Chained, Exact and Superlative Hedonic Price Changes: Estimates from Micro Data

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Abstract: Using micro scanner data results of estimates of chained exact (and superlative) hedonic price indexes for television sets are presented. The data source is available for a wide range of goods, the application providing an example of how this method can be more widely applied. The estimates correspond to a constant-utility, hedonic cost-of-living index defined in economic theory as the ratio of expenditure functions at constant utility allowing for changing prices and characteristics of goods. They improve on the existing *direct method* which is prevalent in the literature and takes its estimates directly from the coefficients on a time dummies in an hedonic regression, and on the *matched model method* used by statistical offices. A particular innovation in the specification of the monthly hedonic regressions which underlie the method, is the inclusion of price-cost margin variables to correct for omitted variable bias. Individual monthly regression estimates are found to be satisfactory, the difference between actual and quality-adjusted price changes being substantial with base-period and current-period weighted estimates being similar, thus providing good approximations to monthly, superlative indexes.

1. Introduction

The concern of this paper is with the estimation of chained, exact (and superlative) hedonic price indexes as measures of quality-adjusted price changes. Such indexes correspond to constant-utility, cost-of-living indexes as defined from economic theory. While the theory for such measures is well-developed (Feenstra, 1995), the authors are unaware of its practical implementation. Recent concern as to the serious potential for bias in Consumer Price Indexes due to an inability to properly incorporate quality changes (for example, Advisory Commission, 1995) argues for serious consideration of approaches based on new data sources. Recent estimates of the bias resulting from an inability to properly incorporate such changes in the US CPI range from 1.0 to 2.7 per cent per year (Advisory Commission 1995) - though Lebow *et al.* (1994) and Shapiro and Wilcox (1996) provide interval and point estimates of 0.4 to 1.5 and 1.0 respectively. For the UK Cunningham (1996) provides estimates of 0.35 to 0.8 per annum.

This paper first outlines the suitability of Electronic-Point-Of-Sale (EPOS) scanner (micro) data for such purposes, a source available for a wide range of consumer durables and fast moving products. Second, using such data, hedonic regressions are successfully estimated for television sets (TVs), as a case study on a monthly basis for a three-year period. As an innovation the estimated regressions incorporate price-cost margin variables, as tests for, and to avoid omitted variable bias when markets are not competitive. Finally, estimates of chained, exact, hedonic price indexes are provided.

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Section 2 briefly outlines alternative approaches to estimating quality-adjusted price changes drawing attention to deficiencies in the matched model method and the direct hedonic approach used by statistical offices and found in the academic literature respectively. The section concludes with a detailed exposition of the theoretical basis for the exact hedonic approach. Section 3 provides details of the data and diagnostics of the hedonic regressions, followed by the results for the chained, exact hedonic price indexes in section 4. Conclusions are drawn in section 5.

1. Alternative approaches to measuring quality-adjusted price changes

There are three main approaches to estimating quality-adjusted price changes, these being considered in turn.

2a. The direct method

The direct method provides estimates directly from an hedonic regression. A set of $k = 1...K$ characteristics of a product are identified and data over $i = 1...N$ product varieties (or models) over $t = 1...T$ periods, are collected for a regression of the price of model i in period t on its characteristic set X_{tki} to estimate:

$$ln\, P_{ti} = \beta_0 + \sum_{t=2}^{T} \beta_t D_t + \sum_{k=1}^{K} \beta_k X_{tki} + \varepsilon_{ti} \qquad (1)$$

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

The coefficients β_k 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 t, having controlled for the effects of variation in quality (via $\sum_{k=1}^{K} \beta_k X_{tki}$). The β_k coefficients need not of course be fixed over time 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).

A concern with the approach is that first, it implicitly treats each product variety (model) as being of equal importance when, for example for TVs, some models will have substantial sales volumes while for others sales will be minimal.[2] Second, the prices recorded are not usually the transaction prices averaged over a representative sample of types of stores and regions, but often a single, unusual (e.g. catalogue) supplier.

[2] The problem is not solved by using a weighted least squares estimator as this simply transforms the variables being used, for example, to help prevent bias in the standard error the coefficients. The general absence of sales data is, in any event, the reason why the direct method is not further developed.

2b. The matched model method

Avoiding bias from quality changes in the measurement of consumer price changes is of natural concern to statistical offices in the compilation of Consumer Price Indexes (CPIs). 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 some of the specifications of a model and records in this and subsequent periods the prices of models with the same specification, on the assumption that the characteristics do not change. The matched models method attempts to compare 'like' with 'like'. With the direct method the regression partials out for changes in quality characteristics while statistical offices use price collectors to undertake this task.[3]

2c. Exact hedonic indexes

Diewert (1976) defines a price index as *exact* if it equals the ratio of expenditure functions in two periods at a constant level of utility. The price index measures the change in expenditure necessary to keep utility constant. Analogously, Feenstra (1995) defines an *hedonic* price index - depending on observed prices, quantities, marginal values and characteristics - as *exact* if it equals the ratio of expenditure functions at constant utility, but also allows for changing prices and characteristics.

Feenstra (1995) provides the conditions under which hedonic price indexes can provide meaningful measures of changing consumer welfare conditional on constant 'quality' of goods consumed. The first problem is to derive the aggregate utility function, or expenditure function at any given level of quality, as captured by the product characteristics. Starting from the agent's utility function and for the product in indirect form as:

$$V_i = \ln\ \Phi_0(y) - \ln\ \Phi_i(p_i, z_i) + \varepsilon_i,\ i = 1,\dots, N, \qquad (2)$$

where y is the income of each consumer, and p_i denotes the price for product i, $z_i \in R_+^K$ denotes a vector of characteristics. Assume that $\Phi_0 > 0$ and $\partial\Phi/\partial p_i > 0, \partial\Phi_i/\partial z_{kk} \leq 0$. We can interpret $\Phi_i(p_i, z_i)$ as a 'quality-adjusted' price. We denote $q_i = \Phi_i(p_i, z_i)$ and invert it, to obtain $p_i = \pi_i(q_i, z_i)$. The *marginal value of characteristic k* in good i is defined by $\partial\pi_i(q_i, z_i) / \partial z_{ik}$, which is the change in the price p_i that a consumer would be willing to pay for a change in charac-teristic z_{ik}, keeping the quality-adjusted price q_i, and therefore utility V_i, constant.

The problem now is to establish the conditions which allow the aggregation of individuals and thus establish that the demands resulting from equation (2) are consistent with those of a representative consumer. Crucial to the solution is the manner by which consumer heterogeneity is modelled. From equation (2), consumer heterogenity is manifested additively in the stochastic term ε_i. Provided that its distribution function $F(\varepsilon_i)$ obeys the conditions derived by McFadden (1983), we can define an aggregate utility function for M consumers with total income Y of the form:

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[3] A difficulty arises when a price collector can no longer obtain a price quotation for a given specification. In such circumstances either the comparison is omitted on the assumption of similar price changes (the *link* method); a replacement similar model is used, the price differential between the two models in the *overlap* period being equated to the quality differential; or estimates of the difference in quality between the 'old' and 'replacement' models are used, the estimates being from the β_k in equation (1) or costs of production plus a profit margin. (Turvey *et al.*, 1989 and Liegey, 1994) Furthermore Diewert (1996) and Reinsdorf and Moulton (1994) have shown the use of the arithmetic mean of relative prices which is the basis of the aggregation can lead to substantial error in the compilation of the CPI.

$$V\left[\Phi_1\left(p_1, z_1\right), \ldots, \Phi_N\left(p_N, z_N\right), Y\right] = M ln \Phi_0\left(Y/M\right) + M ln G\left[\Phi_1\left(p_1, z_1\right)^{-1}, \ldots, \Phi_N\left(p_N, z_N\right)^{-1}\right] \quad (3)$$

which can be further transformed as:

$$\hat{V} = \exp\left(V/M\right) = \Phi_0\left(Y/M\right) G\left[\Phi_1\left(p_1, z_1\right)^{-1}, \ldots, \Phi_N\left(p_N, z_N\right)^{-1}\right]. \quad (4)$$

From the properties of the distribution function of ε_i, G is homogenous of degree one in its arguments and all individuals have unbounded utility functions (i.e. their utilities tend to infinity). The aggregate utility function exhibits weak separability in $\Phi_i\left(p_i, z_i\right)$, a property which arises from the specification of the individual utility function; the dependence of individual preferences on individual attributes can also be overcome in this framework as aggregate demands can still be derived from the utilitarian social welfare function using Roy's identity (McFadden 1983).

The expenditure function corresponding to equation (4) for a given level of utility can be written as

$$U_t = V_t \quad (5)$$

and letting Φ_0^{-1} denote the inverse function of Φ_0, we solve for the level of expenditure $E(p_t,z_t,U_t)$ needed to obtain aggregate utility of U_t as

$$E(p_t,z_t,U_t) = M\Phi_0^{-1}\left[U_t G\left[\Phi_1\left(p_{1t}, z_{1t}\right)^{-1}, \ldots, \Phi_N\left(p_{Nt}, z_{Nt}\right)^{-1}\right]^{-1}\right]. \quad (6)$$

$E(p_t,z_t,U_t)$ measures the expenditure on the varieties $i=1,...,N$ plus the numeraire good Q_{ot}. As the indirect utility function is convex in prices p_t, provided that $ln \Phi_i(p_{it}, z_{it})$ is concave in p_{it}, $i=1,...N$, then the expenditure function is also concave. To generate bounds on the exact hedonic price indexes we also assume that quality adjusted prices are concave in the characteristics.

Denoting the marginal value of each characteristic by $\beta_{it} = \partial\pi_i\left(p_{it}, z_{it}\right) / \partial z_{it}$, with additional assumption that the expenditure function is homogenous of degree one, the base and current period weighted quality-adjusted bounds are given by:

$$\prod_{i=1}^{N}\left(\frac{p_{it}}{\hat{p}_{it-1}}\right)^{s_{it}} \leq \frac{E(p_t, z_t, U)}{E(p_{t-1}, z_{t-1}, U)} \leq \prod_{i=1}^{N}\left(\frac{\hat{p}_{it}}{p_{it-1}}\right)^{s_{it-1}} \quad (7)$$

where $\hat{p}_{it-1} \equiv p_{it-1} \exp\left[\beta_{it-1}(z_{it} - z_{it-1})\right]$

$$\hat{p}_{it} \equiv p_{it} \exp\left[-\beta_{it}(z_{it} - z_{it-1})\right].$$

and s_{it} are the shares in total sales of product *i* in period *t*. The ratio of the expenditure functions in equation (7) is of course the constant-utility index as the ratio of expenditures required to maintain a level of utility as prices and characteristics change between periods *t-1* and *t*.

3. The hedonic regressions: data, model and results

3a. Data

EPOS (electronic point-of-sale) scanners data are collected by bar-code readers 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. There is thus available 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 which stores, and thus 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 store visits of retailers without EPOS systems, the estimated coverage being ".well over 90% of the market", thus providing an excellent data source for measuring price changes (Silver, 1995). The data used were taken from monthly 'hit lists' compiled by GfK Marketing Services Ltd providing, for each model, variables relating to product features: possession of (i) Fastext (Fxt) (ii) Teletext (Txt) (iii) Flatscreen technology (Fst) (iv) Remote control (RC) (v) Remote for 169 (RC169) (vi) Remote for satellite (RCsat) (vii) Nicam (viii)European styling of monitor (COP); (ix) Manufacturer (make) X_i by about 50 brands (x) Size of screen X_j by 18 groups; and (xi) Sales (units) (xii) Price (average) (xiii) Purchases by retailer during period, (xiv) stock at end of period (xv)Unweighted and (xvi) Weighted (by sales) number of stores at which available (Distribution).

Hedonic estimates were derived using monthly data for June 1992 to May 1995. In each month there were about 350 models (observations) each of which had sales of 30 or more in the month, to ensure estimates were not unduly biased by unusual pricing behaviour.

3b. The model

The basic estimated model for a given month was:

$$ln\ P = \beta_0 + \beta_1 Fst + \beta_2 COP + \beta_3 Txt + \beta_4 Fxt + \beta_5 Nicam + \tag{8}$$

$$\beta_6 RC + \beta_7 RC169 + \beta_8 RCSat + \sum_{k=9}^{57} \beta_k X_k + \sum_{k=58}^{75} \beta_k X_k + \varepsilon .$$

The make and screen size dummies each have one make and size excluded to avoid perfect multicollinearity, the benchmark being a 14" Sony TV. Ordinary least squares estimates are used throughout. In particular it should be noted that:

(i) The make dummies capture unmeasured attributes including reliability, screen and sound quality, make effects being commonly used in hedonic regressions (e.g. Berndt *et al.* 1995).

(ii) There is an emerging theoretical literature arguing for the use of linear functional forms as opposed to the log-linear used above (see Arguea *et al.* 1994 and Feenstra 1995). Such theories relies on restrictive assumptions of competitive markets or arbitrage, neither of these being applicable here. Choice of functional form for most studies is held to be an empirical matter and the results of the PE tests in this study supports a log-linear formulation.

(iii) Feenstra (1995) has shown how equation (1) may yield biased estimates of the coefficients due to omitted variable bias arising from the exclusion of price-cost margin variables in markets where prices exceed marginal cost. An innovative feature of this work will be the addition to the right-hand site of equation (1) of proxies for the price cost margin to correct for such bias. We include (SALES) and weighted (by sales) DISTRIBUTION (number of stores a model is sold in) to proxy differential costs (and therefore margins) due to economies of scale effects. In addition STOCKS at end of period is included as a quadratic term, it being likely that models with higher stocks reflect higher demand and thus price-cost margins, though excessive stocks will require destocking via lower prices. Tests for the inclusion of price-cost margin variables (following tests for 'weak' exogeneity) are favourable, estimates of the marginal arguing against perfectly competitive markets. The estimates of the marginal values of characteristics required in equation (7) and adopted in equations (9) and (10) thus benefit from the improved specification of the hedonic function, though the coefficient for these proxies are not themselves used.

(iv) Old models coexist with new models. The new models attract a premium on the old. As such a vintage variable is also derived being, for any make with (and also without) nicam the model with the lower sales. This was found to be collinear with the price-cost margin as expected in theory, the explicit modelling of the price-cost margin outlined above being preferred, results not being included for the vintage effects.

3c. Results of the hedonic regressions

The results of the 36 individual monthly regression equations are available on request from the authors, a summary of the diagnostics being given in Table 1. The $\bar{R}^2$ are consistently high with a mean of 0.92, standard deviation of 0.02 and minimum of 0.84. As noted earlier, Feenstra (1995) and Arguea *et al.* (1994) have argued for the use of a linear functional form contrary to the usual practice of semi-log forms. A non-nested PE test (Maddala, 1989) consistently rejected the null of linearity against the alternative of log-linear specification used in this study, though for 10 out of 36 tests the null of log-linear against linear was rejected, thus finding a preference for log-linear in 20 of the 36 tests and inconclusive results in the remaining 10. Reassuringly the RESET tests show no evidence of misspecification, the *p*-values consistently failing to reject the null at a 5% level. The null of homoskedasticity is rejected in 10 out of 36 months at a 5% level, though *t*-statistics used in the analysis are heteroskedasticity consistent. The use of sales on the right-hand side required a test for the exogeneity, the null of exogenity not being rejected in 27 out 36 months.[4] This suggests that the choice of estimator (OLS) is broadly justified. The null of the exclusion of the price cost margin set of variables was rejected in 8 out of 36 months at the 5% level and 13 months at a 10% level, thus confirming our inclusion of these variables in the model. There was however, consistent evidence of non-normality of residuals (both of skewness and kurtosis) probably due to the effects of a few specialised models or unusual pricing at 'sales' periods.

[4] The reduced form was obtained by including 'purchases' in the set of explanatory variables.

4. Chained, exact quality-adjusted price changes

In this section we provide the results of the estimates of chained, quality-adjusted exact price indexes. The estimates not only utilise a more comprehensive database, but include regularly updated weighting systems to take account of any changes in the 'marginal values' and usage of characteristics which is intuitively appealing, as well as being justified in economic theory as *exact* hedonic indexes or, as an average of base-period and current-period indices, *superlative* hedonic indexes. While in theory the aggregation is over models as given in equation (7), the practice is that individual models of TVs do not continue to exist over long periods; they are not always replaced by manufacturers, or several new models could replace (or coexist with) an existing model. As such we adopt a two-stage procedure of aggregating within a screen size, and then across screen sizes[5]. More formally we adopt the notation of $k^* \equiv k$=58..75 screen sizes in equation (8). The predicted, *quality-adjusted, weighted* average price for (each of the $k=58...75$) screen sizes k^* for the current period c is given by

$$\hat{P}_{k^*c} = \overline{P}_{k^*c}\left[1 - \exp\left[-\left(\beta_0 + \beta_{k*} + \sum_{k=1}^{57}\beta_{k^*kc}\left(\overline{X}_{k^*kc} - \overline{X}_{k^*kb}\right)\right)\right]\right] \qquad (9)$$

and for the base period b by

$$\hat{P}_{k^*b} = \overline{P}_{k^*c}\left[1 + \exp\left[-\beta_0 + \beta_{k^*} + \sum_{k=1}^{57}\beta_{k^*kc}\left(\overline{X}_{k^*kc} - \overline{X}_{k^*kb}\right)\right]\right] \qquad (10)$$

where our estimated β are from a log-linear functional form and $\overline{X}_{kb}$ and $\overline{X}_{kc}$ are weighted mean usage rates of characteristic k for each screen size k^*. Thus if for an individual screen size k^* there are j models with each model having sales of Q_j, then $\overline{X}_{k|k*}$ is given by

$$\overline{X}_{k\,|k*} = \left[\sum_j Q_j X_{jk} / \sum_j Q_j\right] \qquad (11)$$

for each of periods b and c and $\overline{P}_{k*c}$ and $\overline{P}_{k*b}$ are the average prices for each screen size obtained by summing the prices of all transactions in the respective periods (effectively using quantity weights), and dividing by the number of transactions.

A fixed base-period weighted index of price changes between periods b and c is given by

$$\prod_{k^*}\left(\frac{\hat{P}_{k^*c}}{\overline{P}_{k^*b}}\right)^{V_{k^*b}} = I_{b\to c} \qquad (12)$$

[5] It is as if we are redefining the item at a lower level of aggregation, that is a television of a certain size, providing estimates quality-adjusted price changes for each screen size and then aggregating across screen sizes.

and a current-period weighted index by

$$\prod_{k^*}\left(\frac{\overline{P}_{k^*c}}{\hat{P}_{k^*b}}\right)^{V_{k^*c}} = I*_{b \to c} \tag{13}$$

where

$$V_{k^*b} = \overline{P}_{k^*b}\sum_j Q_{k^*jb} \;\; / \;\; \sum_{k^*}\overline{P}_{k^*b}\left(\sum_j Q_{k^*jb}\right)$$

and

$$V_{k^*c} = \overline{P}_{k^*c}\sum_j Q_{k^*jc} \;\; / \;\; \sum_i \overline{P}_{k^*c}\left(\sum_j Q_{k^*jc}\right),$$

that is value shares for each of the screen sizes, with the multiplicative formulation as opposed to traditional (Laspeyres and Paasche) additive formulation being conducive to the semi-logarithmic functional form for the hedonic estimates (Feenstra 1995).

The above is for a comparison between periods *b* and *c*. We can further improve on this by adopting a chained formulation. For example, a chained base-period weighted index comparison between periods *t* and *t +n* using equation (12) is given by

$$I_{t \to t+n} = I_{t \to t+1} * I_{t+1 \to t+2} * I_{t+2 \to t+3} * .... I_{t+n-1 \to t+n} \tag{14}$$

and similarly for a chained current-period weighted index using $I*$ from equation (13) in equation (14). Forsyth and Fowler (1981) and Diewert (1978) have discussed the theoretical and practical advantages of chained index numbers. It should be noted that we update β, the shadow prices of each characteristic, on a monthly basis in equations (9) and (10) and chain the results from each of equations (12) and (13) using equation (14).

Table 2 shows month-on-month and chained actual price changes, base-period weighted quality-adjusted price changes (QAP) and current-period weighted QAP changes. Over the three year-period actual prices of TVs fell by 1.8%, base-period prices fell by 11.3% and current-period weighted QAPs by 11.4%. A *superlative* estimate (Fisher's) would be the geometric mean of these latter two figures.

Figure 1 shows the evolution of the indices. First, the quality-adjustment for the indices is substantial. The comparison is between the change in the actual (weighted) average prices using the data set, and the QAP change adjusting for the fact that some of the change in average prices is due to consumers purchasing bigger sets, sets with more features and more upmarket makes of sets. It provides good estimates of these two concepts of price changes.

Second, the results from the base-period and current-period weighted QAP indices are very similar. This is to be expected from theory since we found the parameters to be relatively stable (Feenstra 1995, 646).[6] Furthermore the difference between the measures arises from a substitution bias as consumers substitute away from features and makes with relatively large positive price changes. However, for consumer durables we would not expect consumers to be well-informed as to relative price *changes*, their purchases being infrequent, never mind the implicit changes in the shadow prices of features and makes. Nonetheless the base-period weighted estimate is generally lower than the current-period weighted estimate as would be expected from theory, though the differences are very small. As such, on the above evidence, a base-period weighted index would not only accord with current RPI methodology, but yield a good approximation to a *superlative* index of QAP changes.

Conclusions

This paper has shown how scanner data can be used to estimate exact, quality-adjusted hedonic indexes which correspond to constant-utility hedonic price indexes derived from economic theory, improving on estimates from the *matched models* and *direct* methods. The example is for TVs, though the data source is available for a wider range of goods whose sales are recorded electronically. The data source also allows a correction for omitted (price-cost margin) variable bias in the hedonic regression where prices are above marginal cost; estimates of the marginal values of characteristics benefit from this fuller specification. This is something of an innovation in such work. The findings reveal substantial differences between changes in average prices and quality-adjusted prices, though due to relative parameter constancy, little difference between (chained) base and current period weighted estimates, either of these providing good estimates of a superlative (in a Diewert, 1976 sense) index.

[6] Overall within years tests of stability did not reject the null at a 5% level. The null of stable coefficients within each of July 1992/ June 1993, 1993/94 and 1994/95 was tested using a likelihood ratio test for a constrained (coefficients held constant across months) against an unconstrained model yielding test statistics of 657.12, 614.10 and 542.88 respectively, $\chi^2_{0.05,840} = 908.24$, thus not rejecting the null. However for between years the null was rejected, though many of the coefficients on makes when tested for stability using slope dummy variables for the years were found to be stable even with a Bonferonni adjustment to the *t*-statistic (Hendry 1995, 491) Detailed results are available from the authors on request.

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