

An Evaluation of the Use of Hedonic Regressions for Basic Components of Consumer Price Indices

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Abstract: The importance of adjusting for quality changes in the measurement of consumer prices, and the role hedonic regressions can play in achieving this, is well recognised. However, the use of such regressions can take different forms, including (i) adjustments by statistical offices for non-comparable substitution in the *matched models method*, (ii) *direct estimates* from the coefficients on dummy variables for time, and (iii) *exact hedonic indexes* corresponding to a constant utility formulation from an economic theoretic approach. The literature on these approaches generally deals with them in isolation, the purpose of this paper being to outline and evaluate these approaches in order to draw conclusions as to their practical suitability for the compilation of quality-adjusted consumer prices indexes. The case is argued for a move towards the last of these approaches which developments in electronic data retrieval (scanner data) now makes feasible.

1. Introduction

The concern of this paper is with the use of hedonic regressions in the measurement of quality-adjusted consumer price indices. Gordon (1990) provides many examples of how lack of appropriate adjustments for quality changes can lead to serious bias. An Advisory Commission (1995) for the US estimated the range of such bias for the US to be from 1.0 to 2.7 per cent per year, though there have been other estimates (e.g. Lebow *et al.*, 1994 and Shapiro and Wilcox, 1996). Hedonic regression are used, for example, by the Bureau of Labor Statistics in the US for quality adjustment for a limited number of items (Liegey, 1994).

We consider three different approaches to the use of hedonic regressions for measuring quality-adjusted price changes. The first complements the existing matched models approach generally used by statistical offices, by helping to identify key quality characteristics and, when matches are not available, providing adjustment factors to allow 'like' to be compared with 'like'. The second is the direct method, found in the academic literature, which uses the coefficients on the dummy variables for time in an hedonic regression as estimates of quality-adjusted price changes. The third method requires quite extensive data for the compilation of 'exact' hedonic price indices as defined from economic theory. In section 2 we outline each of these approaches and in section 3 provide an evaluation. Attention is drawn to the superiority of the third approach along with the practical means by which statistical offices might move towards its adoption and the implications for the construction of micro-indices. Taking into account quality features implicitly increases the level of disaggregation of items, from, for example, 21" televisions to 21" televisions with nicam sound systems. The proper weighting of the aggregation is critical to this framework. The use of micro data to support such work is also discussed. It is argued that taking advantage of technological developments in data retrieval may well be one of the important challenges of the future. Conclusions are drawn in section 4.

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2. Hedonic regressions and alternative methods of quality adjustment

The hedonic approach involves the estimation of the implicit, shadow prices of the quality characteristics of a product. The product will be sold, to adopt the terminology of consumer durables, by a number of manufacturers, (makes), each manufacturer usually supplying more than one model, each model having different characteristics.² A set of $j = 1..m$ characteristics are identified and data over $k=1..l$ models collected for a regression of the price of model k (P_k) on its characteristics (X_{kj})

$$\ln P_k = \beta_0 + \sum_{j=1}^m \beta_j X_{kj} + \varepsilon_k \quad (1)$$

The β_j are estimates of the marginal value of the characteristics (in perfectly competitive markets or where arbitrage exists (Diewert 1983; we relax this later)³. A semi-logarithmic functional form is used here, though Feenstra (1995) and Arguea *et al.* (1994) have recently argued for a linear form; this will be considered later.

The econometric and theoretical issues are not trivial and while some of these are considered in section 3, Rosen (1974), Gordon (1990), Griliches (1990), Triplett (1990), Arguea *et al.* (1995), Berndt *et al.* (1995), and Silver (1996), discuss these in more detail. We now consider three ways by which hedonic regressions may be used to help estimate quality-adjusted price changes; the matched model method, the direct method, and exact hedonic indexes.

2a. Matched model method

Consider the highest level of disaggregation of a price index, the elementary aggregates, for which there are no weights where price changes will usually be measured as (Szulc, 1989 and Dalén, 1992)

$$i) \quad \text{the ratio of arithmetic means} \quad \frac{\sum P_t/n}{\sum P_0/n} = \frac{\sum \{(P_t/P_0)P_0\}/n}{\sum P_0/n} = A, \quad (2)$$

that is, a price weighted index of price changes, and

$$ii) \quad \text{the arithmetic mean of price relatives} \quad \frac{\sum P_t/P_0}{n} = \left[\frac{\sum P_t \cdot \frac{1}{P_0}}{\sum P_0 \cdot \frac{1}{P_0}} \right] = R, \quad (3)$$

that is, an equally (democratic) weighted index of price changes if only one observation is collected for each model; otherwise the implicit weights are the number of observations (comparisons) for each model.

² A single manufacturer may sell more than one 'model' of a product, each model having different features aimed at different segments of the market. Our concern in principle should be with 'product varieties' as our observations, though since we identify make-effects as a characteristic; 'models' and 'product varieties' become synonymous for practical purposes.

³ Parameters can of course be re-estimated to (almost) keep pace with changing preferences or be kept fixed at some base period. A Laspeyres index measures changes in prices for a fixed, base-period weighted basket of goods with the marginal utility of characteristics also held constant in the base period.

Turvey *et al.* (1989) and Dalén (1992), advised consideration of the geometric mean. Let us assume for simplicity that the n in periods 0 and t are the same in (i), which is necessary in (ii). Now A and R may increase because the basket of goods purchased in period t are of a better quality than in period 0 . For example, for televisions sets, they are purchasing a larger proportion of sets with nicam than without, or made by Sony, or whatever. If the prices of sets of a given specification have remained constant, A and R would show an increase: there will be an upwards bias because the mix of sets in period t are of better quality than period 0 .

The main method used to counter such bias by statistical offices (e.g. Bureau of Labor Statistics (US) and Office for National Statistics (UK)) is the matched model method (Turvey *et al.*, 1989). The price collector notes what are believed to be the important characteristics for the specification of a model and records in this and subsequent periods the prices of models with the same specification, on the assumption that the characteristics chosen for the specification are the salient ones and consumer's marginal values for the characteristics do not change. The matched models method attempts to compare 'like' with 'like'.

However, problems arise when a price-collector can no longer obtain a price quotation for a given specification, for example, because the store does not have the model in stock or a new model has replaced it. Under the matched methods model either

- (i) the problem is ignored and the prices of the old and new (or replacement) model are linked on the assumption of no quality change or the price differential between the old and new model is assumed to equal the quality component.
- (ii) the comparison is omitted on the assumption that the price change is the same as for other products in the sector. For consumer durables where price changes occur irregularly, generally at the time of model changes, such a procedure is particularly problematic since we ignore the pent-up price changes.
- (iii) estimates are made of the effect on price of the quality change and for quality improvements, the price of the old (new) model is marked up (down). The quality change estimate may be derived from production cost (plus profit margin) information or the coefficients of an hedonic regression. Hedonic regressions also benefit the matched model method by helping to determine which product specifications are important to the consumer, thus improving the data retrieval system (Liegey 1994).

It is stressed that the above approach *does* allow for quality-adjustment by matching the specifications of the models. It fails when matches are not available, this being particularly problematic when the new model has a major technological leap and where the quality changes are less observable and quantifiable. Particularly insidious are quality-changes such as improvements in reliability which the consumer may not even observe.

Diewert (1996) models this bias by defining the true price index by:

$$P_T \equiv (1-s)(I+i) + s(I+i)(I+e)^{-1} \quad (4)$$

where $(I+i) \equiv P_L$ is the Laspeyres price index, s is the share of commodities replaced by the new models and e is the relative increase in the efficiency of new models which are linked into the index. He defines the quality change bias B_Q as

$$B_Q \equiv P_L - P_T = (1 - i) se / (1 + e). \quad (5)$$

For example, if the efficiency decline missed was 10% ($e=0.1$), the inflation rate 5% per annum ($i=0.05$), the share of disappearing models replaced by new models 10% ($s=0.1$) then $B_Q= 0.0095$, i.e. approximately 1% per annum.

2b. Direct method

The regression in equation (1) was for cross-sectional regression analysis, the underlying data being the (average) price and the characteristics of each model over a given period of time. However, by including data over $i=1\dots n$ periods equation (1) becomes:

$$\ln P_{ki} = \beta_0 + \sum_{i=2}^n \beta_i D_i + \sum_{j=1}^m \beta_j X_{kji} + \varepsilon_{ki} \quad (6)$$

where D_i are dummy variables for the time periods, D_2 being 1 in period $i=2$, zero otherwise; D_3 being 1 in period $i=3$, zero otherwise etc.

The coefficients β_i are estimates of quality-adjusted price (QAP) changes, that is estimates of the change in the (the logarithm of) price between period 1 and period i , having controlled for the effects of changes in quality (via $\sum_{j=1}^m \beta_j X_{kji}$). The β_j coefficients need not of course be fixed but, by use of dummy *slope* coefficients, be allowed to capture changes in consumer's preferences over time.

There are a plethora of studies of the above form as considered by Griliches (1990), Triplett (1990) and Gordon (1990), but including, more recently, Berndt *et al.* (1995), Nelson *et al.* (1994), Gandal (1994 and 1995), Lerner (1995) and Arguea *et al.* (1994).

The data used for such analyses require prices for different models and their characteristics. Since suppliers wish to advertise their products in terms of salient features, these advertisement are a useful data source. Indeed there is almost a self-fulfilling hypothesis in that the features advertised become the salient ones because these are the main ones readily available to the consumer. In some cases specialist magazines, consumer groups and mail-order firms provide such data in a collated form.

Our concern with this approach lies with the data sources. First, they implicitly treat each model as being of equal importance, when some models will have quite substantial sales, while for others sales will be minimal. Second, the prices recorded are not the transaction price averaged over a representative sample of types of stores and regions but often a single, unusual supplier. In utilising such a source it is as if we are asking statistical offices to forsake the detailed data they collect and instead utilise catalogue listings for the advantage of quality-adjustment.⁴

It may be argued that should statistical offices wish to use this approach their price collectors could obtain data on the average prices (across regions and types of stores) of a wide range of models and relate the derived average prices of each model in each period to the characteristics of the respective model and period. This would be to abandon the current approach based on monitoring price *changes* of matched

⁴ Weighted least squares is not a solution to this problem, this simply transforming the scaling of the variables in an attempt to cure heteroskedasticity (Maddala 1989).

items. Instead of quality being adjusted for by the price collectors matching similar goods (where they exist), the ‘matching’ would be achieved by partialling out quality changes in the regression. The basis of the estimates would become the ratio of average prices as opposed to average of price changes, the former having advantages over the latter (Diewert 1996). We would still however, have the problem of equal weighting being applied to each model in the implicit aggregation process. The compilation of exact hedonic indexes surmounts this problem.

2c. Exact hedonic indexes

Feenstra (1995) has shown how *exact* hedonic price indexes can be compiled. Such an index is defined in economic theory as exact if it equals the ratio of expenditure at constant utility, allowing for changing prices and quality characteristics. Economic theory allows us to develop upper and lower bounds for a general exact index given observed data on prices, quantities (Diewert 1976 and 1983). Feenstra (1995) extends this to exact hedonic indexes requiring data on prices, quantities, and also the marginal values of characteristics. The hedonic regression allows us to determine the marginal values; prices we have; however unlike the direct approach, we also require data on quantities. Feenstra (1995) derives the formula for an exact Laspeyres, base-period weighted hedonic index given by:

$$\left[\frac{X_{0t-1} + \sum_{k=1}^l X_{kt-1} \hat{P}_{kt}}{X_{0t-1} + \sum_{k=1}^l X_{kt-1} P_{kt-1}} \right] \text{ with } \hat{P}_{kt} = P_{kt} - \beta_{kt} (z_{kt} - z_{kt-1}) \quad (7)$$

where X is quantity sold, P is price, and z a vector of characteristics with associated marginal values derived from an hedonic regression over $k=1..l$ product varieties (models). Note that \hat{P}_{kt} corrects the observed prices, P_{kt} , for changes in the characteristics between the two periods, corresponding to the “explicit quality adjustment” described by Triplett (1990, 39). X_0 is consumption on a numeraire commodity.

A Paasche formulation is given by:

$$\left[\frac{X_{0t} + \sum_{k=1}^l X_{kt} P_{kt}}{X_{0t} + \sum_{k=1}^l X_{kt} \hat{P}_{kt-1}} \right] \text{ with } \hat{P}_{kt-1} = P_{kt-1} + \beta_{kt-1} (z_{kt} - z_{kt-1}) \quad (8)$$

and is a current-period weighted hedonic index adjusting previous period prices for changes in the characteristics.

Feenstra (1995) shows that, where $E(P_t, z_k, U_t)$ is the level of expenditure needed to obtain aggregate utility U_t ,

$$\frac{E(P_t, z_{t-1}, U_{t-1})}{E(P_{t-1}, z_{t-1}, U_{t-1})} \leq \text{Laspeyres (7)} \quad (9)$$

and

$$\frac{E(P_t, z_t, U_t)}{E(P_{t-1}, z_t, U_t)} \geq \text{Paasche (8)} \quad (10)$$

i.e. Laspeyres and Paasche quality-adjusted hedonic indices act as upper and lower bounds on constant-utility, quality-adjusted indices. A *superlative* formulation in the Diewert (1976) sense would be a geometric mean of the two, Fisher's 'ideal' index. Chained formulations of equations (7) and (8) might also be compiled (Diewert 1983).

The approach thus, first, utilises the coefficients on the characteristics to adjust observed prices for quality changes; second, incorporates a weighting system using data on quantities sold of each model, rather than treating each model as equally important and finally, has a direct correspondence to a constant utility index number formulation defined from theory.

3. An appraisal of the three approaches

Here we review the three approaches according to a number of criteria, the results being summarised in Table 1. We then consider their data requirements and available sources and draw some conclusions. However, first some salient features of the methods.

The *matched model method* controls for quality changes by the matching of specifications by price collectors. When similar models are not available either an assumption needs to be made of identical price changes to those experienced by similar models (link method), or that the price differential between a closely matched model and the existing model reflects quality change (overlap method), or direct adjustments are made using option costs or the coefficients from hedonic regressions. The coverage of average price changes for each model is often impressive and can involve a large number of price quotations over a representative sample of stores and regions. The weighting applied to each model is implicitly equal to the number of price quotations collected for that model, as is apparent from the calculation of R in equation (3) above. Care thus needs to be exercised in the determination of how many price quotations are used for each model. Because prices of product varieties with improved specifications may increase at a different rate to those with old specifications, the selection of models at the start of a period and the holding of their specifications constant over the period may lead to bias. The model does not allow us to differentiate between quality-adjusted and unadjusted price changes since the specification of goods selected is controlled from the very start. Since the same sample is taken for each comparison the aggregation may be by equation (2) or (3), though the arithmetic mean of price relatives on axiomatic and "weak" economic grounds "...is definitely not recommended". Reinsdorf and Moulton (1994) provide estimates of an upward bias due to its use (as against the geometric mean) of 0.5 per cent for June 1992 to June 1993. Diewert (1996) and Dalén (1992), argue for the use of the geometric mean or ratio of arithmetic means.

The *direct method* controls for quality changes by partialling out such changes in the hedonic regression. The coverage of prices is often very limited if taken from a, for example, mail-order catalogue, but can be more extensive if taken, for example, from a price catalogue of average prices paid for second-hand cars. There is nothing in principle which would prevent a statistical office abandoning the matched model method, in order to use the collected prices to form an average price for each model in each period. Equation (8) could then be used with average prices on the left hand side. The implicit basis of the aggregation is the ratio of arithmetic means which is particularly apparent in the dummy variable formulations for possession of characteristics, and which is preferable to the arithmetic mean of price relatives as noted above. However, the method ascribes equal weights to each model.

The *exact hedonic approach* controls for quality changes by identifying the change over time in each of the quality characteristics of each model, and then applying to any change in a characteristic an estimate of the marginal value of the respective characteristic derived from the hedonic regression. This allows us to generate estimates of constant quality average prices. The price (change) of each model is then aggregated weighted by sales, unlike the direct method. As with the direct method the estimates of quality-adjusted price changes can be compared with unadjusted price changes. However, unlike the direct method the exact hedonic approach has a correspondence to a constant-utility cost-of-living comparison with constant quality characteristics. Equations (7) and (8) depict the basic aggregation as a (weighted) mean of the ratio of price changes, a formulation which Diewert (1996) argued against, particularly on axiomatic grounds. However, equations (7) and (8) can take the form of geometric means, as preferred by Dalén (1992), and Diewert (1996) and indeed Feenstra (1986) shows that such a formulation is appropriate when the hedonic regression equation takes a semi-logarithmic formulation as opposed to a linear one.⁵

All of this argues well for the exact hedonic approach. However, the missing criterion in Table 1 is data requirements. Our question is “how would a statistical office currently using the matched models method change its procedures to provide results akin to the exact hedonic approach (which is preferable to the direct method because of the weighting procedure and correspondence with theoretical entities)?”

To adapt the current matched model methodology to an exact hedonic approach we might treat each observation as the model observed by a price collector in an individual store. The price collector would have to observe the price, make and characteristics (or model number to later retrieve its characteristics), the quantities being derived as the sum of how many models of a specific type were observed. Any objection or concern as to the reliance of the weighting system on the sample selection procedure might be met with the point that the current methodology requires a similar reliance⁶. However, the method would benefit from information on sales quantities of each model.

Such sales data are not too hard to come across. Estimates from the spending patterns of a panel of consumers (the HES or reports by market research agencies) are particularly suitable for fast-moving product lines. For durable products scanner data are particularly suitable. Such data are derived from EPOS (electronic point-of-sale) scanners, the data being collected by bar-code readers or the associated number typed in for each transaction at the point-of-sale. In many product areas (at least in the UK) just about all such retailers pass their data to an agency for compilation for the market as a whole, which is then sold to manufacturers and other interested parties and returned to the retailers. Data on average prices and sales are available on a monthly basis in the UK for each model, the model number being linked to a file on the attributes or characteristics of the model mainly provided by the manufacturers. We thus have, for each model, average prices, sales quantities and product characteristics by model. Since EPOS systems are linked to inventory planning systems, data on purchases and inventories are also included along with information on the number of stores in which a model is sold. In 1993 for televisions in the UK, for example, the data covered over 2.8 million transactions, being supplemented by data from

⁵ Feenstra (1995) does favour a linear formulation when pricing is above marginal cost. This, he argues helps correct for bias arising from misspecification of the hedonic equation through omission of price-cost margin variables. Ioannidis and Silver (1996) show how the semi-logarithmic formulation is maintained by including price-cost margin variables from scanner data.

⁶ The implicit weight for a price *change* using the *R*-form is the quantity sold of a model, i.e. $\sum X_{t-1}(P_t/P_{t-1})/\sum X_{t-1}$, the summation being over models. Equation (7) is weighted by values, for Laspeyres: $\frac{\sum X_{t-1}P_t}{\sum X_{t-1}P_{t-1}} = \frac{\sum (X_{t-1}P_{t-1})P_t/P_{t-1}}{\sum X_{t-1}P_{t-1}}$.

store visits of retailers without EPOS systems, the estimated coverage being “.. well over 90% of the market”⁷. Scanner data would provide a suitable source of data on quantities for weights.

An alternative is of course to abandon price collection in stores in favour of the aforementioned scanner data which, as outlined by Silver (1995), can be superior to data collected from stores in terms of

- (i) selection of representative items, all items being covered;
- (ii) the selection of date/ time of sampling, all transactions being covered,
- (iii) selection of stores, all stores using scanners being covered, or a sample taken of those not;
- (iv) weighting system incorporated at the micro-level. Laspeyres and Paasche and Fisher’s estimates can be derived directly from such data using equations (7) and (8) as explained earlier.⁸

An advantage of the approach is that we go some way to meeting some of the aggregation problems at the level of the basic components, as raised by Triplett (1996). Outside of North America the Laspeyres index, as noted by Triplett (1996), is the guiding principle for the construction of Consumer Price Indexes as opposed to a constant-utility index. As such scanner data and/or consumer panels can be used to derive base-period weights at a very high level of disaggregation to estimate Laspeyres hedonic price indexes as described by equation (7), thus having a correspondence to current methodology in outside of North America countries. However, as Triplett (1996) has shown Laspeyres indexes compiled using micro-data, never mind Laspeyres quality-adjusted indexes with base-period weights for the quality-adjustment, are prone to serious aggregation bias especially in view of outlet substitution and ‘sale’ price bias. However, scanner data (which is available in the UK for a wide range of products including electrical goods, white goods, DIY, food, pharmaceuticals) allows for base-period and current period weights to be used along with, for each month, base and current period estimates of the coefficients from hedonic regressions (Ioannidis and Silver, 1996). Furthermore, the base and current period weighted exact indexes could be constructed using geometric means as the basis for aggregating the elementary units. We can thus not only compile superlative indexes at the very basic level as demonstrated by Silver (1995) using scanner data, but also superlative and exact *hedonic* indexes. The challenge of aggregation may to some extent be met by future developments in the technology of data retrieval.

⁷ Estimates are from GfK Marketing Services. Since there is no data on the overall size of the market such estimates of coverage may at first sight be open to doubt. However, first, TV retailing in the UK is highly concentrated and all major multiples and department stores are included in their list of providers of data. The data are supplemented by store audits of suppliers not using EPOS systems. Second, the manufacturers of TVs as users of the data also provide information to GfK on quantities supplied to the UK market to help validate their estimates.

⁸ In practice equations (7) and (8) might be aggregated over makes and not models. If only scanner data is used we need to track a model over time recording its average price and quality characteristics. If models of, for example, TVs change annually in a way that is difficult to determine replacement models, we need to generate \hat{P} as the average (sales weighted) quality-adjusted price for a make (e.g Sony), being the average (sales weighted) of actual prices \bar{P} , of Sony, less the sum of the changes in the average (sales weighted) mix of each characteristic (e.g change in the number less mix of each characteristic (e.g. change in the average number of sets with nicam for Sony) multiplied by the shadow ‘worth’ of that characteristic (the coefficient on nicam from the hedonic regression), this being continued for each characteristic. Once we have generated \hat{P} for each make, equations (7) and (8) are utilised by summing over makes as opposed to models.

3. Summary

Thus to summarise, there have been two quite distinct approaches used in practice to estimate quality-adjusted price changes: the matched models method generally used by statistical offices and the direct hedonic method generally found in the academic literature. A third approach, to date neglected in the empirical literature, is the recently formulated exact hedonic approach. The matched model approach was devised to militate against bias from quality changes. However, a cost of this was a quite separate form of bias inherent in the use of the *R*-form at this elementary level (Diewert, 1996). Furthermore, the method failed to adjust for quality changes when models could not be matched, though hedonics can be used to complement the matched model method by use of the coefficients as adjustment factors. The direct method, mainly because of shortcomings relating to the implied weighting of price changes and the representativity of price data, is not suitable for use in its present form by statistical offices. Many of the ways of overcoming the shortcomings in of the direct method lead to the use of exact hedonic indices which can be implemented practically either by reorganising the way existing data are used or by the use of scanner data.

Exact hedonic indices provide a methodology, with a rational in economic theory, by which we can move away from the limitations of the matched model method without incurring the problems of the direct method. The disadvantage is the need for sales data at the model level for weights. It is suggested that data from manufacturers, retailers, consumer panels or, more importantly, scanner data might prove helpful here. The approach would serve to provide a better basis for quality-adjustment.

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Table 1. Some criteria for the evaluation of different approaches

	Matched models method	Direct method	Exact hedonic estimates
Control for quality change	Price-collectors match specifications with adjustment from hedonics.	Partiallying out in regression.	Partiallying out in regression.
Coverage of price quotations for each model	Sample; representative by store and region.	Single quotation from catalogue.	Weighted by relative sales; may be current period or base period weighted or average.
Weighting of price (changes) across models	Relative number of price quotations.	Each model has equal weight.	Weighted by relative sales; may be current period weighted or average.
Bias in product specifications	Product specifications held constant in base period.	Determined by availability of data on quality characteristics.	Determined by availability of data on quality characteristics.
Comparison of quality-adjusted and unadjusted price changes	Not possible.	Possible.	Possible.
Accordance with economic theoretic approach	No.	No.	Yes.
Aggregation of elementary price index	Arithmetic mean of price ratios or mean of price ratios.	Ratio of arithmetic means .	Arithmetic or geometric mean of price ratios.