<td>35</td>
<td>69 (90)</td>
<td>46</td>
</tr>
<tr>
<td>1992</td>
<td>723</td>
<td>33</td>
<td>36</td>
<td>69 (88)</td>
<td>45</td>
</tr>
<tr>
<td>1993</td>
<td>799</td>
<td>31</td>
<td>39</td>
<td>74 (89)</td>
<td>42</td>
</tr>
<tr>
<td>1994</td>
<td>882</td>
<td>32</td>
<td>42</td>
<td>72 (88)</td>
<td>42</td>
</tr>
<tr>
<td>1995</td>
<td>962</td>
<td>35</td>
<td>43</td>
<td>70 (86)</td>
<td>36</td>
</tr>
<tr>
<td>1996</td>
<td>1083</td>
<td>38</td>
<td>43</td>
<td>67 (87)</td>
<td>31</td>
</tr>
<tr>
<td>1997</td>
<td>1015</td>
<td>35</td>
<td>43</td>
<td>63 (85)</td>
<td>33</td>
</tr>
<tr>
<td>1998</td>
<td>922</td>
<td>36</td>
<td>43</td>
<td>65 (85)</td>
<td>31</td>
</tr>
</tbody>
</table>

Note: (1) The concentration ratios are by make rather than by firm. So, Lexus is treated as separate from Toyota and Eunos as separate from Mazda.
TABLE 2.—PRICE MOVEMENTS 1987 – 1998

<table>
<thead>
<tr>
<th>Year</th>
<th>Sample Index</th>
<th>ABS Motor Vehicles CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>1988</td>
<td>111.4</td>
<td>109.5</td>
</tr>
<tr>
<td>1989</td>
<td>116.4</td>
<td>115.9</td>
</tr>
<tr>
<td>1990</td>
<td>126.2</td>
<td>118.6</td>
</tr>
<tr>
<td>1991</td>
<td>130.4</td>
<td>121.3</td>
</tr>
<tr>
<td>1992</td>
<td>139.9</td>
<td>124.9</td>
</tr>
<tr>
<td>1993</td>
<td>153.8</td>
<td>132.0</td>
</tr>
<tr>
<td>1994</td>
<td>159.0</td>
<td>136.7</td>
</tr>
<tr>
<td>1995</td>
<td>167.7</td>
<td>142.2</td>
</tr>
<tr>
<td>1996</td>
<td>165.4</td>
<td>142.3</td>
</tr>
<tr>
<td>1997</td>
<td>163.0</td>
<td>134.1</td>
</tr>
<tr>
<td>1998</td>
<td>164.2</td>
<td>128.1</td>
</tr>
</tbody>
</table>

Average annual inflation rate 1987 – 1998: 4.69% 2.37%
Average annual inflation rate 1987 – 1995: 6.71% 4.52%
### Table 3. Earlier Empirical Work on Automobiles

<table>
<thead>
<tr>
<th>Reference</th>
<th>Type of Sample</th>
<th>Functional Form Used</th>
<th>Number and Types of Variables</th>
<th>Period of Data</th>
<th>Other Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ohta and Griliches (1975)</td>
<td>US 52 models each year, 1961 – 1971 (standardized models)</td>
<td>Semi-log</td>
<td>3 continuous, 3 dummies, make effects</td>
<td>Adjacent years</td>
<td>Significant make effects</td>
</tr>
<tr>
<td>Ohta and Griliches (1975)</td>
<td>US models, tested 1963 – 66 (new and used)</td>
<td>Semi-log</td>
<td>8 scale variables, 5 continuous, 1 dummy</td>
<td>Full sample</td>
<td></td>
</tr>
<tr>
<td>Cowling and Cubbin (1972)</td>
<td>UK family saloon cars, and log</td>
<td>Linear, Semi-log,</td>
<td>4 continuous, 3 dummies</td>
<td>Single year</td>
<td>Used weighted least squares</td>
</tr>
<tr>
<td>Gordon R. (1990)</td>
<td>US 1947 - 1983 stripped prices, 4 door sedan, excludes luxury makes</td>
<td>Semi-log</td>
<td>3 continuous, 1 dummy, 1 scaled</td>
<td>Full sample, adjacent years</td>
<td></td>
</tr>
<tr>
<td>Shiratsuka, (1995b)</td>
<td>Japan - all local models 1990 – 1994</td>
<td>Box-Cox, Semi-log, linear</td>
<td>3 continuous, 21 dummies, make effects</td>
<td>Full sample, adjacent year</td>
<td>Also divided sample by size and styling</td>
</tr>
<tr>
<td>Raff and Trajtenberg (1997)</td>
<td>US 1906 – 1940</td>
<td>Semi-log</td>
<td>3 continuous, 6 dummies</td>
<td>Adjacent year</td>
<td></td>
</tr>
<tr>
<td>Murray and Sarantis (1999)</td>
<td>UK 1977 Q1 - 1991 Q4</td>
<td>Semi-log</td>
<td>7 continuous, 1 scaled, 2 dummies</td>
<td>Single quarter</td>
<td>Used weighted least squares</td>
</tr>
<tr>
<td>Name of data set</td>
<td>Values of the condition indexes over 30 for each data set</td>
<td>Set of explanatory variables in each dataset</td>
<td>RSS*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>----------------------------------------------------------</td>
<td>---------------------------------------------</td>
<td>------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clean</td>
<td>33.3</td>
<td>Torque, all characteristics and make dummies except, the make dummy for BMW</td>
<td>300.483</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi-Clean</td>
<td>31.3, 51.9, 97.6</td>
<td>All variable in the Clean dataset with Size, Fuel-Highway</td>
<td>274.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complete</td>
<td>44.8, 57.8, 75.5, 127.0, 160.2</td>
<td>All variables in the Semi-Clean dataset, with Weight, Power and the BMW make effect</td>
<td>189.7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Residual sum of squares for log-linear hedonic regression of log price on explanatory variables in each dataset, full sample.
### Table 5. – Stability Tests of Three Specifications

<table>
<thead>
<tr>
<th>Specification</th>
<th>RSS</th>
<th>Chow Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Sample</td>
<td>189.693</td>
<td></td>
</tr>
<tr>
<td>By Year (twelve annual cross section regressions)</td>
<td>139.701</td>
<td>4.364</td>
</tr>
<tr>
<td>By Make: (separate regressions for each local</td>
<td></td>
<td></td>
</tr>
<tr>
<td>manufacturer and importers as a group)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>By Type: (separate regressions for small, medium</td>
<td>128.582</td>
<td>20.802</td>
</tr>
<tr>
<td>and sports/luxury)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note when the sample is divided some variables become perfectly collinear in the sub samples and so are removed.
<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Full Sample Regression</th>
<th>By Year Regressions</th>
<th>By Type Regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Small</td>
</tr>
<tr>
<td>Size</td>
<td>-0.00005</td>
<td>-0.00015</td>
<td>0.00068*</td>
</tr>
<tr>
<td>Fuel</td>
<td>0.23961*</td>
<td>0.2269</td>
<td>0.42592*</td>
</tr>
<tr>
<td>Weight</td>
<td>0.63265*</td>
<td>0.65682</td>
<td>0.38288*</td>
</tr>
<tr>
<td>Torque</td>
<td>-0.26308*</td>
<td>-0.24327</td>
<td>0.09109*</td>
</tr>
<tr>
<td>Power</td>
<td>0.84392*</td>
<td>0.83488</td>
<td>0.24454*</td>
</tr>
</tbody>
</table>

**Coefficients on Dummy and Scaled Characteristics:**

- Number Positive and Significant: 16, 10.83 (3.51)
- Number Negative and Significant: 9, 3 (1.71)
- Number Insignificant: 12, 17.75 (2.86)
- $R^2$: 95.473, 95.94, 91.64, 87.42, 94.19

Note, * represents significantly different from zero at 5%. This significance level is also used in categorizing the coefficients on the dummy and scaled variable characteristics. Note, for annual case – the arithmetic average and standard deviation of the set of annual coefficients are presented.
<table>
<thead>
<tr>
<th>Year</th>
<th>Full Sample</th>
<th>By Year</th>
<th>By Year (with weights)</th>
<th>By Type (with weights)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>1988</td>
<td>103.7</td>
<td>101.3</td>
<td>103.9</td>
<td>106.5</td>
</tr>
<tr>
<td>1989</td>
<td>105.0</td>
<td>110.5</td>
<td>106.9</td>
<td>111.3</td>
</tr>
<tr>
<td>1990</td>
<td>108.6</td>
<td>111.1</td>
<td>112.2</td>
<td>118.6</td>
</tr>
<tr>
<td>1991</td>
<td>107.3</td>
<td>110.8</td>
<td>112.8</td>
<td>120.9</td>
</tr>
<tr>
<td>1992</td>
<td>106.9</td>
<td>110.8</td>
<td>114.0</td>
<td>124.7</td>
</tr>
<tr>
<td>1993</td>
<td>112.2</td>
<td>114.7</td>
<td>117.2</td>
<td>133.3</td>
</tr>
<tr>
<td>1994</td>
<td>114.4</td>
<td>112.5</td>
<td>120.0</td>
<td>136.9</td>
</tr>
<tr>
<td>1995</td>
<td>117.6</td>
<td>116.3</td>
<td>122.6</td>
<td>140.3</td>
</tr>
<tr>
<td>1996</td>
<td>114.7</td>
<td>113.4</td>
<td>119.6</td>
<td>138.1</td>
</tr>
<tr>
<td>1997</td>
<td>111.2</td>
<td>111.5</td>
<td>114.7</td>
<td>133.5</td>
</tr>
<tr>
<td>1998</td>
<td>111.6</td>
<td>110.2</td>
<td>114.9</td>
<td>133.4</td>
</tr>
</tbody>
</table>

Average annual inflation rate 1987–1998

Average annual inflation rate 1987–95

Indices constructed using the Full Sample, By Year, and By Type regressions.
TABLE 8. – PRICE INDICES FOR TYPES OF CARS

<table>
<thead>
<tr>
<th>Year</th>
<th>Small</th>
<th>Medium</th>
<th>Sports/Luxury</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>100.000</td>
<td>100.000</td>
<td>100.000</td>
</tr>
<tr>
<td>1988</td>
<td>103.839</td>
<td>104.395</td>
<td>107.768</td>
</tr>
<tr>
<td>1989</td>
<td>106.417</td>
<td>108.108</td>
<td>107.121</td>
</tr>
<tr>
<td>1990</td>
<td>109.247</td>
<td>112.729</td>
<td>110.530</td>
</tr>
<tr>
<td>1991</td>
<td>110.98</td>
<td>116.264</td>
<td>103.978</td>
</tr>
<tr>
<td>1992</td>
<td>111.101</td>
<td>118.010</td>
<td>102.803</td>
</tr>
<tr>
<td>1993</td>
<td>120.336</td>
<td>124.778</td>
<td>105.876</td>
</tr>
<tr>
<td>1994</td>
<td>122.189</td>
<td>125.998</td>
<td>106.339</td>
</tr>
<tr>
<td>1995</td>
<td>125.070</td>
<td>130.423</td>
<td>108.391</td>
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<td>1996</td>
<td>119.759</td>
<td>129.485</td>
<td>106.661</td>
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<td>1997</td>
<td>114.977</td>
<td>125.182</td>
<td>106.373</td>
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<td>1998</td>
<td>112.978</td>
<td>124.839</td>
<td>108.610</td>
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</table>

Average annual inflation rate 1987 – 1998
- Small: 1.17
- Medium: 2.07
- Sports/Luxury: 0.81

Average annual inflation rate 1987 – 1995
- Small: 2.86
- Medium: 3.39
- Sports/Luxury: 1.08

Indices constructed using the results of the By Type regressions.
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<td>0.009</td>
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<td>Share Small</td>
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