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AN EVALUATION OF THE USE OF HEDONIC REGRESSIONS FOR BASIC COMPONENTS OF CONSUMER PRICE INDICES

BY MICK SILVER

Cardiff University

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 substitutions via the *matched models method,* (ii) *direct estimates* from the coefficients on dummy variables for time, and (iii) *exact hedonic and superlative indices* corresponding to a constant utility formulation from an economic theoretic approach. The literature on these approaches generally deals with each in isolation; the purpose of this paper is to outline and evaluate them 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 make feasible. The paper concludes with the results of some empirical work comparing the results of the direct method with those from the exact, superlative, approach.

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 a lack of appropriate adjustments for quality changes can lead to serious bias. An Advisory Commission (1995) for the U.S. estimated the range of such bias for the U.S. to be from 1.0 to 2.7 percent per year, though there have been other estimates (e.g. Lebow *et al.*, 1994, and Shapiro and Wilcox, 1996). Hedonic regressions are used, for example, by the Bureau of Labor Statistics in the U.S. 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

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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 exploiting technological developments in data retrieval may well be one of the important challenges of the future. The paper concludes with a comparison of empirical results using the direct method and exact superlative estimates in Section 4 and conclusions in Section 5.

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 by a number of manufacturers. In the terminology of consumer durables, each manufacturer's "make" of product is usually available in more than one model, each model having different characteristics.[1] A set of $j=1,\ldots,m$ characteristics is identified and data over $k=1,\ldots,l$ models collected for a regression of the price of model k (P_k) on its characteristics (X_{kj}):

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

the β_j are estimates of the marginal value of the characteristics. A semi-logarithmic functional form is used here, though Feenstra (1995), and Arguea *et al.* (1994) have recently argued for a linear form.[2]

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.* (1994), and Berndt *et al.* (1995) discuss them in more detail. We now consider three ways in which hedonic regressions may be used to help to estimate quality-adjusted price changes. The first is the use of the coefficients β_j to adjust for quality differences when using the matched model method; the second is the application of the hedonic direct method, the third is the use of exact hedonic indices.

(a) *Matched Model Method*

The matched model method relies on the price collector selecting comparable items in each month and comparing their prices. If the items are not strictly

[1]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. It should also be noted that new and old models with similar features by one manufacturer can coexist in a market.

[2]Feenstra (1995) does favour a linear formulation when pricing is above marginal cost. This, he argues, helps correct for bias arising from mis-specification 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.

comparable according to some identifiable and measurable characteristic,

> "The coefficients of these [hedonic] regressions can then be used to infer the value of changes in characteristics of the goods in the sample. For example, the observed valuation of computers with different processor speeds could be used to estimate the quality improvement of a new computer with a faster processor." (Moulton, 1996, p. 170.)

While hedonic estimates can be used for the matched model method when items are not comparable, the very matching of items is an attempt to ensure quality changes are excluded as outlined below.

Consider the highest level of disaggregation of a price index, the elementary aggregates, for which there are no weights—for example, a 14″ television set without Nicam, Fastext or Teletext. A price collector will select a model in a store in month 0, note its price and details, and then collect its matching price in the following t months in the same store. If, for an elementary aggregate, there are $h = 1, \ldots, n$ such prices collected in each month, then the price changes will usually be measured (Szulc, 1989, and Dalen, 1992) as either:

(i) *The ratio of arithmetic means*

$$\frac{\sum P_{ht}/n}{\sum P_{ho}/n} = \frac{\sum \{(P_{ht}/P_{ho})P_{ho}\}/n}{\sum P_{ho}/n} = A \tag{2}$$

or

(ii) *The arithmetic mean of price relatives*

$$\frac{\sum P_{ht}/P_{h0}}{n} = R. \tag{3}$$

Equation (2) is a price-weighted index of price changes, while equation (3) is an equally (democratic) weighted index of price changes. If more than one observation is collected for each model, the implicit weights are the number of observations (comparisons) for each model. Reinsdorf and Moulton (1997), Diewert (1995 and 1996), Dalén (1992), Szulc (1989), Turvey *et al.* (1989), and Fisher (1922) all caution against the use of R due to an upward bias and advise consideration of the geometric mean, which is now being adopted by a number of countries including the U.S.

Note that in the hedonic regression given by equation (1) we are dealing with different models of a good and their representative or average prices. The number of observations will at most be the number of models or types of TVs being sold. For statistical offices, the observations are the prices of types of TVs in different stores across the country. Let us assume for simplicity that the "n" in periods 0 and t are the same in (i), which is necessary in (ii). Both formulae require the quality specifications of the TVs in both periods to be the same. If the prices collected in period t were for sets of a higher quality than in period 0, there will be an upward bias.

The main method used to counter such bias by statistical offices [e.g. Bureau of Labor Statistics (U.S.) and Office for National Statistics (U.K.)] is the matched model method (Turvey *et al.*, 1989). The price collector notes what are believed to be the important characteristics or specification of an observed 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. 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 the model because, for example, the store does not have the model in stock or a new model has replaced it. Under the matched model method, the problem is resolved in one of the following ways:

(i) *Direct comparison*—a replacement model of the same or similar quality to its predecessor is selected and the prices of the old and replacement models are directly compared on the assumption of no quality change. The procedure is not without difficulties, as noted by Armknecht *et al.* (1997, p. 382).

> "To the extent that the replacement version of an item deemed to be of comparable quality is in fact of higher quality than the discontinued variety, the estimate of constant-quality price change for that item will be biased upwards. For example, televisions often fall in price while they improve their features; in that case, we treat the replacement as comparable to show the decline in the market price of the television, but we miss the additional decline due to the improved quality unless we can put a value on the improved features."

(ii) *Link method*—the price change of a comparable class of goods is used to estimate the price change of the old, discontinued variety. The assumption is that the price of the original version would have changed at the same rate as the other items (see Moulton, 1996). The *class-mean imputation method* is similar to the link method except that the price change is imputed from a set of similar items that are classed as comparable substitutes or that are directly quality adjusted (Moulton and Smedley, 1997).

(iii) *Overlap method*—when the prices of the old and new versions are both available in an overlap period the difference in price level between the versions is used as an estimate of the quality difference.

(iv) *Direct adjustment*—estimates are made of the effect on price of the quality change. 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 thus only when comparable products are unavailable that the coefficients from hedonic regressions may be used for quality adjustment under the matched models approach.

It is stressed that the matched models approach is a way of avoiding a quality adjustment judgment because it matches the specifications of the models. It fails when matches are not available, this being particularly problematic when the new model represents 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 arising from not (fully) incorporating the efficiency of quality improvements by defining the true price index by:

$$P_T = (1-s)(1+i) + s(1+i)(1+e)^{-1} \tag{4}$$

where $(1+i) \equiv P_L$ is the Laspeyres price index (for example, $i = 0.05$ is an inflation rate of 5 percent per annum), s is the share of disappearing models replaced by the new models (for example, $s = 0.1$ is 10 percent) and e is the relative increase in the efficiency of new models which are incorporated into the index (for example, $e = 0.1$ is a 10 percent increase). He defines the quality change bias B_Q as:

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

For example,

$\beta_Q = 1.05(0.1)(0.1)/1.1 = 0.0095$, i.e. approximately, 1 percent per annum.

(b) *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 $i = 1, \ldots, n$ periods equation (1) becomes:

$$\text{In } P_{ki} = \beta_0 + \sum_{i=2}^{n} \beta_i D_i + \sum_{j=1}^{m} \beta_j X_{kji} + \varepsilon_{ki} \tag{6}$$

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 $\sum_{j=1}^{m} \beta_j X_{kj}$).

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.[3] Second, the prices recorded are not the transaction price averaged over a representative

[3]Weighted least squares is not a solution to this problem, this simply transforms the scaling of the variables in an attempt to cure heteroskedasticity (Madalla,, 1992).

sample of types of stores and regions, but often a single, unusual supplier. In utilising such a source it is as if we were asking statistical offices to forsake the detailed data they collect and instead utilise catalogue listings for the advantage of quality-adjustment.

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 their characteristics and relate, using regression, the derived average prices of each model in each period to the characteristics of the respective model and period. 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. We would still, however, have the problem of equal weighting being applied to each model in the implicit aggregation process. The compilation of exact and superlative hedonic indexes surmounts this problem.

A final problem arises with the manner in which the direct method takes account of changing marginal values (coefficients) over time. It is the usual practice that the coefficients are held constant and thus not allowed to reflect changes in the evaluation by consumers of the marginal worth of the characteristics. At first sight this may be considered to be a potential omitted variable(s) bias which

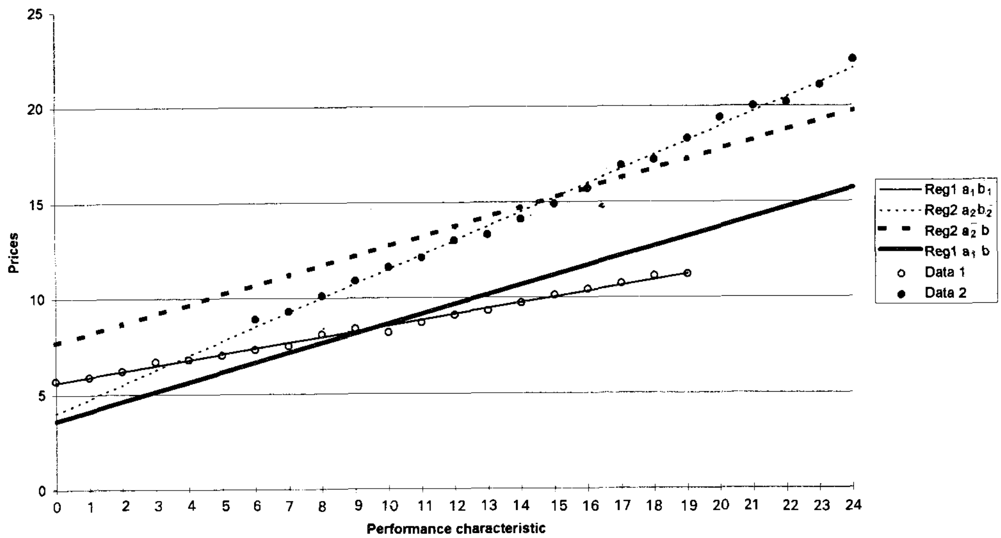

Figure 1. Hedonic Regression Equations

inclusion of dummy slope variable(s) would rectify. Figure 1 illustrates the problem for two sets of data in periods 1 and 2. The lines in bold marked "Reg1 a_1b" and "Reg2 a_2b" are regression equations of price on a performance characteristic for the data over each period with a common restricted slope and different intercepts. This follows the conventional formulation in equation (6). The difference in the intercepts—which apply for all values of the performance characteristic given the common slope—is $7.67 - 3.61 = 4.06$. It is an estimate of the change in prices between periods 1 and 2, having controlled for changes in the performance characteristics with the marginal values ascribed to such changes being fixed as an average of the individual coefficients of the two periods.

If we were to attempt to take account of changing preferences using the direct method, this would require the inclusion of dummy intercept *and* dummy slope coefficients for each period. This is equivalent to estimating two separate regressions, (Maddala, 1992) and would yield the lines marked "Regl a_1b_1" and "Reg2 a_2b_2" for periods 1 and 2 respectively. As is apparent from Figure 1, we have a problem in that incorporating changing consumer preferences renders the estimate of the difference in quality-adjusted price dependent on the value of the performance characteristic. A simple inclusion of dummy slope variables takes the form:

$$y = \alpha_1 + (\alpha_2 - \alpha_1)D_1 + \beta_1 x + (\beta_2 - \beta_1)D_2$$

where the subscripts refer to periods, D_1 is the dummy intercept equal to 1 in period 2 and 0 otherwise, and D_2 is the dummy slope variable equal to x in period 2 and 0 otherwise.

This inclusion of the dummy slope variable develops the approach with the estimate of quality-adjusted prices now being $(\alpha_2 - \alpha_1) = 3.26 - 5.30 = -2.04$: a *fall* of 2.04 as opposed to an *increase* of 4.06. Yet this implicity provides a valuation of quality-adjusted price change at the intercept, when $x = 0$. A more appropriate value of the performance characteristics at which to estimate the change in quality-adjusted prices would be the mean value of the performance characteristics of 11.73 or median of 12.4 yielding estimates of quality-adjusted price increases of 3.27 and 2.67 respectively. The prices in each period are being predicted for a constant average value of the performance characteristic as is apparent in Figure 1. The average (mean) value of the performance characteristic should be sales-weighted. Note how the methodology has been transformed. We now have varying coefficients over time to allow changes in the marginal values of characteristics to be estimated. Furthermore, these may be applied to a sales-weighted mean of the usage of each characteristic. We will see in the next section how the exact and superlative formulations also allow for varying coefficients in equations (7) and (8) via β_{kt} and β_{kt-1} and sales-weighted average values for the performance characteristics via z_{kt} and z_{kt-1}.

(*c*) *Exact and Superlative Hedonic Indexes*

Feenstra (1995) has shown how *exact* hedonic price indices 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 constant-utility index given observed data on prices and quantities (Diewert, 1976 and 1983). Feenstra (1995) extends this to exact *hedonic* indices requiring data on prices, quantities, and also the marginal values of characteristics. The hedonic regression allows us to determine the marginal values. We have prices; however, and unlike the direct approach, we also require data on quantities. Feenstra (1995) derives the formulae for Laspeyres and Paasche upper and lower bounds for an exact hedonic index based on a general expenditure function, the Laspeyres bound being:[4]

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

where X is quantity sold, P is price, and z a vector of characteristics with associated marginal values (β) derived from an hedonic regression over $k = 1, \ldots, l$ product varieties (models). Changes in the quality of models are picked up via changes in their characteristics $(z_{kt} - z_{kt-1})$ which are multiplied by estimates of their associated marginal values, β_{kt}. With sales data available the vector z can be the sales-weighted average usage of each characteristic in each period. 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, p. 39). X_0 is consumption of a numeraire commodity.

A Paasche formulation is given by:

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

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:

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

and

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

i.e. Laspeyres and Paasche quality-adjusted hedonic indices act as upper and lower bounds on constant-utility, quality-adjusted indices. A *superlative* index in the Diewert (1976) sense is one which corresponds to a flexible functional form for the expenditure function. Laspeyres and Paasche price indices act as upper and lower bounds on superlative index numbers one such index being the geometric mean of the two, Fisher's "ideal" index. Chained formulations of equations (7), (8) and of Fisher's index might also be compiled (Diewert, 1983).

The advantages of this approach are threefold. First, it utilises the coefficients on the characteristics to adjust observed prices for quality changes. Second, it incorporates a weighting system using data on quantities sold of each

[4]Diewert (1976) has shown how a particular index number formula corresponds (is exact for) particular functional forms of the aggregator function (expenditure/utility function). The Laspeyres formula would be appropriate for a representative consumer having a Leontief aggregator function. There are a class of functional forms which are flexible in that they approximate a wide range of functional forms. Any index number formula which correspond to (is exact for) a flexible functional forms is described as *superlative*. Laspeyres and Paasche can be shown to act as bounds on a superlative index.

model, rather than treating each model as equally important. Finally, it has a direct correspondence to a constant utility index number formulation defined from theory.

Before moving on, some comments on the functional form of the hedonic regression are necessary. Feenstra (1995) argued the case for a linear functional form for hedonic regressions as opposed to the more usual log-linear and double logarithmic formulations. The basis of Feenstra's case is that when pricing is above marginal cost there will be an upward bias in the coefficients of a log-linear hedonic regression due to the omitted variable (bias) of the price–cost margin. However, he demonstrates that a linear formulation would compensate for the bias. An alternative approach used in Ioannidis and Silver (1998) is to explicitly model the price–cost margin while maintaining the best functional form as found from appropriate econometric tests. While either of these approaches are appropriate for the exact method, they may be misleading for the direct method. There may be variation in the price–cost margin over time as prices are, for example, increased to take account of increased demand. We would not wish these to be absorbed by price–cost margin variables or inappropriate linear forms since the very purpose of the dummies on time is to reflect such price variation. However, for the exact approach we need to use the coefficients on the hedonic regressions as estimates of the marginal values of the characteristics in equations (7) and (8). These coefficients should not be tainted by omitted variable bias.

3. An Appraisal of the Three Approaches

In this section, we review the three approaches according to a number of criteria. We then consider their data requirements and available sources and draw some conclusions. First, however, we outline 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 assumptions need 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 item is often impressive and can involve a large number of price quotations over a representative sample of stores and regions. For example, if the item is a basic 14″ TV, prices are collected across stores for the calculation of A in equation (3) above. The weighting applied to the price change of each model will be the number of price quotations collected for the model multiplied by its price in the base period, as a share of the total value in the base period. Care thus needs to be exercised in the determination of how many price quotations are used for each model if the price changes differ between models.

Since 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. Furthermore, when comparable items are not available, assumptions have to be made about the extent of the quality change or direct estimates made. The matched models method 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. Finally, the basis of the aggregation at the elementary level can be either A or R in equation (3). The use of R (equation 3) on axiomatic and "weak" economic grounds "... is definitely not recommended," Reinsdorf and Moulton (1997) providing estimates of an upward bias due to its use (as against the geometric mean) of 0.5 percent 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 former gaining acceptance by statistical offices.

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, for example, a mail-order catalogue. However, coverage can be more extensive if taken from for example, a price catalogue of average prices paid for second-hand cars or from scanner data. There is nothing in principle to prevent a statistical office from 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 in a *linear* hedonic regression 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. For a semi-logarithmic formulation, the implicit basis is the geometric mean.

The method as described in equation (6) is also problematic in that in the estimation of the regression coefficient and thus, quality-adjusted price changes, equal weight is given to each model irrespective of its sales. A development of this approach was outlined above in which (changing) marginal values of characteristics were applied to sales-weighted average usage of the respective characteristics, a feature of the next approach.

The *exact (superlative) hedonic approach* controls for quality changes by identifying the average or proportionate (sales-weighted) change over time in each of the quality characteristics of each model, and then applying to any change in a characteristic an estimate of its marginal value derived from the hedonic regression. This allows us to generate estimates of constant-quality average prices. The constant-quality average price (change) of each model is then aggregated, the aggregation being 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. The aggregation of prices at the basic level for each model is via the A formulation in equation (3). Equations (7) and (8) can be combined to compile Fisher's ideal index as a *superlative* index or each of equations (7) can take the form of geometric means. Feenstra (1995) shows that such a formulation is appropriate when the hedonic regression equation takes a semi-logarithmic formulation as opposed to a linear one (see footnote 2). The exact approach also naturally allows for varying coefficients (marginal values) over time to be incorporated into the analysis.

What is of particular interest is that the modification to the direct method incorporating changing marginal values outlined at the end of Section 2(b) requires an average characteristic usage. If this is sales-weighted in both the base period and current period we can derive bounds on a cost-of-living index. Thus this development of the direct approach provides results analogous to the exact and superlative approaches.

All of this argues well for a superlative hedonic approach. However, the missing criterion 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 a superlative 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 elementary aggregate as a model of the product: for example, a particular make and vintage of TV. The average price for each model is placed alongside its characteristics and an hedonic regression is estimated. The quality adjusted prices in equations (7) and (8) can then be derived. The price collector would have to observe the price, make and characteristics (or model number to later retrieve its characteristics). The quantity weights for each model would be how many of each model were observed. Any objection or concern as to the reliance of the weighting system on the sample selection procedure might be met with the argument that the current methodology requires a similar reliance. However, the method would benefit from information on the sales quantities of each model.

Such sales data are not too difficult to obtain. Estimates from manufacturers, or the spending patterns of a panel of consumers by market research agencies are suitable for fast-moving product lines. For infrequently purchased, 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 U.K.), most retailers pass their EPOS data to an agency for compilation for the market as a whole and the processed data 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 U.K. for each model of many durable goods, the model number being linked to a file on the attributes or characteristics of the model which is usually provided by the manufacturers. We thus have, for each model, average prices, sales quantities and product characteristics. 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. For example, in 1993 the data on televisions in the U.K. covered over 2.8 million transactions and was supplemented by data from store visits to retailers without EPOS systems, the estimated coverage being "... well over 90 percent of the market." 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; and (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.

An advantage of this approach is that it smoothes 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 indices as opposed to a constant-utility index. 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 indices as described by equation (7), and there is thus a correspondence to current methodology in countries outside of North America. However, as Triplett (1996) has shown, Laspeyres indices compiled using micro-data, particularly 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 U.K. 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, 1998). Furthermore, the base and current period weighted exact indices could be constructed using geometric means as the basis for aggregating the elementary units. We can thus compile not only superlative indices 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.

4. Empirical Estimates

In this section some results are provided for the direct and exact hedonic approach using scanner data for television sets (TVs) in the U.K. Details of the methodologies are given in Ioannidis and Silver (1998) and Silver, Ioannidis and Haworth (1998) available from the authors. It would be inappropriate to compare these approaches with the matched models method since the latter relies on sample data collected by price collectors. The data are EPOS scanner data on average transaction prices, sales and characteristics of goods collected by barcode readers from all major suppliers in the U.K. and compiled and provided by GfK Marketing Services for each model of TV. The data are monthly for June 1994 to May 1995 and include only models of TVs with monthly sales of 30 or more, about 350 models per month for each of the 12 months under study covering 7.38 million transactions and 3,889 observations. The regressions take a semi-logarithmic form with 8 features (including possession of Teletext, Nicam, and flat screen technology), 48 make (brand) dummies and 17 screen size dummies. The hedonic regression for the direct method included 11 dummy variables for

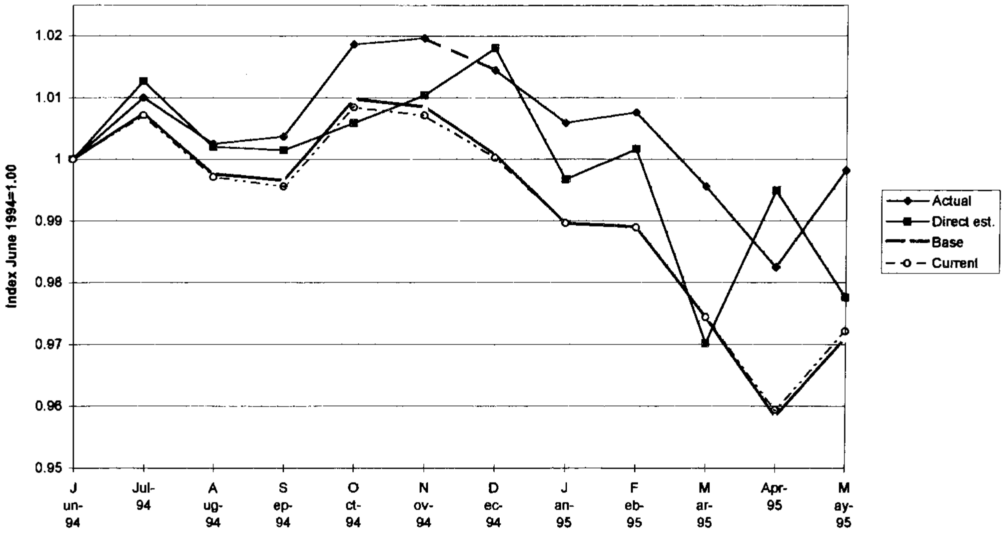

Figure 2. Estimates of Quality-Adjusted Price Changes

each month following equation (6), the model fitting the data well ($\bar{R}^2 = 0.85$).[5] The results are given in Figure 2 along with the actual data and estimates from the exact method.

The results for the exact method are both base period and current period weighted indices.[6] The methodology is similar to that described by equations (7) and (8) except that a chained formulation is used with sales weights and hedonic coefficients being updated on a monthly basis. Again, the hedonic regressions fitted well with the mean $\bar{R}^2$ for the monthly regressions, being 0.92 with a minimum of 0.88.[7] All of the expressions in equations (7) and (8) are sales-weighted including the (change in) the proportion of sets with different features/makes.

A number of results are apparent. First, the base and current period exact estimates are very close and thus either of these estimates provide a good approximation to a superlative index. Towards the end of the series the current period weighted index is an upper bound. The economic theory which requires the base period weighted index to be the upper bound assumes a downward-sloping demand curve which may not be appropriate in the early months of 1995 when new models are about to be launched and old models "dumped."

Second, the quality-adjusted estimates are consistently below the actual price; the actual (sale-weighted) average price fell by 0.18 percent over the period. When

[5]Silver, Ioannidis, and Haworth (1998) include variables reflecting the price–cost margin though they are excluded for the direct estimates, since they would pick up movements in quality-adjusted prices instead of the monthly dummies.

[6]The formulation is slightly different from equations (7) and (8) being based not on a weighted arithmetic average, but a geometric average due to the log-linear formulation of the hedonic regression (see Feenstra, 1995). The indices are base period and current period weighted geometric means, details being given in Ioannidis and Silver (1997). It was noted earlier that coefficients for a log-linear model were biased due to the omission of a price–cost margin variable and the linear form was preferred. In this study for exact estimates we explicitly model the price–cost margin.

[7]Details of other diagnostics are given in Ioannidis and Silver (1998).

adjusted for the quality mix the fall was about 2.84 percent, reflecting an improvement in quality. Third, the results from the direct method are generally lower than the actual, unadjusted changes and track some of the movements, though the substantial differences between the direct and exact estimates for December and April are disturbing. It must be stressed that the actual, unadjusted figures are sales-weighted while the direct estimates treat each model with equal importance, the exact method also being preferred on theoretical grounds. As noted earlier, it is quite possible to develop the direct method to allow it to possess the features of the exact approach.

5. Conclusions

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 (superlative) hedonic approach. The matched model approach was devised to militate against bias from quality changes. However, 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 of the direct method lead to the use of exact hedonic indices which can be practically implemented either by reorganising the way existing data are used or by the use of scanner data. The empirical results show a clear divergence between the results from the direct method and the exact (superlative) results. Thus changing preferences (marginal values) and/or the use of sales-weighted average usage of characteristics can be useful. The framework for doing this is quite different from existing procedures. These use price collectors to match models and hedonic (and other) adjustments to correct for instances when "like" cannot be compared with "like." The framework given here is concerned with estimating weighted average price changes, weighted average usage of characteristics and hedonic coefficients for the worth of these characteristics.

Exact (superlative) hedonic indices provide a methodology, with a rationale in economic theory, by which we can move away from the limitations of the matched model 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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