On The Stability of Hedonic Coefficients and their Implications for Quality-Adjusted Price Change Measurement

Saeed Heravi and Mick Silver

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Cardiff Business School
Cardiff University
Colum Drive
Cardiff CF10 3EU
U.K.

Telephone: +44 (0)29 2087 4276
Facsimile: +44 (0)29 2087 4419
Email: Silver@cardiff.ac.uk

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ABSTRACT

This paper uses scanner data to provide estimates from hedonic regressions of the coefficients on brands and characteristics of products and the outlet-type in which the transaction transpired. However, the concern here is with tests of the stability of these estimates and, if rejected, their evolution over time. Estimated hedonic regression equations have an indirect role to play in the compilation of consumer price indices and any instability has implications for their proper use. However the main concern here is with the more direct determination of quality-adjusted price changes using hedonic regressions to control for quality changes. The focus is on two methods: hedonic imputations which value a base period basket of characteristics, using both base period and current period hedonic coefficients, to derive a Laspeyres index. Equivalent Paasche indices are derived using a current period basket of characteristics. In both instances the change in coefficients are the essence of the price change, the measures differing in their use of which month's characteristics to value. Substantial divergence between the equally justifiable Laspeyres and Paasche indices are taken as evidence not to use either one alone. The second method uses a hedonic regression with price changes being estimated from the coefficients on dummy variables for time. In this case the parameter stability is not part of the measure. Indeed, the slope parameters are constrained to be the same. This method is argued to be preferable to either Laspeyres or Paasche hedonic imputed indices when the results diverge significantly. The study uses extensive scanner data on a monthly basis over January 1998 to December 1999 for five consumer durables: washing machines; dishwashers; television sets; vacuum cleaners, and cameras. Tests of stability are undertaken and hedonic quality-adjusted indices are calculated using both methods, to help ascertain whether any instability matters for such measures. The concept of stability is extended to examine, for television sets, parameter stability across three countries using results from Heravi, Heston and Silver (2001).

Keywords: Hedonic regressions; parameter stability; scanner data; product differentiation; outlet types.

1. INTRODUCTION

There is a natural interest in, and extensive literature on, product differentiation in the marketing and economics literature. In both cases theory argues for the likely extensive use by firms of what (Bergen *et al*., 1996) terms, 'branded variants' of products, and that products, differentiated by brands and quality characteristics will command quite different prices (Motta, 1993, Shaked and Sutton, 1982). Rather than there being a tendency for the Walrasian law of one price to operate, there may be imperfect, monopolistic competition by multi-product firms producing differentiated varieties – something borne out by the scanner data on consumer durables in this study.

The influence on price of branding and quality-differentiation has an empirical side. Hedonic regressions relate observed prices on the left hand side to a quality characteristic on the right hand side. The resulting coefficients arise from the outcome of optimisation behaviour by consumers and producers in characteristics space (Rosen, 1974, Triplett, 1988). There is an extensive empirical hedonic literature covering a diverse range of products, including consumer durables, housing, clothes, food and wine, baseball players and even partner-search. In economics hedonic regressions correspond to Lancaster's (1971) theory of demand wherein items are considered in terms of tied bundles of their characteristics. Moreover, they have a specific role in the measurement of inflation since account has to be made of the changing quality of the evolving bundle of goods (Greenlees, 2000).

Little attention has been given to the stability of the estimated hedonic coefficients over time. A notable exception to this is Berndt and Rappaport. (2001), which used extensive annual data for personal computers over the period 1976 to1999, and found evidence of parameter instability. For example, from 1987 to 1999 they found for desktop PCs the null hypothesis of adjacent-year equality to be rejected in all but one case. And for mobile PCs the null hypothesis of parameter stability was rejected in eight of the 12 adjacent-year comparisons. The study continued to contrast the results from quality-adjusted indices based on restricting parameters to be constant, to those that relax this restriction. Quality-adjusted prices indices were also calculated in a way that identified the change in average prices over time as the characteristic quantity-weighted change in the shadow prices (coefficients) of each characteristic. Parameter stability over time in this case reflects no price change in the characteristics concerned. The extent of any instability is the essence of the price measurement. The quantities of characteristics had to be held constant in such calculations, allowing base period weighted Laspeyres and current period Paasche indices to be calculated.

Since both formulae are equally justifiable, the greater the Laspeyres-Paasche spread, the more uncertainty there is as to the 'true' measure.

Ioannidis and Silver (1999), Silver and Heravi (2001 and 2002) undertook a similar analysis and estimated Laspeyres, Paasche and Fisher hedonic indices allowing for changing parameters and mix of quality-characteristics for television sets and washing machines. They found sizeable differences in the results. Heravi, Heston and Silver (2001) tested for parameter stability and estimated Laspeyres, Paasche and Fisher hedonic indices for *cross-country* price comparisons, the results on parameter stability being summarised here in section 7. Yet the results of such studies were confounded by changes in other factors: for example, chained indices were used so any instability preceding the comparison impinged on the index. Furthermore the aggregation was undertaken in two stages with simple sales weighted price changes between strata being combined with hedonic-adjusted measures within strata, the sales weights being changed each month, the results not simply being ascribed to parameter changes or their weighting. Finally, the analysis was restricted to a single year, this being extended over two years.

This study follows Berndt and Rappaport (2001) using from scanner data on a *monthly* basis for five consumer durables over a two year period. Hedonic regressions are estimated to derive coefficients on *brands*, *characteristics* and *outlet-types,* and to identify how they evolve over time. In section 2 the hedonic approach is outlined, along with its potential use in the measurement of quality-adjusted price indices. Specific attention is given to how parameter instability might affect such use. This is followed in section 3, by a description of the extensive data set for the application - monthly scanner data for vacuum cleaners, washing machines, dishwashers, television sets and cameras for January 1998 to December 1999. In section 4 tests of parameter stability are undertaken between and within years. Furthermore, estimates are provided of the coefficients on characteristics and brand names, and their evolution over time, for example, how estimates of the coefficients on the Sony make has evolved on a monthly basis over the period. In section 5 we address the stability of the coefficient on the outlet type in which the transactions took place and consider how such estimates have evolved. In section 6 we ask whether any such instability matters for the measurement of quality-adjusted price changes. Estimates of hedonic indices using dummy variables on time and those using hedonic imputations are derived. The first method is based on restricting the coefficients to be the same, while the second allows the coefficients to vary, but restricts the quantity weights of characteristics to be the same over the price comparison.

The quantity weight – or fixed basket of characteristics –can be held constant at the base (Laspeyres) or current (Paasche) month and, since either is equally justifiable, a divergence between the two argues against the use of either such measure alone. Hedonic indices using a dummy variable on time constrain the two months' coefficients to an average of the coefficients and implicitly weight the indices using an average basket of characteristics. They are thus akin to superlative indices and are preferable to estimates of either a Laspeyres *or* a Paasche bound. In section 7 the concept of the stability of hedonic parameters is extended for television sets for June and July 1998 across three countries: the U.K., France and Netherlands using the results from Heravi, Heston and Silver (2001). Conclusions are provided in section 8.

2. THE HEDONIC APPROACH

a) Theory

The hedonic approach involves the estimation of the implicit, shadow prices of the quality characteristics of a product. Products are often sold by a number of manufacturers who brand them by their 'make'. Each make of product is usually available in more than one model, each having different characteristics. A set of (z_k = 1,….K) characteristics of the models are identified and data over i=1,…N or models over t=1,…,T periods are collected. A hedonic regression of the price of model i in period t on its set of quality characteristics z_{tki} is given by:

$$1np_{ti} = \beta_0 + \sum_{k=1}^{K} \beta z_{tki} + \varepsilon \qquad (1)$$

The β_k are estimates of the partial, marginal valuations the data ascribes to each characteristic and can be equated in economic theory to a mapping of the intersections in characteristic space of production possibility curves and indifference curves of specific distributions of optimising consumers and producers with varying tastes and technologies.

The theoretical basis for the regression has been derived by Rosen (1974) where a market in characteristic space is established (see also Triplett, 1988, Arguea *et al*., 1994 and Diewert, 2002). Empirical studies and econometric issues are surveyed in Griliches (1990), Triplett (1990) and Gordon (1990), but see also Cole (1986), Dulberger (1989), Gandal (1994), Nelson *et al.* (1994), Berndt *et al.* (1995), Combris *et al.* (1997), Moulton *et al.* (1998), Hoffmann (1998) and Silver (1999).

Briefly, following Triplett (1988), the hedonic function is given by:

$$P= h(c) \tag{2}$$

where P denotes the prices of a cross-section of goods, i.e. one for each 'variety' or 'model' available in a given period, and the matrix c has a row of characteristics for each model. The hedonic approach (Rosen, 1974 and Triplett, 1990) identifies heterogeneous products as aggregations of characteristic, thus:

$$Q = q(c, z) \tag{3}$$

Where Q is utility (scalar output), z a vector of other homogenous products and, for simplicity, one homogenous product with characteristic (c). Equation (2) can be written as

$$Q = Q\ (q(c), z) \tag{4}$$

where $q(.)$ is an aggregator over the characteristics (c) that are embodied in the heterogeneous product. A parallel development of the theory on the producer side makes the production of a heterogeneous product the joint output of the set of characteristics.

The economic behaviour of buyers and sellers of heterogeneous products can be described by sets of demand and supply functions for characteristics. These demand and supply functions are derived from the optimisation of buyer's and seller's objective functions over characteristics. On the demand side, for example, $q(.)$ above carries information about preferences (using technology) and the hedonic function - $h(.)$ from equation (1) - provides information about the characteristics price surface.

Rosen (1974) showed that if there are n competitive buyers, with dispersion in tastes, the hedonic function, $h(.)$, will trace out an envelope to the set of preferences, described by the n aggregator functions, $q_1(.),..., q_n(.)$. As with an envelope, the form of $h(.)$ is thus independent of the form of $q(.)$ - except for special cases - and is determined on the demand side by the distribution of buyers across characteristics space. A parallel condition exists on the seller's side.

The hedonic function represents a price surface in characteristic. The price surface may relate to the input or output side, with corresponding utility or profit functions. The distinguishing feature is that this surface relates to the *characteristics* of the product. Feenstra (1995) and Diewert (2002) provides a theoretical derivation of the hedonic regression from the consumer side from which the coefficients on characteristics can be identified as estimates of their marginal value.

b) Hedonic regressions and quality adjustment for CPIs: the effect of parameter stability

The matched models method for measuring consumer price indices (CPIs) is used by statistical offices for since it allows price changes to be untainted by quality changes. However, it fails when an item is missing and a comparable item is not available to continue the price series. It also fails because the sample it draws on for the continuing matching ignores, for a price comparison between periods 0 and *t*, the price of 'old' items in the period 0 which are unmatched in, period *t*, and the prices of 'new' items in period *t*, unmatched in period 0 (Silver and Heravi, 2002a). A number of methods exist for using hedonic regressions in this context. These are outlined and the implications for parameter instability discussed.

(i) Filling in missing unmatched prices - patching

The first is where the matched models method is being used and statistical agencies have missing unmatched models. The price collector can only find a replacement model which is not directly comparable and the coefficients from a hedonic regression are used to make a quality adjustment, so that the old and new price can be compared. This is a 'patched' solution in the sense that adjustments for quality differences are made to non-comparable models and the adjusted 'patched' price used for price comparisons.

(ii) Hedonic imputations for given quality points

The second method is an extension of the 'patching' approach to the whole data set. Hedonic regressions are estimated for periods 0 and *t*. The features of models in period 0 are inserted into the hedonic regression equation for period *t* and price imputations made for each observation: the estimates are the prices in period *t* of the period 0 sample. Some average of the actual period 0 prices can then be compared with the imputed period *t* one, akin to a Laspeyres comparison. Alternatively the imputations could be made for period *t* using the period 0 regression and period *t* features: the imputations would be the prices in period *t* using period 0 valuations. Some average of the imputed period *t* prices would be compared with the actual period *t* ones, akin to a Paasche comparison.

(iii) Dummy variable hedonic

A third approach is the dummy variable method. This is again separate from the matched models method. The sample required does not have to be matched. A set of (z_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. A hedonic regression of the price of model i in period t on its characteristics set z_{tki} is given by:

$$\ln p_{ti} = \beta_0 + \sum_{t=2}^{T} \beta_t D_t + \sum_{k=1}^{K} \beta_k \, z_{tki} + \varepsilon_{ti} \tag{5}$$

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_t are estimates of quality-adjusted price changes, that is estimates of the change in time (the logarithm of) price between period t and period $t+n$, having controlled for the effects of variation in quality (via $\sum_{k=1}^{K} \beta_k z_{tkj}$).

iv) Superlative/exact hedonic framework

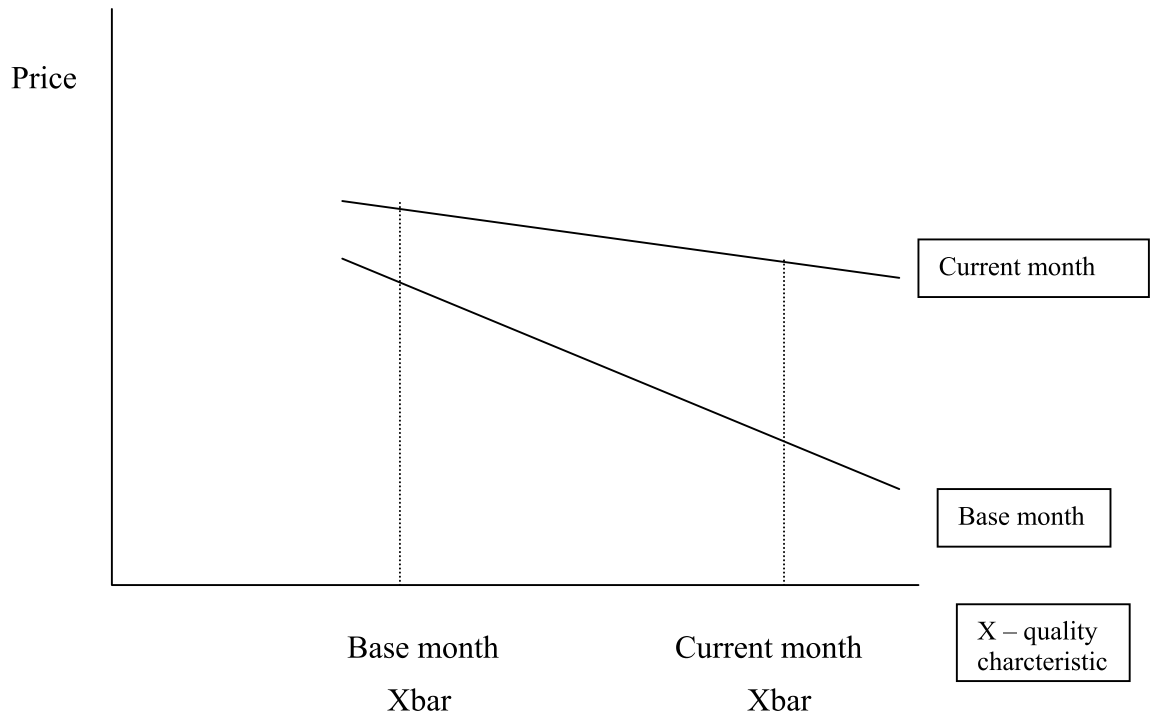
The final approach arises out of the economic theory of price indices and involves the compilation of superlative/exact hedonic indices (Fixler and Zieschang, 1992, Feenstra, 1995 and Diewert, 2002). Superlative indices can, and will, be calculated using matched scanner data. However, the superlative/exact *hedonic* framework attempts to minimise loss of data through failures to match. This is not the subject of this study but is considered in Silver and Heravi (2001 and 2002).

v) On the relationship between the measures

In section 6 indices will be calculated using hedonic imputations as in (ii) above and hedonic indices with dummy variables as in (iii) above. It is important to outline how these quite different approaches based on hedonic regressions differ. Hedonic imputations recognise that the regressions in the two months being compared, the base and current months, might have different slope and intercept coefficients. As Figure 1 shows, the measure of quality-adjusted price change, the vertical difference between the regression lines, depends on the average quality characteristics used – for example, the average spin-speed of washing machines. Laspeyres and Paasche provide equally justifiable answers by estimating the difference between the lines at different points: the base period and current period means respectively. The difference between the two indices is thus critically defined by parameter instability on the one hand and the average of each of the characteristics that make up the item on the other. The average price of a product is the sum of the shadow prices of its characteristics, each multipled by the average amount of each characteristic. If the parameters are stable the price of the item may change as quantities of different characteristics change. If the quantities are constant prices may change with the change in the coefficients.

Hedonic indices as described in (iii) and equation (5) above do not use the change in the parameters as part of the estimated average price. They are not based on parameter instability. For a comparison between a base and current month they constrain the slope parameters to be the same. In Figure 1 the two lines would have the same estimated slope based on the data in the two months, but would differ by the vertical difference between the two lines. Since this is the same at all values of X, it is enumerated at the intercept. This hedonic regression method is thus neither interested in the means of X in each month nor any parameter instability.

[Figure 1 about here]



Silver (1999) has shown that both methods are but limited forms of superlative indices. A critical feature of the hedonic imputation is the implicit weights for the Xbar used to place the Laspeyres and Paasche indices. If weights were available a geometric mean of these weighted quality-adjusted indices would yield an estimate of a quality-adjusted Fisher index (see Silver and Heravi, 2001). A wide Laspeyres-Paasche spread may be indicative of a poor weighting system.

Consider the case of a highly valued red switch on only a few washing machines in the base period, but a majority of consumers switch to such machines in the current month. Assume that the coefficient attached to the red switch has a relatively large fall – it becomes less valued. The Paasche index would diverge from the Laspeyres, and significantly so. The (Laspeyres) price of machines in the base month valued at each of the base and current month's coefficients will show only a small fall as a result of the switch, since relatively few machines have the switch. In the current period many more machines have the red switch so the relatively large price fall receives more weight. Laspeyres and Paasche diverge even though they both include the same hedonic price changes. It is the weighting of the characteristics that affects the difference between the two indices in this case. Thus critical to the proper use of hedonic imputations is a proper weighting system for the Xbars and indeed, for a weighted least squares estimator of the regression surfaces.

The dummy variable hedonic indices averages the coefficients from the two periods by constraining them to be the same. Hedonic coefficients have been shown by Rosen (1974) and Triplett (1988) to be a realisation of a mapping in characteristics space of the intersections that emerge between the indifference curves and production possibility frontiers for distributions of tastes and technologies of optimising consumers and producers. But these tastes and technologies change over time. *Hedonic imputations* hold them constant in the base and current months to yield respective Laspeyres and Paasche hedonic indices, and (should) look to a, say, Fisher average of the resulting two estimates. *Hedonic indices* consider some average of these realisations by constraining all the coefficients, except for one denoting the month, to be the same. The coefficient on the month is an estimate of the quality adjusted price change. Note that had an interaction term with the time dummy been included in the specification, say the red switch with time, on the assumption that red switches are more highly valued in the first month, then the estimate of quality-adjusted price change from the dummy variable hedonic index is conditioned on the mean of red switches, the Xbar. Once again the result will depend on whether a base or current month Xbar is used. And, under such circumstances, sales may need to be employed for estimating an appropriate hedonic surface using a WLS estimator used. Diewert (2002) has argued for the inclusion of such interaction terms to equate with flexible functional forms which in turn correspond to superlative index number formulae.

Thus the two approaches are but limited form so superlative indices, hiding their implicit assumptions in different ways.

Hedonic adjustments using *patching* may either use estimated hedonic coefficients for period 0 to quality-adjust the price of the original 'old' item in period 0 to make it comparable to its period t replacement. The parameters may change over time, but this will not affect the validity of the comparisons between period 0 and t+1, t+2, and so forth, since the adjustment is to period 0 using period 0 coefficients. However if, for example, a feature is rare in period 0 with a high shadow price, which then declines as it becomes more standard, say a wide-screen on a television set. Consider the matched pricing of a model with a standard screen which becomes replaced by a wide-screen version. To use the high marginal value in period 0 to adjust the period 0 price for the value of the wide-screen, to make it comparable, may lead to exceptional high price falls, or even negative current period prices. The adjustment to period t prices, based on a period t hedonic functions is preferable, but a similar problem would emerge if the parameters were changing and were not regularly updated. It is important to monitor the extent to which parameters change if the coefficients used for the adjustments are not to become out-of-date. Similar concerns arise out of the use of the second approach, (ii) above.

The dummy variable approach (iii) above implicitly constrains the $ß_k$ in equation (5) to be the same. If the coefficients were constrained to be the same as in period 0 (along with the basket of quality) then a Laspeyres-type estimate results. If they are constrained to the same as in period t, a Paasche type estimate will result. Silver (1999) and Diewert (2002) show how geometric mean of such estimates may be justified as a Fisher type superlative estimate, as in (iv) above. If the coefficients are unstable the constraining of them to be the same in the dummy variable approach is akin to providing a single symmetric average when the Laspeyres and Paasche spread is quite large. A large Laspeyres-Paasche spread is undesirable since both approaches are equally justifiable. Fisher-type estimates would be preferable as discussed in Diewert (2002).

3. DATA

(a) Scope and coverage

The time series part of this study in sections 4 and 5 is on UK data for washing machines, vacuum cleaners, dishwashers, television sets (TVs) and cameras in 1998 and 1999 for different outlet types using monthly scanner data. Scanner data are compiled from the scanner (bar code) readings of retailers. The electronic records of just about every transaction includes the transaction price, time of transaction, place of sale and a code for the item sold – for consumer durables we refer to this as the 'model' number. The model numbers are linked to a file on the characteristics or attributes of the model. The transactions are counted and prices aggregated for each model sold in each store type in each month (the data being supplemented by visits to independent outlets without scanners) to yield the volume and total value of sales. The latter are divided by the former to provide the unit value or 'price' of each model in each month/outlet-type.

The observations are thus for a model of the product in a given month in one of four different outlet types: multiples, mass merchandisers, independents and catalogue for vacuum cleaners, dishwashers, and TVs, three outlet types for cameras: specialised camera shops, independent chemists, multiples.

The coverage of the data is impressive both in terms of transactions and features. For the UK for example in 1998, Table 1 shows the data to cover about 3 million transactions for vacuum cleaners, 2.25 million for TVs and just over 2.1 million for cameras . The coverage of stores is estimated (by GfK Marketing Services) to be "...well over 90%" with scanner data being supplemented by data from price collectors in stores that do not possess bar-code readers.

The number of observations for which there was a transaction are given for each product in Table 1 for 1998 and 1999. The data are for each month in both years, there being, for example, 9,043/12 – about 750 models of vacuum cleaners sold in each month on average in 1998. However, these figures treat the same model sold in a different outlet type as a separate observation since their prices may differ. For example, for vacuum cleaners in 1998 there were 9,043 observations on 4,088 models, each model on average being sold in 2.21 outlet types. There were thus approximately (750/2.21) 340 models sold per month. In practice the data is richer than this since models may be specific to individual stores or chains, rather than types. Of the 9,043 models sold in 1998 25.7% were sold in multiples, 25.3% in mass merchandisers, 29.2% in independents and 19.7% in catalogue outlets.

The data thus consists, for each observation, of monthly prices and volumes of transactions and numerous quality characteristics, describing each model in an outlet type, over January

1998 to December 1999. From Table 1 the data for the five products can be seen to amount to 92,923 such observations representing 19.4 million transactions valued at £4.94 billion.

Table 1:Details of the data, 1998 and 1999

	Number of transactions (millions)		***Number of models by store (observations)***		***Total sales value (£ millions)***	
	1998	***1999***	***1998***	***1999***	***1998***	***1999***
Dishwashers	0.382	0.436	4,621	4,483	140	140
Cameras	2.120	2.334	8,957	9,486	220	230
TVs	2.247	2.382	15,578	15,899	780	890
Vacuum cleaners	3.077	3.174	9,043	9,378	420	420
Washing machines	1.517	1.732	7,750	7,728	550	600

(b) The variables

The variable set of **performance characteristics** naturally varies between products. They are given in Annex 1 and, in their dummy variable representation, are particularly extensive including about 80 variables for television sets, for example. Common to just about all products are:

Price is the unit value of a model in a month/store across all transactions. The transaction prices are simply summed and divided by the number of transactions to yield the single observation: the price of this model in this outlet type in this month (see Balk, 1999 for the statistical properties of unit values).

Volume is the sum of the transactions during the period. Many of the models sold in any month have relatively low sales. Some only sell one of the model, in a month/store type. Showrooms often have alongside the current models with their relatively high sales, older models, which are being dumped, but need the space in the showroom to be seen to achieve this. For example, there were 646 observations for dishwashers out of the total 4,621, i.e. 14.8%, selling only one model in any outlet type/month accounting for (0.646/382)*100=0.17% of sales and 40 observations selling between 1,000 and 5,000 in any month accounting for (60.5/384)*100=15.8%. For television sets 30.8% of observations had less than 10 transactions in any month. It may be that some of these were relatively high-priced small volume sets and some of an earlier vintage. However, they only accounted for a derisory 0.78% of sales volume.

Vintage is the year in which the first transaction of the model took place. With durable goods models are launched (usually) annually. The aim is to attract a price premium from consumers who are willing pay for the cachet of the new model, as well as to gain market share through any innovations which are part of the new model. New models can coexist with old models, both as a result of an inability to dump the old model before the launch of the new one and as an appreciation that different sub-markets exist for models of different vintages. Models of older vintages may also exist in some niche markets in which manufacturers do not find it profitable to launch a new model. Unfortunately vintage was not available for vacuum cleaners (about 80% of observations missing).

4. PARAMETER STABILITY: MAKE AND PRODUCT CHARACTERISTICS

(a) Summary statistics

Table 2 provides sales volume weighted mean prices for the five products for major makes, accounting for more than 5% of total sales value. Average prices can be seen to fall over the two years. The product markets can also seen to be highly concentrated with; for example, the major four makes of washing machines in 1999 accounting for nearly three-quarters of the sales value. Yet each make will account for a larger number of brands, for example in 1999 there were 1,056 observations for Hotpoint; an average of 1,056/12 =88 each month, although some of these were for the same model in a different outlet.[1] Average prices can also be seen to be quite different for major makes, as their product portfolios target different market segments. This is particularly clear for the relatively expensive Dyson vacuum cleaners whose average price is about double that of major competitors and, accordingly, whose market share *by value* is quite substantial. However, the introduction of up-market bagless machines by other suppliers in 1999 has eaten into what is a volatile market. Such analysis of price variation by makes begs a hedonic multivariate framework in which dummy variables on makes and variables on quality characteristics and outlet types together act as explanatory variables.

[Table 2 about here]

(b) Regressions

The OLS regressions were estimated on a data set that excluded models with sales of 30 or less in any month and a minimal number of models with extreme prices arising from variables not included in the data, such as stainless steel washing machines. A failing of the dummy variable approach is that models with only one transaction are given the same importance in the regression as a model with, say 10,000 transactions. The choice of 30 was based on some experimentation. The loss in the number of observations was quite severe for washing machines from 7,750 to 3,957, while the loss in terms of the *volume* of sales was minimal, from 1.517 million to 1.482 million. The corresponding figures were: dishwashers 4,605 to 1,890 observations, 381.2 thousand to 358.5 thousand sales; vacuum cleaners 9,043 to 5,367 observations, 3.077 million to 3.036 million sales; cameras 8,954 to 5,034 observations and 2.121 million to 2.071 million sales; and TVs 15,578 to 8,000 observations and 2.247 million to 2.172 million sales. As should be apparent from the above, many of the models had often only a single transaction in the UK in the year, being the end of an old line.

The OLS estimated regressions all fitted well by the standards of such things, as shown by Table 3, with F-tests rejecting the null hypothesis of all coefficients equalling zero, $\overline{R}^2$ of around 0.85 and individual coefficients having the expected signs and magnitudes (individual results available from authors). Semi-logarithmic formulations were used as is traditional in this area, though tests of their superiority against linear models was inconclusive (Curry *et al.*, 2001 and Silver and Heravi, 2001).

Table 3: Regression Diagnostics

	98			**99**		
	N	$\overline{R}^2$	***F***	***N***	$\overline{R}^2$	***F***
Washing Machines	3590	0.82	273	3939	0.81	280
Dishwashers	1659	0.75	86	1738	0.73	82
Television Sets	7799	0.95	1554	8028	0.86	584
Cameras	3780	0.89	372	3090	0.86	213
Vacuum Cleaner	5006	0.81	395	5024	0.80	382

As should be apparent from Annex 1 the regression specifications are quite extensive. Since the focus of the paper is on the stability of the estimated coefficients, the details of each of the five estimated regression equations in each year (and subsequently, for each month) are not presented here. However, Table 4 reproduces the results for television sets in 1998. The coefficients on the makes are benchmarked on Sony and are, as expected for the UK market, generally negative. The screen sizes are benchmarked on a 14-inch screen and are generally monotonic as size increases. Added characteristics have positive coefficients. For example a 21 inch screen size had a premium of (exp (0.426) –1)*100 = 53%, or more properly, with the adjustment of half the standard error (Goldberger, 1968), i.e. (exp (0.426 + 0.0045) – 1) * 100 = 54% over a 14 inch and Nicam stereo sound a 18% premium and a Sharp brand had an estimated marginal valuation against a Sony of minus 14%, other things being equal.

[Table 4 about here]

(c) Stability: between years

First, we tested whether the coefficients differed between regressions using 1998 and 1999 data. The regression equations were first estimated separately using each year's data and the two sums of the squared errors taken (RSS_{98} and RSS_{99}). These were both based on unconstrained regressions, the coefficients having been allowed to differ across the years. A further regression was estimated based on both years' data, thus effectively constraining the coefficients to be the same for each year. This constrained RSS_c was compared with the sum of the unconstrained counterparts ($RSS=RSS_{98}+RSS_{99}$), using an F-test.

$$\mathrm{F}=\frac{\left(\mathrm{RSS_c}-\mathrm{RSS}\right)/r}{\mathrm{RSS}/\left(n-2k-2\right)} \tag{6}$$

where k is the number of explanatory variables, n is the number of observations, (n-2k-2) the degrees of freedom of the unconstrained model and r is the number of restrictions.

The above test procedure has been criticised for their assumption of constant variances of the error terms, in the context of Chow tests. Although Chow (F) tests are routinely used in econometrics, by Ohtani and Toyoda (1985), and Thursbury (1992) show that even a relatively small degree of heteroskedasticity can lead to serious distortions in the power of the test. Tsurumi and Sheflin (1985) show that pre-tests are unsatisfactory, because modest degrees of heteroskedasticity, unlikely to be detected by pre-tests, can cause substantial distortion in the Chow test. The approach adopted here was to use an asymptotic Chow test (AChow) with modified bounds, c_1 and c_2 making up the MACE2 critical values as explained in note 2 to this paper[2].

Table 5 Model stability for comparison between 98 and 99

	Chow-F	p-value	AChow-F	c_1	c_2	MAC2
Washing Machines	13.75	0.000	13.77	1.53	1.53	1.53
Dishwashers	5.94	0.000	5.97	1.54	1.54	1.54

Television Sets	26.1	0.000	25.9	1.41	1.41	1.41
Cameras	8.79	0.000	8.64	1.43	1.44	1.44
Vacuum Cleaner	6.08	0.000	6.11	1.53	1.53	1.53

Table 5 finds the hedonic coefficients from one year to the next cannot be assumed to be stable. The difference between the sets of coefficients is over and above that expected from sampling error at a 1% level.

(d) Stability within years

The next step was to test whether there was any overall stability *within* each year using a similar testing strategy[3]. If this null hypothesis of no difference between each of the coefficients across the months within a year is rejected, consideration can then be given to which of the main characteristics are 'responsible' for it.

Table 6 Model stability for months within years for 98 and 99

	Year	Chow-F	p-value	AChow-F	c_1	c_2	MAC2
Washing Machines	98	2.11	0.000	2.01	1.21	1.34	1.22
	99	1.84	0.000	1.86	1.18	1.32	1.19
Dishwashers	98	1.69	0.000	1.66	1.21	1.50	1.23
	99	1.11	0.093	1.37	1.22	1.49	1.24
Television Sets	98	1.81	0.000	1.78	1.21	1.30	1.29
	99	1.59	0.000	1.75	1.21	1.28	1.27
Cameras	98	0.62	1.000	0.62	1.28	1.30	1.28
	99	0.65	1.000	0.65	1.16	1.36	1.18
Vacuum Cleaner	98	1.41	0.000	1.39	1.21	1.27	1.22
	99	1.32	0.000	1.29	1.19	1.29	1.20

Table 6 shows the null to be rejected at a 1% level for television sets, washing machines and vacuum cleaners in both years, though in the vacuum cleaners case, the AChow test statistic was very close to the 1% MAC2 critical value. The null was also rejected for dishwashers in 1998. Thus within years there was again definite evidence of instability, but there were exceptions.

(e) Tests of Stability for Individual Coefficients within Years

We now turn to investigate which characteristics had unstable parameters. This need only be undertaken for those products and years for which the null of parameter stability was rejected in Table 6. The regressions included a substantial number of coefficients as outlined in Annex 1. These include characteristics and brand names with relatively limited sales. The focus of the analysis was on brands and characteristics with relatively high expenditure shares, which are also easily identifiable and meaningful to the consumer. Brands selected were generally those responsible for more than 5% of sales value. The analysis focussed on which variables were responsible for any instability found in Table 7. For example, for washing machines, it may be particular brands, e.g., Hoover, Bosch or features, such as a 1400 spin-speed. Such tests were conducted by allowing each variable to take separate coefficients in each month in an overall, pooled regression for each year in turn – an unconstrained formulation. The variable of interest, say the make Hoover, using a dummy variable was then constrained to be the same across months and the regression re-estimated. Again an F-test was used to test the difference between the constrained and unconstrained version, that is, whether the β remain constant over the year. Furthermore, estimates of the β characteristics and brands in each month could be derived in order to see how they evolve.

The results are given in Table 7. Given the similarities in Tables 5 and 6 between the AChow-F and F tests, and the bounds for the critical values, a simple F-test was used. The results for washing machines found parameters to be stable for the main brands and features, with the exception of Hoover in 1998. The instability found in Table 6 in 1999 for washing machines must have its source in less ‘important’ variables, though the low F-statistic in Table 6 signals very little underlying instability. The results for 1998 for dishwashers in Table 7 were also heartening with the null hypotheses of stability for the main coefficients not being rejected at a 1% level. Also included were the 1999 results for dishwashers and they confirmed the lack of instability found in Table 6. For television sets, the stability of “wide screen” sets and two brands, Sony and Toshiba were rejected in 1998, confirming the lack of stability found in Table 6. For 1999 the null of stability was rejected in Table 6 for television sets, yet this was not confirmed in the individual tests for the main coefficients in Table 7. Therefore this instability must have its source in less important brands and characteristics. Table 6 showed within year parameter stability to not be rejected for cameras, this being confirmed for the main coefficient in Table 7. However, for vacuum cleaners where unstable coefficients were expected, based on the Table 6 results, the null hypothesis of stability for the main variables were not rejected, the instability arising elsewhere.

[Table 7 about here]

Thus in summary for 1999, the general picture for the *major* brands and *major* characteristics was one of within year parameter stability. Parameter instability for the *regressions as a whole* within years was found for television sets, washing machines and vacuum cleaners in both years, yet for the main brands and characteristics (with the exception of "wide screen", Sony and Toshiba television sets and the Hoover washing machine brand name in 1998), the main brands and characteristics were not the source of this instability.

(f) Evolution of parameter estimates over the 24 months

The F-tests for within year variation gives no insight into the pattern of change. However, estimates of the coefficients can be provided for interaction terms of each month with the characteristic or brand variable in question. Dummy slope variables for each major characteristic in each year were generated, benchmarked on January of the year. The coefficient on 'being a Panasonic television', for example, will, for 1998, have 11 dummy variables. These will be 1 if it is a Panasonic in February 1998 and 0 otherwise, and similarly for March, April...December. These coefficients estimates of the change in the coefficients on each characteristic, e.g.. being a Panasonic, for the month in question, compared with January 1998[4]. The exercise was repeated for 1999.

[Figures 2 to 5 about here]

Figures 2 to 4 show the values of the coefficients and t-statistics for "wide screen", Sony and Toshiba televisions sets for each month in 1998 compared with January 1998, and then again for each month in 1999 compared with January 1999. The absolute magnitude of the coefficients are of no concern, being conditioned here on the benchmark, set for the host of other variables. For "wide screen" variable in Figure 2, the upward drift is quite clear. The differences from January are statistically significant for 1999, but only at the end of 1998. The upward trend is also clear for the brand names Sony and Toshiba in 1998, in Figures 3 and 4, and statistically significant towards the end of 1998. We might expect some drift as the time between each month and its benchmark January increases. Thus within year variation for televisions is for "wide screen" and the two major brand names, Sony and Toshiba. For washing machines, few of the major brands of our characteristics were the source of the instability. An exception was Hoover in 1998 as shown in Figure 5. There was a marked drift in the difference between estimated coefficients between each successive month and January, with this difference becoming statistically significant in the latter part of 1998.

5. PARAMETER STABILITY: OUTLET-TYPES

One may argue that product differentiation

> "…may be based upon certain characteristics of the product itself, such as exclusive patented features; trade-marks; trade design, color, or style. It may also exist with respect to the conditions surrounding its sale. In retail trade, to take only one instance, these conditions include such factors as the convenience of the seller's location, the general tone or character of his establishment, his way of doing business, his reputation for fair dealing, courtesy, efficiency, and all those personal links which attach his customers either to himself or to those employed by him. In so far as these and other intangible factors vary from seller to seller, the "product" in each case is different, for buyers take them into account, more or less, and may be regarded as purchasing them along with the commodity itself." (Chaimberlain, 1933, pp.56-57 *cited* in Anderson, de Palma and Thisse, 1992).

The scanner data made available to us for research was quite extensive in that it distinguished between the following outlet-types: multiples; (ii) mass merchandisers; (iii) independents; (iv) catalogues for dishwashers, washing machines, television sets and vacuum cleaners and for cameras, between (i) specialised camera stores; (ii) non-specialised camera store (iii) independent chemists.

The analysis in the previous sections has been implicitly constrained by examining parameter stability over time, as opposed to over time for individual outlet-types. This was deemed appropriate not least because of the magnitude of extending the work to such detail, but also because the inclusion in the regression specifications of dummy variables on outlet types controlled for some (fixed) differential effects. Such effects are considered in more detail here.

(a) Summary statistics

Table 8 provides summary statistics for the major outlet types. There was a conspicuous pattern of prices falling between the two years. Also apparent is that average prices varied considerably for different outlet types. Multiples and catalogue outlets were generally much cheaper than independents and mass merchandisers. In part this may have been due to the different brand and characteristic mix of the models sold in each outlet type. However, also shown in Table 8 are the estimated coefficients and *t*-statistics for each outlet type, benchmarked on the 'multiple' outlet type. These estimated coefficients are from regressions that include the full gamut of characteristics and makes as given in Annex 1. They control for differences in the mix of makes and types of models sold. Table 8 shows that all the coefficients are statistically significant at the 1% level of significance, except the coefficient for the independent chemists which is not statistically different from the benchmark of "specialised" for the case of cameras.

[Table 8 about here]

(b) Parameter stability: across outlet-types for 1998 and 1999

Separate regressions were first estimated for each outlet-type and then again with the coefficients constrained to be the same across outlet-types in a further regression. An F-test was used to test for constancy of coefficients across outlet-types, i.e., where there are ...*j* outlets for ...*k* characteristics (including brands) the null hypothesis was:

$$\beta_{11} = \beta_{21} = ...\beta_{j1}\,; \beta_{12} = \beta_{22} = ...\beta_{j2}\,; \beta_{k1} = \beta_{k2} = ...\beta_{kj}$$

against the alternative hypotheses of their not being equal. The tests were repeated for 1999, the results being given in Table 9. For all products the null hypotheses were rejected with very small *p*-values. We now turn to examine the estimated coefficient for these variables.

Table 9: Model Stability for outlet-types within years 98 and 99

	Year	Chow-F	*p*-value	AChow-F	c_1	c_2	MAC2
Washing Machine	98	14.92	0.000	16.61	1.34	1.38	1.35
	99	19.30	0.000	24.59	1.33	1.38	1.35
Dishwasher	98	4.06	0.000	15.44	1.39	1.65	1.59
	99	4.69	0.000	16.25	1.38	1.61	1.55
Television Sets	98	22.06	0.000	24.2	1.28	1.32	1.30
	99	12.16	0.000	14.0	1.28	1.32	1.30
Cameras	98	11.39	0.000	11.93	1.49	1.50	1.49
	99	8.39	0.000	16.78	1.47	1.49	1.48
Vacuum Cleaners	98	12.67	0.000	13.30	1.35	1.35	1.35
	99	12.85	0.000	13.13	1.33	1.33	1.33

(c) Estimated Coefficients and their Stability within Years for Outlet-types

Included here for each year in the hedonic regression were interaction terms for each month by each outlet-type. The months were benchmarked on January. The exercise was undertaken separately for each of 1998 and 1999, the subject of the analysis being within year stability. The results are given in Table 10. For dishwashers, none of the within year stability were found to be statistically significant at a 5% level. That is, the null hypothesis of no difference between the estimated coefficient on mass merchandisers, for example for July 1999, and mass merchandisers for January 1998, was not rejected at this level. The same applied for each month in 1998 compared with January and then again for 1999 and then again for independent and catalogue outlets [the results are not presented here, but available on request]. For vacuum cleaners, the coefficients for independent outlet in 1998 proved to have differences that were statistically significant. The difference between January and July was smaller – closer to the January sales as expected. The coefficients for catalogue outlets in 1999 had also differences that were statistically significant. For washing machines only differences in 1998 for catalogue stores were statistically significant. For catalogue outlets there was a clear increase in the estimated coefficients over the latter part of 1998. The instability of the coefficients for television sets only occurred in 1999 but across two types of stores. For independents it was higher in the later months as expected. However for catalogue outlets, the differences extended to the latter part of the year and were quite marked at around 20%. It must be borne in mind that we examined coefficients over the twelve months for three outlet-types (benchmarked multiples) for four of the products and two outlet types for cameras, each for two years, i.e., 28 sets of coefficients. The 5 reported in Table 10 were the only ones where the monthly changes from January were statistically significant. January is in any event unusual in that 'sales' take place then, thus 'biasing' the tests towards rejection of the null of no difference. Even allowing for all of this, the percentage differences in the coefficients, with the exception of catalogue television sets, were under 10%. All in all, not a lot of evidence of instability within years for the coefficients on outlets.

Table 10: Coefficients and t-statistics on stability of outlet types

Vacuum cleaners	**vacuum cleaners**	**Washing machines**	**Television sets**	**television sets**
Independents(1998)	**Catalogue(1999)**	**Catalogue(1998)**	**Independent(1999)**	**catalogue(1999)**

	Coefficients	t-statistics	Coefficients	t-statistics	Coefficients	t-statistics	Coefficients	t-statistics	Coefficients	t-statistics
Feb	-4.77	-1.30	0.85	0.23	3.56	1.10	-2.73	-1.26	2.80	0.91
Mar	-5.02	-1.35	0.20	0.05	0.70	0.21	-2.10	-0.99	-0.19	-0.05
Apr	-7.10	-1.97	-0.69	-0.18	0.37	0.10	-0.35	-0.17	-2.58	-0.85
May	-8.31	-2.34	-2.87	-0.75	0.08	0.02	1.33	0.55	-3.09	-0.80
Jun	-7.72	-2.11	-3.49	-0.87	5.14	1.82	0.85	0.37	-0.44	-0.14
Jul	-4.35	-1.16	-3.29	-0.83	5.97	2.04	2.31	0.99	-2.30	-0.69
Aug	-7.94	-2.19	-6.71	-1.64	5.62	1.93	7.97	2.63	-25.94	-2.88
Sep	-7.30	-2.01	-5.73	-1.37	8.39	2.96	5.43	2.08	-18.34	-2.80
Oct	-7.39	-2.03	-7.29	-1.79	7.44	2.52	4.57	1.72	-20.31	-2.86
Nov	-7.74	-2.10	-9.28	-2.32	8.58	2.87	3.42	1.26	-21.56	-2.96
Dec	-7.10	-1.87	-8.28	-1.99	9.46	3.14	8.93	3.01	-28.55	-3.91

6. DOES INSTABILITY MATTER

The next concern is whether the instability matters, in the sense that methods such as the dummy variable on time hedonic indices with parameters constrained to be the same produce much different results to those whose parameters are unconstrained. Hedonic indices are estimated for the five products for unweighted OLS for models with sales of 30 or less. Sales weights are available for such scanner data and both base (current) period sales weights and base (current) period hedonic beta coefficients could be used to weight the prices and quality adjustment to form Laspeyres (Paasche) indices akin to those in Silver and Heravi (2001 and 2002). In this study prices are unweighted to focus on the effects of the instability of the quality adjustment coefficients, though the sales constraint of sales of 30 or less helps endure the results are not unduly affected by low-selling items. Fixed base variants are used so that the results of instability in previous links of chained indices cannot be argued to contaminate the results. Four forms of such indices are estimated:

- first, are *hedonic indices* as outlined in equation (5) in section 2(b) (iii). The coefficients are constrained to be the same in *all months* using hedonic regressions and pooled cross-sectional times series data with dummy variables for each ,month (excluding January) for the whole of 1998 - the constraint is that $\beta_{ikt} = \beta_{ik}$ over the t=12 months;
- second, are *base and current month* constrained *hedonic indices* for January on February using January and February data and a time dummy for February; then on January on February using January and February data and a time dummy for March… January on December using January and December data and a time dummy for December; in any paired comparison the restriction is that $\beta_{ikt} = \beta_{ik}$ over the t=1,2 months, then again for t=1,3…t=1,12;

- third, are *hedonic imputations* using the method outlined in section 2(b) (ii): base month (January) *Laspeyres* indices are estimates of the average price in the current month using the base month's characteristics valued at the current month's hedonic coefficient's prices, compared with the actual average price in January. The latter is the base month's characteristics valued at the base month's hedonic coefficient's prices. In any paired comparison the restriction is that $X_{ikt} = X_{ik1}$ over the t= 1,2 months, then again for t= 1,3…t=1,12 where t=1 is January;
- a final procedure are *hedonic imputations* akin to *Paasche* indices using the method outlined in section 2(b) (ii). These current month Paasche indices are the average price in the current month (equivalent to using the current month's characteristics valued at the current month's hedonic coefficient prices), compared with an estimate of the average price in January using the current month's characteristics valued at the January month's hedonic coefficient prices. In any paired comparison the restriction is that $X_{ikt} = X_{ik2}$ over the t= 1,2 months, then again for t= 1,3…t=1,12 where t=1 is January.

[Table 11 about here]

The results for these four indices are given in Tables 11a and 11b for 1998 and 1999 respectively. The constraint for the coefficients to be the same in all months can only be undertaken retrospectively and uses, for example, for a comparison between January and March, constrained coefficients over the whole 12 months. The current and base months constrained hedonic indices are more relevant. The coefficients are constrained to be the same in only the two months being compared. Yet the former, more restrictive assumption is widely used in academic econometric studies in which real time estimates are not required. Tables 11 show the constraints can matter: for washing machines in 1998 the fall using the 12-month constraint was 6.5% compared with 5.5% using the bi-monthly constraint, while for 1999 for washing machines the respective falls were 3.2% and 5.2% respectively and for dishwashers 5.8% and 10.08% respectively. However for the remaining January to December comparisons the results were very similar, though differences in other months were marked.

The differences in imputed Laspeyres and Paasche indices result from the different weighting of the coefficients. Laspeyres uses the quantity of characteristics in the base period to weight the change in shadow price coefficients to form an arithmetic mean if such price changes. Paasche uses current period weights to form an harmonic mean. In just about every case the estimates differ substantially: for example, for dishwashers the Laspeyres:Paasche difference in 1998 was 12.3%:6.7%; for washing machines 5.7%:3.2%; television sets 3.8%:11.1% and for these same products in 1999: a staggering 15.3%:0.9%; 7.0%:11.3% and 2.8%:5.4%, with similar differences for these and other products in intervening months in 1998 and 1999.

In section 2(v) it was argued that such differences may arise from changes over time in the composition of the basket of characteristics produced and consumed. Both results are equally valid, the spread reflecting an alarming change in the mix of characteristics purchased and their differential price changes over a matter of months. The results from this study demonstrate that neither Laspeyres nor Paasche hedonic imputations are appropriate by them selves, though a Fisher or other superlative index will have some credence (Diewert, 2002).

Hedonic indices which constrain the parameters to be the same and, by ignoring interaction terms, conditioning the estimates on overall mean values for the quality characteristics, have more justification than either Laspeyres and Paasche imputations alone. Hedonic indices provide fairly close results to Fisher indices using hedonic imputations, though the results are not presented here but are easily derived from Table 11. Formal comparisons of hedonic indices and Fisher hedonic imputations are not undertaken here since, they are not strictly comparable. The first uses an arithmetic aggregation for Laspeyres and Paasche, while the second is based on semi-logarithmic regressions which use implicit geometric aggregation.

Both estimates could be improved by the use of sales weighted averages of X and sales WLS estimators, though this is not the subject of this paper and has been considered elsewhere as noted above.

7. PARAMETER STABILITY ACROSS COUNTRIES

The previous sections have been concerned with parameter stability *over time*. In this section we borrow the results from Heravi, Heston and Silver (2001) to examine parameter stability *across countries*. The interest in stability over time was driven by the potential use of hedonic regressions results in CPI measurement. Its spatial equivalent is the concern of the measurement of purchasing power parities (PPP). Scanner data for television sets for three countries are used: the UK, the Netherlands and France for June and July 1998. The results are of interest for the following reasons.

First, the 'patching' method (section 2b(i)) could be based on hedonic regression estimates for a single country if the parameters were stable, thus saving resources for statistical offices Second, the dummy variable approach (section 2b(ii)), which constrains parameters to be the same for the countries being compared, would have further support. Any rejection of the null hypotheses of stability would lead to 'bounds' on a true index, as with Laspeyres and Paasche, with the approaches in sections 2b(iii) and 2b(iv) providing separate results based on each country's parameters. In these latter cases, a symmetric average of the results is justified, though the constraining coefficients to be the same in the dummy variable method goes some way towards this (Silver, 1999).

(a) Summary Statistics

Table 12 provides summary statistics for television sets for June and July 1998 in three countries, U.K., France and the Netherlands. For June and July 1998 there were 4827 observations, 1186 for the Netherlands, 2146 for France, 1495 for UK, representing over a million transactions: about 0.2,0.6, 0.3 million transactions in each of the Netherlands, France and the UK respectively. The Netherlands has the lowest average price of television sets , £374.4, compare with the average price of £418.9 for France and £466.6 for the U.K. (prices are converted to pounds with the June/July exchange rate of fl/£=3.497 and fr/£=9.9708). The Netherlands has also the lowest price variation. However, in terms of sales weighted average , France has the lowest price, £304.7, compare with £321.9 and £369.5 for the Netherlands and UK respectively. The Netherlands has only international market share of 17% compared with market share of 30.7% for UK and 52.3% for France .

Table12: Summary Statistics for Netherlands, UK and France for June and July 1998

	N	Mean (£s)	Standard deviation (£s)	Coefficient of variation	Sales volume	Total sales value	Market share	Sales weighted average(£s)
Netherlands	1186	374.4	288.3	0.77	197197	£63m	17.0.	321.9
France	2146	418.9	333.8	0.80	635220	£194m	52.3	304.7
UK	1495	466.6	432.2	0.93	308547	£114m	30.7	369.5

(b) Stability tests across countries

In this section the assumption is tested that the coefficients attached to each quality variable is constant across the three countries. By including interaction effects for each of France and the Netherlands benchmarked on the UK, an unconstrained model in which coefficients can vary across countries can be estimated. An F-test for the constrained versus unconstrained model test the null hypothesis that:

$\beta_k = \beta_{jk}$ for all K = 1,...K in (3)

i.e. that the coefficients are the same across countries. Not all makes, though all characteristics were available in all countries, the unconstrained model having 128 variables, compared with 57 in the constrained model. Of interest is to identify which characteristics are subject to inter-country variability in their estimated preferences. These are given in Table 13. The omitted, benchmarks for the *t*-tests for these interaction terms are based on the UK, for example, the test in Table 13 for the Blaupunkt make being that $(\beta_{FR,Blaupunt} - \beta_{UK,Blaupunt}) = 0$, and similarly for other characteristics. The Phillips brand, for example, is estimated to have a marginal value of about (exp (0.15 + 0.5 (0.04) – 1) * 100 = 18.5% above that of the UK for both the Netherlands and France and the estimated marginal values of digital facilities exceeds the UK in both countries. It should be noted that the 32 differences listed in Table 13 are only those coefficients where the differences are statistically significant, there being a further 96 bilateral comparisons where the differences were not statistically significant.

Table 13, Constancy of coefficient across countries

	$(\beta_{France} - \beta_{UK})$	Standard error	$(\beta_{NL} - \beta_{UK})$	Standard error
Makes (Sony omitted)				
Blaupkunt	-0.099*	0.043	-	-
Daewoo	0.222***	0.051	0.254***	0.048
Grundig	0.202**	0.074	0.207*	0.080
Mitsubishi	-0.183*	0.086	-	-
Nokia	-0.413***	0.111	-	-
Panasonic	0.106*	0.041	-	-
Phillips	0.156***	0.039	0.154***	0.041
Telelun	-0.235**	0.078	-	-
Thomson	0.190*	0.092	-	-
Amstrad	-	-	0.450***	0.067
Hitachi	-	-	0.259***	0.059
JVC	-	-	0.135*	0.056
Tatung	-	-	0.130*	0.054

Characteristics				
Flat screen technology	0.097**	0.034	-	-
Digital	0.075**	0.023	0.055*	0.022
Satellite	-0.249**	0.080	-	-
S-VHS	0.059*	0.027	0.117***	0.038
Fastext	-	-	0.115**	0.038
PAL/SECAM	-	-	0.068*	0.033
PAL/SECAM/NTSC	-	-	0.132**	0.047
Vintage	-	-	-0.028*	0.012
Outlet (multiples omitted)				
Catalogue	-0.313***	0.029	-	-
Independents	-0.074**	0.024	-0.189***	0.037
Mass merchandisers	-0.245***	0.025	-0.125***	0.030

Standard errors are heteroskedastic consistent ***,**, * denote statistically significant at 0.1, 1 and 5% level respectively for 2 tailed tests

Comparisons are only given when the differences are statistically significant at a 5% level or less.

7. CONCLUSIONS

Parameter instability has implications for the use of hedonic estimates of quality-adjusted price changes. These extend beyond the 'patched' adjustments to unmatched price comparisons used by statistical offices for their consumer price indices. The focus here is on the use of two methods to measure quality-adjusted price changes: hedonic imputations whereby a base (Laspeyres) set of characteristics is used with each of base and current months hedonic coefficients to estimate price changes of a fixed bundle of *base* period characteristics; and a current (Paasche) set of characteristics is used with base and current months hedonic coefficients to to estimate price changes of a fixed bundle of *current* period characteristics. The (either base or current period) weighted sum of hedonic characteristic prices are estimates of the average prices in each month. Parameter instability in this context is at the essence of price change measurement. The second approach is to use hedonic regressions with a dummy variable for the current month. This constrains the coefficients to be the same in each month, though allows for intercept changes for price level measurement. In this approach parameter instability does not impinge on price change measurement, though both method rely on the same data and estimation techniques. The relationship between the different methods was examined in section 2. Empirical results using scanner data on five products on the nature and extent of such instability were provided in sections 4 and 5. In section 6 it was shown that Laspeyres and Paasche hedonic imputations yield quite different results and given each is equally justifiable, we caution against the use of either alone. Fisher indices are advised in this context. Hedonic indices based on constraining the current and base period coefficients are an alternative approach and are recommended against the use of either of the above indices alone. Hedonic (constrained) indices use averages of the parameters and in this sense are akin to superlative indices. The analysis was extended to tests of parameter instability across countries and the evidence of some instability reported.

Annex 1 – Characteristic sets included in regression formulations.

Television sets

(i) manufacturer (make) – dummy variables for about 50 makes; (ii) size of screen – dummy variables for about 15 screen sizes; (iii) Nicam stereo sound; (iv)6 tuner types; (v) teletext; fastext; no text retrieval system; (vii) picture tube – flat screen technology; (viii) monitor style; (ix) dolby system; (x) wide screen; (xi) s-vhs socket; (xii) satellite tuner; (xiii) digital; (xiv) vintage; (xv) outlet-types: multiples, mass merchandisers, independents, multiples.

Washing machines

(i) Manufacturer (make) – dummy variables for about 20 makes; (ii) type of machine: 5 types – top-loader; twin tub; washing machine (WM); washer dryer (WD) with and without computer; WD with /without condensors; (iii) drying capacity of WD; (iv) height of machines in cms; (v) width ; (vi) spin speeds: 5 main - 800rpm, 1000rpm, 1100rpm, 1200rpm and 1400rpm; (vii)water consumption; (viii) load capacity; (ix) energy consumption (kWh per cycle); (x) **f**ree standing, built-under and integrated; built-under not integrated; built-in and integrated; (xi) vintage; (xii) outlet-types: multiples, mass merchandisers, independents, multiples.

Dishwashers

(i) Manufacturer (make) – dummy variables for about 22 makes; (ii) type of machine: 4 types – built under; built under integrated; table top; free standing; (iii) with micro chip; (iv) width; (v) height; (vi) kWh per cycle; (vii) number of plates; (viii) number of programmes; (ix) partly integrated; fully integrated; non-integrated switch panel; (x) water consumption; (xi) stainless steel (xii) vintage; (xiii) outlet-types: multiples, mass merchandisers, independents, multiples.

Vacuum cleaners

Manufacturer (make) – dummy variables for about 29 makes; (ii) wattage; (iii) integrated/separate; (iv) remote control; (v) cord rewind; (vi) shampoo; (vii) speed control; (viii) soft/hard box; (ix) type of machine: 6 types – cylinder; upright; wet/dry; steam; handstick; rechargable; (x) outlet-types: multiples, mass merchandisers, independents, multiples.

Cameras

(i) Manufacturer (make) – dummy variables for about 25 makes; (ii) type of camera: 6 types – 135; roll film 120/220; instant; cassette 110; disc; APS; (digital excluded); (iii) view system: single lens reflex (SLR); viewfinder; bridge; (iv) exposure system: manual; aperture; programme; (v) lens: bifocal; fixed; zoom; (vi) water resistant (vii) compact zoom range: less than 60; 1-80; 1-90; 1-105; 6-115; 115 mm and more; (viii) panoramic (APS); (ix) dateback (APS); (x) titles (APS); (xi) film specifications (APS); (xii) camera specifications (APS); (xii) mid roll change (APS); (xiv) medium format SLR 6x6; (xv) DX coding; (xvi) automatic loading (drop in); (xvii) motor advance; (xix) mini (108mm or less); (xx) auto focus; (xxi) built-in flash; (xxii) red eye reduction; (xxiii) vintage; (xxiv) vintage; (xxv) outlet types: specialised stores; independent chemists; non-specialised.

Notes

1. An analysis of the data found there to be, on average, 75 models of Hotpoint machines with at least one sold in a month in 1999, irrespective of the type of outlet it was sold in.

2. These approaches are mainly based on the calculation of a test statistic after the application of a weighted squared estimator (WLS) to correct for heteroskedasticity. The weights are the variances of the residuals in each period, more commonly known as the asymptotic Chow test (AChow). The statistic, *w/k*, has a critical value of F_{α}, though some of the rejection region is subsequently allocated to an inconclusive region with the AChow bounds test where $c_1 = F_{\alpha}$ is the lower bound and $c_2 = F(k, \min(n_1 - k, n_2 - k))$ the upper bound where n_1 and n_2 are respective sample sizes and k the number of parameters. These bounds have been further modified to allocate the inconclusive region to acceptance and rejection areas via the modified AChow tests. One modification is the MAC2 which uses a critical value of: $c_{12} = c_1 + (c_2 - c_1)|n_1 - n_2| / (n_1 + n_2)$

   When $n_1 = n_2$ we have the AChow test but as they depart, the critical value approaches the upper bound of the AChow bounds test. In simulations this is one of three tests recommended by Thursby (1992) being computationally simple and having reasonable sampling properties under the null being slightly conservative.

   There appears to be no downside to using these heteroskedastic-adjusted tests. When homoskedasticity holds the loss of power from using a corrected test is minor (Thursby, 1992). Tsurumi and Sheflin (1985) find that when sample sizes are equal, the Chow test is fairly robust, almost comparable to an adjusted Chow. However, as sample sizes increasingly differ, the effect of heteroskedasticity on the Chow test becomes increasingly severe. For our tests the sample sizes in each period are relatively similar so even under heteroskedastic errors, we do not expect much error from using the Chow test. Indeed the results of Table 4 bear this out with similar test statistics and imperceptibly narrow bounds. In part this is because the data are well-balanced – smaller sample sizes in one period leading to further bias in the Chow test.

3. The null hypotheses here, for each of 1998 and 1999 *(as separate exercises)* are that:

$$
\begin{aligned}
H_0: \quad & \beta_{1,Jan} = \beta_{1,Feb} = \beta_{1,Mar} = \beta_{1,Apr} \;..........\beta_{1,Dec} \\
& \beta_{2,Jan} = \beta_{2,Feb} = \beta_{2,Mar} = \beta_{2,Apr} \;.........\beta_{2,Dec} \\
& \quad . \qquad . \qquad . \qquad . \qquad . \\
& \quad . \qquad . \qquad . \qquad . \qquad . \\
& \quad . \qquad . \qquad . \qquad . \qquad . \\
& \beta_{k,Jan} = \beta_{k,Feb} = \beta_{k,Mar} = \beta_{2,Apr} \;.........\beta_{k,Dec}
\end{aligned}
$$

   against the alternative hypothesis that these coefficients are not equal.

4. More formally: if we have 14" sets or otherwise in January, February and March, the equations for each month are:

$$
\begin{aligned}
y &= \beta_0 + \beta_{1,14} \quad January \\
y &= \beta_0' + \beta_1'{}_{14} \quad February \\
y &= \beta_0'' + \beta_1''{}_{14} \quad March
\end{aligned}
\tag{A.1}
$$

   or:

$$
\begin{aligned}
y = \beta_0 &+ (\beta_0' - \beta_0)Feb + (\beta_0'' - \beta_0)Mar + \beta_{1,14} + (\beta_1' - \beta_1)14\,Feb ... \\
&+ (\beta_1'' - \beta_1)14\,March + \varepsilon
\end{aligned}
\tag{A.2}
$$

where all variables are equal to one if the condition is met, e.g. *14 March*, being if a 14” set in March, is satisfied. By inserting appropriate values into equation (A.2) it reduces to equations (A.1). The coefficients for each month for a 14” set is thus the difference in the marginal values of a 14” set between the month in question and January 1998, the exercise being repeated for 1999. The hedonic equations are in log-linear form so the coefficients can translate into percentage changes.

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Table 2: Summary statistics on major makes

	Sales weighted mean prices		Market share	
	1998	**1999**	**1998**	**1999**
Washing machines:				
Bosch	459.20	434.60	11.7	14.8
Hoover	331.00	323.17	10.6	8.7
Zanussi	385.97	363.25	12.8	16.0
Hotpoint	359.07	341.55	39.3	32.9
Dishwashers:				
Bosch	374.32	349.8	29.1	31.7
Zanussi	313.32	299.2	14.9	12.1
Hotpoint	331.65	321.8	21.3	21.7
Vacuum cleaners:				
Hoover	102.33	113.53	9.2	11.0
Dyson	216.02	202.61	55.4	29.3
Electra	110.57	106.15	12.1	12.7
Television sets:				
Sony	462.37	518.77	21.0	22.2
Panasonic	411.39	453.43	17.8	17.2
Toshiba	489.03	491.67	15.1	14.1
Philips	509.37	547.90	9.5	11.6
Cameras:				
Cannon	153.44	141.38	30.0	28.7
Olympus	86.84	92.55	13.1	14.6
Kodak	46.22	48.39	5.8	7.0
Minolta	145.98	138.55	14.0	12.7
Fuji	96.08	64.42	5.9	5.5
Pentax	169.63	150.92	9.8	10.3

Table 4: Regression of log of price of TVs for hedonic regression, 1998.

	Estimated coefficient	Standard error		Estimated coefficient	Standard error
Constant	4.952	0.200***			
Months (January omitted)			**Screen size** (14" omitted)		
February	-0.008	0.008	6 inches	0.523	0.047***
March	-0.013	0.008**	10 inches	0.469	0.022***
April	-0.022	0.008**	15 inches	0.364	0.154**
May	-0.023	0.009***	16 "	0.248	0.028***
June	-0.042	0.008***	18 "	0.403	0.018***
July	-0.048	0.008***	20 "	0.370	0.009***
August	-0.058	0.008***	21 "	0.426	0.009***
September	-0.074	0.008***	24 "	0.628	0.022***
October	-0.083	0.008***	25"	0.742	0.010***
November	-0.087	0.008***	28"	0.879	0.011***
December	-0.111	0.008***	30 "	1.029	0.012***
Makes (Sony omitted)			32 "	1.375	0.016***
Akai	-0.263	0.030***	33 "	1.465	0.012***
Akura	-0.204	0.109*	35 "	1.599	0.056***
Alba	-0.210	0.035***	36 plus	1.623	0.037***
Amstrad	-0.604	0.027***	**Characteristics**		
Beko	-0.424	0.014***	Flat screen tube	0.007	0.007
Bang & Olufsen	0.584	0.039***	Super planar tube	0.126	0.074*
Bush	-0.292	0.012***	Built-in cable tuner	-0.03	0.035
Crown	-0.383	0.032***	Hyperband cable tuner	0.086	0.032**
Daewoo	-0.278	0.012***	Teletext text retrieval	0.069	0.008***
Decca	-0.200	0.033***	Fastext text retrieval	0.087	0.006***
Ferguson/Ultra	-0.314	0.013***	Pal tuner	0.012	0.030
Goodmans	-0.332	0.036***	Pal 1 tuner	0.000	0.006
Grundig	-0.151	0.022***	Pal/Secam tuner	-0.111	0.034***
Hitachi	-0.110	0.009***	Pal/Secam/NTSC tuner	0.048	0.007***
JVC	-0.103	0.009***	Pal/Secam/NTSC/D2 Mac tuner	-0.142	0.117
LG	-0.246	0.014***	Pal plus tuner	-0.041	0.078
Loewe	0.416	0.041***	Satellite tuner	0.072	0.049
Mitsubishi	-0.105	0.010***	Digital	0.026	0.006***
NEC	-0.634	0.155***	S-VHS socket	-0.012	0.005**
NEI	-0.337	0.021***	Wide screen	0.254	0.010***
Nokia	-0.293	0.077***	Dolby pro-logic/surround	0.214	0.603***
Orion	-0.362	0.024***	Monitor type	0.052	0.011***
Panasonic	-0.003	0.008	Nicam stereo	0.165	0.007***
Philips	0.020	0.008**	Vintage (year)	0.001	0.002
Pye	-0.262	0.016***	**Store** (Multiples omitted)		
Samsung	-0.214	0.014***	Mass merchandisers	0.087	0.005***

Sanyo	-0.147	0.011***	Independents	0.149	0.005***
Sharp	-0.154	0.011***	Catalogue	0.264	0.006***
Tatung	-0.073	0.012***			
Thompson	-0.252	0.016***	n = 7,799		
Toshiba	-0.037	0.009***	$\overline{R}^2 = 0.9459$		
Others	-0.354	0.020***			

one-tailed tests: *, **, *** denotes statistically significant at a 5%, 1% and 0.1% level respectively

Table 7: Stability of selected variables within year

Year	Television set	F	*p*-value	Camera	F	*p*-value	Vacuum cleaner	F	*p*-value
98	Sony	2.46	0.004	Cannon	0.29	0.98	Dyson	0.18	0.99
99		1.12	0.29		0.13	0.99		0.22	0.99
98	Panasonic	0.29	0.29	Olympus	0.15	0.99	Electrolux	0.53	0.87
99		1.22	0.26		0.34	0.97		1.05	0.34
98	Toshiba	2.41	0.005	Kodak	0.19	0.99	Hoover	1.48	0.12
99		0.078	0.99		0.13	0.99		1.61	0.08
98	Phillips	0.33	0.97	Minolta	0.15	0.99	Black&Decker	0.31	0.98
99		0.48	0.91		0.53	0.88		0.18	0.99
				Fuiji	0.29	0.98	Cylinder	0.51	0.89
					0.36	0.96		0.27	0.98
98	14”	0.67	0.76	Pentax	0.15	0.99	Upright	0.53	0.87
99		0.37	0.96		0.25	0.99		0.25	0.99
98	21”	0.34	0.97	F135	0.39	0.95	Tools	0.50	0.89
99		0.72	0.71		0.38	0.96		0.30	0.98
98	25”	0.27	0.99	APS	0.64	0.78			
99		0.50	0.90		0.16	0.99			
98	Nicam	0.33	0.97	Bi	0.45	0.93			
99		0.23	0.99		0.54	0.87			
98	Fastext	0.15	0.99	Zoom	1.03	0.41			
99		0.35	0.97		0.74	0.69			
98	Teletext	0.76	0.67						
99		0.68	0.75						
98	Widescreen	3.55	0.000						
99		1.46	0.13						

Table 7 continued: Stability of selected variables within year

Year	Washing Machine	F	*p*-value	Dishwashers	F	*p*-value
98	Hoover	5.19	0.000	Bosch	0.48	0.91
99		0.44	0.93		1.02	0.41
98	Bosch	0.49	0.90	Zanussi	1.10	0.35
99		0.95	0.48		0.57	0.85

98	Zanussi	1.76	0.054	Hotpoint	0.62	0.80
99		0.45	0.93		0.64	0.79
98	Hotpoint	0.89	0.54	Free stand	1.36	0.18
99		0.37	0.96		0.51	0.89
98	800 spin speed	0.10	0.99	Built-under	1.45	0.14
99		1.16	0.30		0.56	0.85
98	1000 spin speed	0.47	0.92	8 plates	0.53	0.88
99		0.25	0.99		0.32	0.97
98	1200 spin speed	0.85	0.58	12 plates	0.83	0.60
99		0.46	0.92		0.23	0.99
98	1400 spin speed	0.39	0.95			
99		1.39	0.16			
98	Wdry	0.62	0.81			
99		0.17	0.99			

Table 8: Summary statistics on outlet types

	Sales weighted mean prices (£s)		Market share, by value (%)		Regression coefficients* and (*t*-statistics)	
	1998	**1999**	**1998**	**1999**	**1998**	**1999**
Washing machines						
Multiples	345.63	329.39	43.8	43.3	cof (t)	cof (t)
Mass merchandisers	400.52	386.25	12.1	11.4	0.05(8.1)	0.04(6.6)
Independents	385.20	369.23	34.2	34.6	0.07(13.3)	0.08(14.2)
Catalogue	346.29	335.60	10.0	10.7	0.19(25.5)	0.24(35.5)
Dishwashers						
multiples	310.3	285.09	39.2	40.5		
mass merchandisers	378.32	347.73	14.6	13.3	0.06(6.2)	0.05(4.8)
independents	412.59	381.44	42.8	42.2	0.09(11.6)	0.08(7.54)
catalogue	326.72	311.85	3.4	4.0	0.20(13.5)	0.21(23.5)
Vacuum cleaners						
multiples	146.64	142.29	36.3	36.7		
mass merchandisers	99.04	92.98	19.4	20.1	0.027(2.71)	0.049(4.4)
independents	158.08	151.89	18.2	15.6	0.083(17.7)	0.091(8.3)
catalogue	156.36	153.64	26.1	27.5	0.242(23.2)	0.254(22.3)
Television sets						
multiples	360.8	395.24	31.8	34.3		
mass merchandisers	288.45	293.15	18.8	18.1	0.087(17.7)	0.0609(8.19)
independents	402.5	434.5	39.8	40.6	0.150(31.4)	0.181(30.8)
catalogue	268.1	263.4	9.5	7.0	0.265(43.9)	0.169(10.5)
Cameras						
Specialised	171.42	160.01	57.4	57.3		
Independent chemists	45.75	53.11	0.30	0.5	-0.004(-0.1)	0.16(0.54)
Non-specialised	70.03	63.17	42.3	42.2	-0.096(-2.8)	-0.073(-2.45)

* From semi-logarithmic formulation

Table 11a, Fixed base hedonic estimates of quality adjusted price changes and varying parameter constraints for year 1998

	Dishwashers hedonic indices, coefs constrained:		hedonic imputations:		Washing machines Coefficients constrained to be the same: hedonic indices:		hedonic imputations:	
	all months	current & base month	base month	current month	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
February	0.998	0.996	1.045	0.993	1.001	1.005	1.003	1.001
March	0.987	0.986	0.981	0.992	1.015	1.013	1.012	1.026
April	0.985	0.983	0.991	0.991	0.995	0.997	1.000	1.017
May	0.967	0.965	0.970	0.994	0.990	0.991	0.995	1.014
June	0.943	0.935	0.945	0.934	0.984	0.986	0.985	1.007
July	0.950	0.940	0.931	0.947	0.969	0.970	0.966	0.989
August	0.942	0.933	0.922	0.964	0.969	0.973	0.969	0.997
September	0.937	0.927	0.942	0.955	0.959	0.968	0.962	0.984
October	0.948	0.939	0.931	0.962	0.957	0.961	0.953	0.984
November	0.930	0.916	0.913	0.931	0.951	0.956	0.952	0.982
December	0.918	0.915	0.877	0.933	0.935	0.945	0.943	0.968

	Vacuum cleaners hedonic indices, coefs constrained:		hedonic imputations:		Television sets Coefficients constrained to be the same: hedonic indices:		hedonic imputations:	
	all months	current & base month	base month	current month	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
February	1.009	1.005	1.010	1.000	0.992	0.993	1.000	0.993
March	1.012	1.010	1.008	1.004	0.987	0.986	0.980	0.984
April	1.014	1.012	1.013	1.003	0.978	0.978	0.973	0.962
May	1.015	1.013	1.004	1.004	0.977	0.977	0.982	0.968
June	1.012	1.014	1.006	1.000	0.959	0.957	0.971	0.955
July	1.002	1.003	0.994	0.992	0.953	0.952	0.901	0.946
August	1.002	1.006	0.999	0.994	0.943	0.942	0.949	0.931
September	0.994	0.998	0.987	0.989	0.929	0.929	0.875	0.921
October	0.994	1.001	0.996	0.988	0.920	0.920	0.931	0.916
November	0.997	1.002	1.000	0.996	0.916	0.918	0.974	0.900
December	0.999	1.010	1.010	0.995	0.895	0.896	0.962	0.889

	Cameras hedonic indices, coefs constrained:		hedonic imputations:	
	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000
February	0.992	0.996	0.990	1.003
March	0.975	0.981	0.962	0.988
April	0.964	0.961	0.949	0.968
May	0.943	0.948	0.961	0.963
June	0.938	0.935	0.946	0.959
July	0.917	0.918	0.923	0.930
August	0.910	0.906	0.901	0.913
September	0.896	0.893	0.903	0.903
October	0.900	0.892	0.884	0.895
November	0.913	0.910	0.871	0.906
December	0.889	0.889	0.884	0.877

Table 11b, Fixed base hedonic estimates of quality adjusted price changes and varying parameter constraints for year 1999

	Dishwashers hedonic indices, coefs constrained:		hedonic imputations:		Washing machines Coefficients constrained to be the same: hedonic indices:		hedonic imputations:	
	all months	current & base month	base month	current month	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
February	0.998	0.992	0.945	0.993	1.006	0.984	0.917	0.964
March	1.001	0.995	0.976	0.989	1.022	1.007	1.001	0.943
April	0.960	0.929	0.940	0.992	1.015	0.989	1.018	0.936
May	0.953	0.903	0.952	0.977	1.017	1.014	1.011	0.933
June	0.924	0.931	0.938	0.960	1.005	0.986	0.994	0.925
July	0.933	0.872	0.833	0.967	0.991	0.963	0.985	0.912
August	0.934	0.898	0.916	0.975	0.975	0.964	0.961	0.891
September	0.925	0.817	0.783	0.983	0.982	0.951	0.936	0.896
October	0.939	0.902	0.926	0.962	0.985	0.980	0.960	0.902
November	0.924	0.845	0.806	0.989	0.977	0.945	0.887	0.899
December	0.942	0.891	0.847	0.991	0.968	0.948	0.930	0.887

	Vacuum cleaners hedonic indices, coefs constrained:		hedonic imputations:		Television sets Coefficients constrained to be the same: hedonic indices:		hedonic imputations:	
	all months	current & base month	base month	current month	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
February	1.008	1.012	1.021	1.013	0.998	0.993	1.007	1.002
March	1.011	1.014	1.027	1.019	0.979	0.975	0.991	0.983
April	1.004	1.002	1.018	1.013	0.967	0.970	0.986	0.988
May	0.994	0.995	1.018	1.002	0.953	0.960	0.992	0.968
June	0.974	0.974	1.006	0.989	0.938	0.943	0.965	0.967
July	0.952	0.947	0.974	0.966	0.926	0.932	0.948	0.965
August	0.954	0.959	0.979	0.974	0.892	0.898	0.961	0.952
September	0.942	0.938	0.958	0.964	0.902	0.901	0.935	0.957
October	0.943	0.932	0.957	0.972	0.884	0.882	0.914	0.937
November	0.954	0.960	0.984	0.980	0.903	0.917	0.937	0.959
December	0.943	0.941	0.972	0.968	0.872	0.872	0.972	0.946

	Cameras hedonic indices, coefs constrained:		hedonic imputations:	
	all months	current & base month	base month	current month
January	1.000	1.000	1.000	1.000
February	1.014	1.010	1.011	1.024
March	1.026	1.027	0.990	1.037
April	1.037	1.030	1.022	1.076
May	1.008	1.006	1.012	1.019
June	0.996	0.994	1.002	1.009
July	0.988	0.971	0.987	0.990
August	0.985	0.989	0.993	0.995
September	0.981	0.976	0.977	0.996
October	0.966	0.968	0.964	0.998
November	0.955	0.956	0.921	0.957
December	0.965	0.966	0.977	0.980

Figure 1.1: Coefficients and t-statistics for wide screen

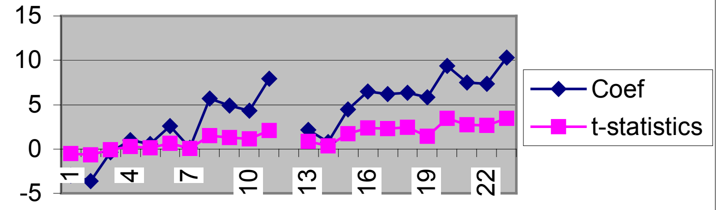

Figure 1.2: Coefficients and t-statistics for Sony

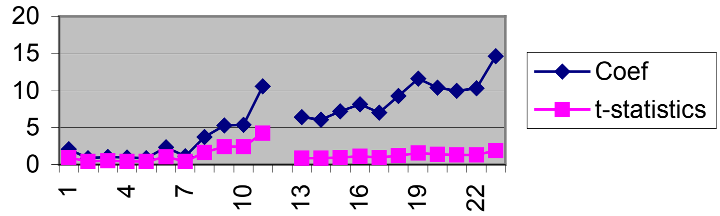

Figure 1.3: Coefficients and t-statistics for Toshiba

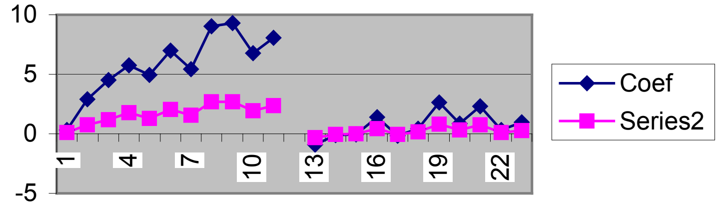

Figure 1.4: Coefficients and t-statistics for Hoover