Hedonic Quality Adjustments for Non-Comparable Items for Consumer Price Indices

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Abstract: This paper provides the results of an hedonic regression for UK televisions formulated as an adjustment matrix to provide a practical tool for quality adjustment to complement the matched models method. The study argues that hedonic adjustments are particularly suitable for consumer durables where 'pent-up' price changes at the time of model changes can lead to bias in the *link* or *overlap* methods. The study is of particular interest because first, the extensive coverage of scanner data benefits the econometric estimates of the hedonic regression equations, and second, allows jointly occurring characteristics to be identified. Furthermore the estimated equation benefits from the inclusion of price-cost margin variables, the omission of which Feenstra (1995) has shown may result in omitted variable bias to the coefficients on the characteristics. Finally, the 'adjustment matrix' formulation is deemed to be new and suitable in this context.

1. Introduction

The concern of this paper is with the practical use of the results from hedonic regressions to adjust for quality changes in the compilation of Consumer Price Indexes (CPIs). Recent estimates of the bias resulting from an inability to properly incorporate such changes in the US, 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.

The matched model method has been adopted by statistical offices to militate against bias from quality changes. Price collectors note the pertinent features of an item, for example, a 21" Sony TV with nicam and fastext (or its model number) and then compare its price with the price of this same model in subsequent month(s). If a comparable model is not available the method breaks down. In such circumstances use is either made of first, the link (deletion) approach in which the price change is imputed as the average change of similar items (possibly by type of store or geographical area). Second, the overlap method which is based on finding a closely related model (e.g. a JVC 21" with nicam and fastext) and assuming the difference between its price and the 'missing' price in the overlap month reflects quality differences between the two models. The quality component of the price change can thus be removed. While these approaches are generally recommended and used (Turvey et al., 1989 and Armknecht and Weyback, 1989) there are particular drawbacks for consumer durables such as electrical and white goods where price changes, due to menu costs, are not made regularly but stored up for model changes, with unusually low prices being necessary when old models need to be 'dumped' for new ones. Assumptions of changes and price overlaps reflecting quality changes may be quite unrealistic under such circumstances.

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The final approach to dealing with substituting items which are not strictly comparable is to make a direct estimate of the quality components of price either by using the results from hedonic regressions or estimates of direct production costs for characteristics, adjusted for profit margins (Turvey et al, 1989). The concern of this paper is with the use of hedonic regression to provide estimates of quality adjustment for measuring price changes of televisions sets in the UK.

The paper first, outlines why the link and overlap approaches are prone to bias when measuring price changes for consumer durables such as television sets. It then provides the results of an hedonic regression using scanner data. While the use of such data has been advocated as a source for estimating basic components of a cost-of-living index (Silver, 1995), this extension to show how it might complement the existing matched methods and data sources for quality adjustment is of further interest and practical relevance to statistical offices. Second, the specification of the hedonic regression is successfully developed to include variables that proxy the price-cost margin. Feenstra (1995) has shown that the coefficients on the characteristics may be biased due to omitted variables when markets are not competitive. The direct inclusion of variables related to the price-cost margin is shown to improve the model. Third, collinearity is recognised as being particularly problematic in this context (Gordon, 1990 and Griliches, 1990) since improved features of goods such as TVs are often introduced together. There is thus a need to not only identify the relevant characteristics, but also their relationship with others and scanner later is shown to be particularly useful in this context. Finally, we provide results for adjusting for quality differentials by way of a novel 'adjustment matrix' derived from the coefficients of the estimated hedonic regression.

The paper is organised as follows: Section 2 provides a brief outline of the use of hedonic regressions for quality adjustment and also argues the case for using hedonic adjustments for consumer durables. Section 3 provides an outline of the data, model and the results of the estimated equation. The practical tool for quality adjustment- the adjustment matrix- is given in section 4, a summary being provided in section 5.

2. The use of hedonic regressions for quality adjustment

The hedonic approach involves the estimation of the implicit, shadow prices of the quality characteristics of a product. 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}):

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

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). A semi-logarithmic functional form is used here, though Feenstra (1995) and Arguea et al (1994) have recently argued for a linear form, though this will be considered later.

There are three main methods for estimating quality-adjusted price changes. First, the direct method includes in the specification of equation (1) intercept dummy variables associated with each time period providing estimates of the change in price (or its logarithm) arising from a change in the time period having controlled for the effects of changes in quality (via $\sum_{j=1}^{m} \beta_j X_{kj}$). The β_j coefficients need not of course be fixed, by augmenting the model with dummy slope coefficients, changes in the consumer's valuation of the characteristics over time, can be identified.

There is a plethora of studies of the above form as considered by Griliches (1990), Triplett (1990) and Gordon (1990) and more recently Berndt et al (1995), Nelson et al (1994), Gandal (1994 and 1995), Lerner (1995) and Arguea et al (1994). However, the implicit aggregation treats each observation (model of TV) equally which, with vastly different sales, goes against the spirit of index number compilation.

The second method is the estimation of exact hedonic indexes, which has the advantage of utilising a weighting system which corresponds to a constant-utility formulation from economic theory (Feenstra, 1995). Such indexes provide estimates of the change in expenditure required to maintain a constant level of utility from goods with constant quality is measures by the characteristics. The data requirements are more substantial for this approach, though preliminary estimates are available (Ioannidis and Silver, 1996) and are the subject of current research.

Finally, the approach adopted in this paper is to use hedonics to complement the current matched models method used by statistical offices. Such a methodology, in spite of the advantages of the exact approach, is likely to be utilised for many years and there is a practical need to develop the use of hedonics to minimise errors from the substitution of non-comparable items. Diewert (1996) has provided a model to show the extent of such errors which result in bias. The existing item may be less 'efficient' than the new substituted item. For example, if the efficiency decline missed due to non-comparability was 10%, the inflation rate 5% per annum, the share of disappearing models replaced by new models 10% then the bias would be approximately 1% per annum.

The need for hedonic estimates is stressed since with consumer durables such as electrical and electronic goods and white goods models change infrequently prices irregularly and to coincide with model changes. When 'pent-up' prices are increased they are unusually high. However, in the 2-3 months preceding the model change, prices may fall as the old models are 'dumped'. The timing of such model changes for the existing and substitute models may not be the same. As such the link (or deletion) approach will ignore the price change for a new model and will implicitly assume it follows the average price changes of such items. The effect of this is to exclude much of the 'pent-up' price changes when they occur, thus potentially seriously biasing the CPI.

When the old and new model coexist, the overlap method is used and the new model's price (P_t^*) can be compared with the old model (P_t) and a new base-period price can be defined for comparison with the new model, i.e., $P_b^* = P_b(P_t^*/P_t)$. This assumes the difference in price reflects the difference in utility derived from the different models. However, if the old model is being effectively 'dumped', the price of the old model may not be reflective of the difference in specification, but the need to clear the market so as the old model does not coexist with the new and 'spoil' the market.

Our focus must be on determining estimates of the adjustment or 'shadow price' of quality differences taking into account the problems identified above. This we approach through hedonic regressions which with the inclusion of 'price-cost margin' variables explicitly model such effects as 'dumping'. Such augmented hedonic regressions allow us to first, identify characteristics likely to be important in explaining price differences. We do this in conjunction with scanner data on the importance, by sales value, of the characteristics. For example, we may find that a screen size of 8" has a quality premium. However, if very few of these are sold we will not draw it to the attention of price collectors, since they are unlikely to come across it. Thus using tables of the relative importance of characteristics by sales (Tables 1 and 2) and the coefficients from the regression, we can identify for the design of data retrieval systems the important price-determining features. Second, we use the coefficients from the hedonic regression as estimates of the importance of such characteristics to adjust for price changes (Liegey, 1994). The results are given below for TVs.

3. Data and estimated equation

3a. Data

The data used were taken from monthly 'hit lists' compiled by GfK Marketing Services Ltd from the scanner (EPOS) data supplied by retail outlets. The raw scanner data amounts to around 3 million purchase incidents per year. These are compiled for each model of TV in each month to provide a listing of the 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 (RC sat); (vii) Nicam; (viii) European styling of monitor; (ix) Manufacturer (make) by about 50 brands; (x) Size of screen by 18 groups (xi) Sales (units) (xii) Price (average) (xiii) Purchases by retailer during period, (xiv) Stock held at end of period (xv) Unweighted and (xvi) Weighted (by sales) number of stores at which the model is available.

Hedonic estimates were derived using monthly data for July 1994 to June 1995 inclusive, corresponding to the UK period for their Household Expenditure Survey. 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:

$$\begin{aligned} \ln P = {} & \beta_0 + \beta_1 Fst + \beta_2 COP + \beta_3 Txt + \beta_4 Fxt + \beta_5 Nicam + \\ & \beta_6 RC + \beta_7 RC169 + \beta_8 RCSat + \sum_{j=9}^{57} \beta_j X_j + \sum_{j=58}^{75} \beta_j X_j + \varepsilon \end{aligned} \qquad (2)$$

The make and screen size dummies each have one make and size excluded to avoid perfect multicollinearity, the benchmark being a Sony 14". Ordinary least squares estimates are used throughout. Details of the rationale behind the formulation in equation (2) are given in Ioannidis and Silver (1996). Briefly:

(i) The make dummies capture unmeasured attributes including reliability, screen, sound quality and the cumulative effect of advertising which may result from oligopolistic market structures, make effects being commonly used in hedonic regressions (e.g. Berndt, Griliches and Rappaport, 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 Feenstra, 1995 and Arguea, Hsiao and Taylor, 1994). Such theory 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 and RESET tests in this study and the Bera-McAleer test in Ioannidis and Silver (1996) support a log-linear formulation.

(iii) Equation (1) may yield biased estimates for the coefficients due to omitted variable bias arising from the exclusion of price-cost margin variables. An innovative feature of this work will be the addition to the right-hand site of equation (1) of ln(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 will be 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 show them to argue against perfectly competitive markets.

3c. Results of the Hedonic regression

Tables 3 provides the results for July 1994 to June 1995 using monthly data on each model, a total of 3,873 observations. Each coefficient is constrained to be the same for each month data being pooled. The only concession to monthly variation is the inclusion of monthly intercept dummies. The coefficients within the year were tested for stability, the likelihood ratio test statistic for the constrained model against an unconstrained model with monthly dummy slope coefficients being 542.88 with $\chi^2_{0.05,840} = 908$, the null not being rejected at a 5% level. In any event the model performed well, the $\overline{R}^2$ being 0.92: over 90% of variation in price between models of TVs is explained by the regression.

The *t*-statistics were generally statistically significant at a 5% level (and less) and had the correct signs, possession of a feature leading to increases in price. The COP styling variable was, as expected, not significant being important in continental European markets. The makes are benchmarked on Sony, there being an almost consistent set of negative signs (where statistically significant) as expected. The sizes are benchmarked on a 14" and again have the expected positive signs. The monthly intercepts dummies (benchmarked on June) are generally not statistically significant at a 5% level. These are usually taken to be estimates of quality-adjusted price changes - changes in the prices in a month having partialled out for the effects of quality changes. However, for these regressions we have included price-cost margin variables which have successfully picked up much of this variation. These have the correct signs and are statistically significant.

The magnitude of the coefficients accord with expectations. Fxt for example has a 16% price premium in Table 3, Txt 13% and nicam 8%. However, as will be shown in the next section the coexistence of Fst and nicam suggests that while the coefficients will not be individually, precisely estimable linear combinations are (Maddala, 1989: 232) An Akai model was found to be worth 25% less than a Sony, though leading Japanese makes such as JVC, Mitsubishi, Hitachi and Toshiba have much smaller disparities. A 6" screen has a 16% mark-up on a 14" and a 21" a 45% mark-up.

Other diagnostics were reassuring. The data were ordered by sales in each month, though the Durbin-Watson showed no evidence of any cross-section 'autocorrelation'. There was evidence of heteroskedasticity (Breusch-Pagan rejected the null at a 5% level in each case) for this constrained model, though we adjusted the standard errors (and thus tests) to ensure they were heteroskedasticity-consistent. We tested separately for excess skewness and excess kurtosis of the residuals and while there was evidence of excess kurtosis, there being no evidence of excess skewness at a 5% level. Other diagnostics include F-tests for the exclusion of the price-cost margin variables, the tests rejecting the null of these variables having no effects, thus justifying their inclusion. It may be argued that the inclusion of sales would generate simultaneity bias; however the F-test for the weak exogeneity of sales rejected this. The PE non-nested tests of log-linear against linear together supported the use of a log-linear formulation and the RESET test results for misspecification bias were also favourable.

The econometric and theoretical issues are not trivial and while some of these have been considered in section 3, Rosen (1974), Gordon (1990), Griliches (1990), Triplett (1990), Arguea et al (1995), Berndt et al., (1995) and Silver (1996) discuss this in more detail.

4. Using the results: tables and the adjustment matrix

There is much too much information in Table 3, in terms of the number of models and screen sizes, to be practically handled by price collectors. We will use two criteria to reduce the variable list. First, we consider how substantial (and relevant) each of the features/ makes/ screen sizes are. Second, their impact on pricing via the coefficients.

Table 1 shows the number of sets sold by different features, makes screen sizes, and Table 2 by combinations thereof. Consider Table 2. If the representative sets are taken to be 14" and 21" (which can be seen to account for 64% of sales in 1994/95) (Table 1), then Table 2 shows that for 14" sets our main concern will be with sets without nicam (99.7% of sales) and without any features (Fst, Fxt or Txt - 67% of sales); without nicam and with Txt (8.7% of sales) and without nicam but with Fst (12.7% of sales). As regards 21" sets our main concern is with those possessing nicam as each of these are substantial groups. As regards features, hardly any have no features, yet most of the sets possessing nicam also have Fst and Fxt, as would be expected from top-of-the-range sets. For non-nicam 21" our sets concern is with those possessing (i) Fst, (ii) Fst and Txt (iii) Txt, Fst and Fxt. TV sets with screen size of 24" invariably have both Fst and Fxt as befits larger, up-market sets. Table 1 shows only 14", 21" and 24" sets to be of major importance in terms of sales.

Features not included in Table 2 are remote controls. Almost all sets now have remote controls and while a very few sets have RC169 and RCsat, these may well increase in number and as we will see, their coefficients are relatively high.

As regards makes, Table 1 shows only those with sales in 1994/95 of not less than 0.1% of the total, thereby leaving us with 31 makes. The argument is that collectors are unlikely to come across the other makes in shops, thus detailed information on adjustment are less useful.

The second criterion is the shadow price or 'worth' of the features/ makes/ screen sizes. Table 3 provided the regression results. Of the features Fst had the smallest coefficient, each of the other features being of some importance. We argue for the inclusion of Fst in spite of this. Table 2 showed how large sets and Fst were linked for example, 99% of 21” sets possessed Fst. However, for 14” sets the position was reversed: only 17% of such sets possessed Fst and these, by and large, did not have nicam. The results suggest the likelihood of some collinearity between Fst, nicam and screen size. While the coefficients may be affected by this, the predicted values will not and, as it will be seen, it is the joint effect which is the basis of our methodology.

As regards the coefficients on the three major screen sizes these are all substantial (with respect to a 14”) and argue for their use. Note that 21” sets have an estimated 45% premium on a 14”, set while a 24” set has a 78% premium. Thus any collector substituting a 24” set for a 21” set will require an adjustment for differential screen size.

Finally, the coefficients on makes should be of interest for price collectors with regard to substituting one make for another. The coefficients are estimates of the difference between each make and the benchmark, Sony. They are not estimates of how generally important each make is, for this in itself is meaningless: the difference between Panasonic and Sony for example may be small, which makes it unimportant as a make vis-à-vis Sony, but it may be very important vis-à-vis Tatung.

Table 3 is too complex for practical use. As such Table 4 has been devised from Table 3 as a matrix of adjustment factors. It is, hopefully, self explanatory, allowing a price collector using, for example a 14” Bush to adjust to a comparison with a 14” Hitachi (if the Bush is not available) via an adjustment factor by multiplying by the cell entry from the column to the row. Similarly, adjustments for size of screen and possession of combinations of features can be undertaken as shown in the examples in Table 4. The compilation of Table 4 is of course straightforward. The coefficient on JVC for example is benchmarked on Sony as the omitted variable, i.e. is equal to ($\beta_{JVC} - \beta_{SONY}$). Similarly the coefficient for Panasonic is given by $(\beta_{PANASONIC} - \beta_{SONY})$. The difference in logarithms of prices between JVC and Panasonic is thus the difference between these two coefficients, the exponents of such differences being the values in the table.

As regards the practical use of the matrix, while it is in itself relatively easy-to-read, its use by price collectors themselves may be impractical. This is especially the case if such matrices are to be used for a wide range of items. The actual adjustment may be better undertaken by ‘desk officers’, with the price collectors making notes of the nature of the change in specification. Where data are collected by hand-held electronic retrieval systems (such as in the UK) it would be possible for the adjustments to be programmed into the system and adjustments made on the basis of a series of prompts.

Summary

There is a practical need to complement the existing matched models method for CPIs with a mechanism for quality adjustment for instances of non-comparable matches. For goods such as TVs where price changes are 'pent-up' to accord with model changes, the hedonic approach provides a more satisfactory approach to the link and overlap methods. We provide an example for TVs. Our estimates benefit from the use of scanner data with its extensive coverage and the satisfactory inclusion of price-cost margin variables to avoid omitted variable bias, as shown in a theoretical context by Feenstra (1995). The results prove to be generally satisfactory. Descriptive results from scanner data to identify characteristics likely to be substantial, and characteristics likely to be collinear (introduced at the same time) along with a specially designed 'adjustment matrix' using the coefficients from the hedonic regression, are argued to provide a useful, practical tool for such adjustments.

References

Advisory Commission to Study the Consumer Price Index (1995), Towards a More Accurate Measure of the Cost of Living, Interim Report to the Senate Finance Committee, Washington DC.

Arguea, N.M., Hsiao, C. and Taylor, G.A. (1994), Estimating Consumer Preferences using Market Data- An Application to US Automobile Demand, Journal of Applied Econometrics, 9, 1-18.

Armknecht, P.A. and Weyback, D. (1989), Adjustments for Quality Change in the US Consumer Price Index, Journal of Official Statistics 5(2), 107-123.

Berndt, E.R., Griliches, Z. and Rappaport, N.J. (1995), Econometric Estimates of Price Indexes for Personal Computers in the 1990s, Journal of Econometrics, 68, 243-68.

Dalén, J. (1992), Computing Elementary Aggregates in the Swedish Consumer Price Index, Journal of Official Statistics, Vol. 8, No.2, 129-147.

Diewert, W.E. (1976), Exact and Superlative Index Numbers, Journal of Econometrics, 4,115-45.

Diewert, W.E. (1983), The Theory of the Cost-of-Living Index and the Measurement of Welfare Changes. In Price Level Measurement, W.E. Diewert and C. Montmarquette (editors), Ottawa: Statistics Canada, 163-233.

Diewert, W.E. (1996), Sources of Bias in Consumer Price Indexes, Discussion paper No.DP-96-04, School of Economics, University of New South Wales.

Feenstra, R.C. (1995), Exact Hedonic Price Indexes, Review of Economics and Statistics, LXXVII, 634-54.

Forsyth, F.G. and Fowler, R.F. (1981), The Theory and Practice of Chain Price Index Numbers Journal of the Royal Statistical Society, A, 144, 2, 224-47.

Gandal, N. (1994), Hedonic Price Indexes for Spreadsheets and Empirical Test for Network Externalities, RAND Journal of Economics, 25,1, 160-170.

Gandal, N. (1995), Competing Compatibility Standards and Network Externalities in the PC Market, Review of Economics and Statistics, LXXVII, 599-608.

Gordon, R.L. (1990), The Measurement of Durable Goods Prices, Chicago: University of Chicago Press.

Griliches, Z. (1990), Hedonic Price Indexes and the Measurement of Capital and Productivity: Some Historical Reflections. In E.R. Berndt and J.E. Triplett (eds.), Fifty Years of Economic Measure-ment: The Jubilee Conference of Research in Income and Wealth, NBER Studies in Income and Wealth, Vol.54, Chicago: University of Chicago Press.

Halvorsen, R. and Pollakowski, H.O. (1981), Choice of Functional Form for Hedonic Price Equations, Journal of Urban Economics, 10, July, 37-49.

Ioannidis, C. and Silver, M.S. (1996), Estimating Exact Hedonic Indexes: An Application to UK Television Sets, Mimeo, University of Wales, Cardiff.

Lebow, D.E, Roberts, J.M. and Stockton, D.J (1994), Monetary Policy and 'The Price Level', Federal Reserve Board, Washington DC.

Liegey, P.R. (1994), Apparel Price Indexes: Effects of Hedonic Adjustment, Monthly Labor Review 117, May 38-45.

Maddala, G. (1989), Introduction to Econometrics, New York: Macmillan Publishing.

Lerner, J. (1995), Pricing and Financial Resources: An Analysis of the Disk Drive Industry, 1980-88, The Review of Economics and Statistics, LXXVII 585-598.

Nelson, R A., Tanguay ,T. L. and Patterson, C.D. (1994), A Quality-Adjusted Price Index for Personal Computers, Journal of Business and Economic Statistics, 12, 1, 23-31.

Rosen, S. (1974), Hedonic Prices and Implicit Markets: Product Differentiation in Price Competition, Journal of Political Economy, 82, 34-5.

Shapiro M.D. and Wilcox, D.W. (1996), Mismeasurement in the Consumer Price Index, National Bureau of Economic Research Working Paper 5590, Cambridge, Massachusetts.

Silver, M.S. (1996), Quality Prices and Hedonics, International Journal of the Economics of Business, 3, 3, 351-366.

Silver, M.S. (1995), Elementary Aggregates, Micro-Indices and Scanner Data: Some Issues in the Compilation of Consumer Price Indices, Review of Income and Wealth, 41, 4, 427-38

Szulc, B.J. (1989), Prices Indices Below the Basic Aggregation Level, in Turvey, R. et al., Consumer Price Indices, An ILO Manual, 167-178, Geneva: International Labour Office.

Triplett, J.E. (1990), Hedonic Methods in Statistical Agency Environments: an Intellectual Biopsy, In E.R. Berndt and J.E. Triplett (eds.) Fifty Years of Economic Measurement: The Jubilee Conference on Research in Income and Wealth, NBER Studies in Income and Wealth, Vol 56, Chicago: University of Chicago Press.

Triplett, J.E. (1996), Estimating Basic Components in a Cost of Living Index: A Review of Formula, or Basic Component Bias. Mimeo, Bureau of Economic Analysis, Washington DC.

Turvey, R. et al. (1989), Consumer Price Indices: An ILO Manual, Geneva:International Labour Office.

Table 1. Number of TVs sold June 1994-July 1995

	Number sold	% of total sold	Number of observations
Features			
Flat Screen technology	1,297,896	60.7	2,566
Style	873,161	40.9	1,127
Fastext	1,160,912	54.3	2,275
Teletext (excl. Fxt)	221,373	10.4	531
Nicam	579,193	27.1	1,444
Remote Control	2,117,876	99.1	3,749
RC169	2,984	0.1	31
RCSAT	2,752	0.1	19
Major Makes			
Akai	5,677	0.3	40
Akura	24,720	1.2	90
Alba	22,139	1.0	66
Amstrad	22,241	1.0	66
Beko	25,847	1.2	92
Beon	12,107	0.5	43
Bang and Olufsen	5,568	0.3	63
Bush	62,125	2.9	138
Crown	3,807	0.2	22
Daewoo	10,004	0.5	58
Decca	4,821	0.2	38
Ferguson	166,173	7.8	219
Goldstar	26,439	1.2	114
Grundig	19,873	0.9	151
Harwood	5,174	0.2	17
Hinari	3,254	0.1	25
Hitachi	160,351	7.5	263
JVC	74,035	3.5	126
Minoka	14,864	0.7	20
Mitsubishi	138,053	6.4	229
Nei	5,929	0.3	47
Nokia	26,150	1.2	91
Panasonic	235,292	11.0	272
Phillips	144,097	6.7	245
Pye	33,858	1.6	23
Samsung	132,315	6.21	189
Sanyo	99,956	4.71	132
Sharp	66,783	3.1	169
Sony	319,508	15.0	322
Tatung	20,320	1.0	141
Toshiba	235,972	11.0	320
Others(40 makes)	6,014	0.1	-
Screen sizes			
6”	1,487	0.0	15
10”	19,978	0.9	43
14”	793,324	37.1	910
15”	3,8160	1.8	107
16”	7,267	0.3	18
17”	25,293	1.2	59
19”	4,879	0.2	59
20”	152,444	7.1	381
21”	572,582	26.8	975
24”	326,632	15.3	709

	Number sold	% of total sold	Number of observations
25”	1,031	0.0	9
26”	2,185	0.1	14
27”	82,256	3.8	354
28”	92,649	4.3	188
30”	12,815	0.0	16
32”	915	0.0	16
33”	36	0.0	1
35”	3,193	0.1	5

Table 2. Number of sales, by features, 1994/95, thousands of sets

Features			14”		20”		21”		24”	
Fst	Fxt	Txt	Nicam	Not Nicam	Nicam	Not Nicam	Nicam	Not Nicam	Nicam	Not Nicam
X	X	X	0.1	1,860.0	0.2	197.4	0.0	3.3	0.0	0.1
X	X	√	4.9	239.9	8.4	116.6	1.3	7.2	2.4	0.0
X	√	X	0.2	196.8	38.1	108.4	7.6	0.9	0.2	13.5
√	X	X	0.0	351.8	0.0	7.0	4.9	270.7	2.3	11.1
√	X	√	2.4	81.0	0.1	1.3	64.1	271.6	21.9	32.1
√	√	X	0.1	31.7	3.6	1.2	603.3	802.7	688.4	341.4
All Sets (a)			7.9	2,760.8	50.3	431.9	681.8	1,356.4	715.2	398.3

Totals may not equal the sum of the components due to rounding.
x denotes a characteristic not included
√ denotes a characteristic included

Table 3. Hedonic regression results for televisions, 1994/95

Variable	Estimated coefficient	t-statistic	Variable	Estimated coefficient	t-statistic
C	5.50696	113.181	PHI	-0.087308	-5.03911
			PRO	-0.506561	-15.8255
FEATURES			PYE	-0.219971	-8.95279
FST	0.014228	0.652157	ROB	0.01597	0.756735
COP	-0.046041	-1.60745	SAL	-0.20267	-1.37322
TXT	0.1319	14.3247	SAM	-0.240248	-14.1112
FXT	0.15558	20.1235	SAN	-0.19163	-11.9493
NICA	0.081932	10.0398	SHA	-0.181378	-9.99322
RC	-0.050511	-1.6868	SSA	-0.474595	-19.703
RC169	0.24125	3.79747	TAT	-0.143321	-6.22422
RCSAT	0.103822	1.49463	TOS	-0.071976	-4.54967
MAKES			**SCREEN SIZES**		
ACA	-0.27881	-14.8932	SZ06	0.164453	4.94202
AIK	-0.17512	-7.42341	SZ10	0.242535	8.7233
AKA	-0.25036	-6.83175	SZ15	0.084727	3.40995
AKU	-0.30501	-8.72263	SZ16	0.197657	7.70469
ALB	-0.279849	-6.95457	SZ17	0.256568	10.2949
AMS	-0.33018	-9.74391	SZ19	0.383684	7.15644
BEK	-0.357101	-16.3421	SZ20	0.314494	10.372
BEO	-0.409971	-21.4332	SZ21	0.44906	11.2421
BO	0.562217	14.2936	SZ24	0.782434	19.2443
BPL	-0.317661	-5.74768	SZ25	0.954182	24.8817
BUS	-0.346065	-16.9024	SZ26	0.745248	17.4269
CRO	-0.393519	-13.6452	SZ27	1.01958	23.9339
DAE	-0.266662	-12.1496	SZ28	1.12005	26.0513
DEC	-0.322397	-14.0796	SZ30	1.60889	31.0465
DEF	-0.23918	-12.4935	SZ32	1.80328	32.248
DUA	-0.321747	-17.5657	SZ33	2.02499	27.817
FER	-0.193231	-11.4948	SZ35	1.29612	7.83554
FIN	0.038698	0.903295	**MONTHLY INTERCEPTS**		
GOL	-0.239429	-12.653	JUL	0.013879	1.09672
GRU	-0.038275	-1.5058	AUG	8.25E-02	0.663607
HAR	-0.495091	-18.7324	SEP	9.75E-02	0.780853
HIN	-0.344904	-9.59614	OCT	0.013833	0.975885
HIT	-0.099366	-6.07979	NOV	0.013275	1.12271
JVC	-0.169149	-9.08347	DEC	0.026865	2.30119
KYO	-0.399298	-20.8333	JAN	5.90E-02	0.46677
MEM	-0.379228	-18.35	FEB	3.21E-02	0.260736
MIN	-0.373597	-17.6288	MAR	-0.021441	-1.62701
MIT	-0.145533	-9.77201	APR	-0.023409	-1.80542
NEI	-0.457932	-19.816	MAY	-0.024147	-1.77221
NIK	-0.311314	-8.83125	**PRICE-COST MARGIN**		
NOK	-0.114987	-4.38486	LSALES	-0.024749	-5.85211
OPT	-0.359882	-15.6271	STOCK	-1.13E-00	-2.05973
ORI	-0.228711	-2.83024	STOCK2	-1.02E-01	-3.36E-02
OSU	-0.538842	-27.6359	WDIST	0.27996	6.89905
PAN	-0.057917	-3.56208			

DIAGNOSTICS table 3

Number of observations: 3,873 (degrees of freedom =3786)
Standard error of regression=162
Adjusted R-squared =0.923

Specified tests:
Test for the exclusion of price-cost margin variables $F_{4,3786}$=19.50*

Test for the exogeneity of "sales" $F_{1,3786}$ =.1180

Misspecification tests:

Breusch-Pagan statistic=309.1*
Durbin-Watson statistic=1.94
PE non-nested test for log-linear:t-statistic=1.91
PE non-nested test for log-linear:t-statistic=10.53*
RESET $F_{3,3780}$ =.0189

Excess skewness $t_{1,3780}$=.0822
Excess kurtosis $t_{1,3786}$=-38.0141*

*indicates rejection at 5%.

The critical values for the test statistics are:
$F_{1,3786}$*=3.841 $F_{3,3786}$*=2.605 $F_{4,3786}$=2.372
$t_{1,3786}$=1.96 Chi-sq,86=113.1