Aug 03 draft

On Hedonic Quality Adjustments, the Stability of Hedonic Coefficients and their Implications for CPI Measurement

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Paper for presentation at NBER/CRIW conference on Hard-to-Measure Goods and Services: Essays in Honour of Zvi Griliches; Bethesda, MD, 19th to 20th September 2003

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Elements of this study are part of a wider study funded by the UK Office for National Statistics (ONS). We are grateful to the ONS for permission to reproduce some of this work in the form of this paper. The views expressed in the paper are those of the authors and not the ONS. Helpful advice has also been received from David Fenwick (ONS), Adrian Ball (ONS) and Pat Barr (GfK Marketing) and at the NBER Summer Institute 2002, particularly from Ernie Berndt (MIT), but also from Ana Aizacorbe (Federal Reserve Board), Erwin Diewert (University of British Columbia) and Matt Shapiro (University of Michigan). The usual disclaimers apply.

ABSTRACT

The proper measurement of inflation is of major importance to both macroeconomic policy formulation and inflation compensation adjustments. It is recognised that a major deficiency of consumer price indexes (CPIs) is their inability to properly account for quality changes (Boskin *et al*, 1996). The use of the matched models method to control for quality changes is inadequate for markets with highly differentiated products and rapid turnover of models. Hedonic regression methods are seen as the most promising alternative. Yet there is still some ambiguity, as highlighted in the recent Report of the Committee on National Statistics (2002)—the Schultze panel, as to how best to use hedonic regression methods. The paper provides an extensive examination of alternative methods for estimating hedonic indexes. Three general approaches are considered: *hedonic imputation (HI) indexes* which value a fixed period's basket of characteristics using both base period and current period hedonic coefficients and take the ratio of the latter to the former. Formulae differ in their use of which period's characteristics are held constant for the valuation. The second approach, *dummy time hedonic (DTH)* indexes, uses the estimated coefficients on the dummy variables for time in a hedonic regression as measures of price changes. For HI indexes the changes in the parameters over time are the essence of the measure. For DTH indexes the slope parameters are paradoxically constrained to be the same. The third approach is *fixed effects models (FE) indexes,* akin to the country product dummy method used in purchasing power parity studies, in which prices are regressed against two sets of dummy-variables. One set contains dummies for time and the second set fixed effects (dummies) for each distinct model as defined by its bar code. We show an equivalent between such methods and matched models comparisons.

All three approaches are applied in this study to three products in a number of ways including weighted and unweighted, chained and fixed base and arithmetic and geometric aggregators—*thirty six* methods in all, and 216 alternative measures in all. The study provides an exhaustive study of the major tools available for dealing with measuring prices in differentiated product markets subject to high model turnover, i.e. when the matched models method breaks down and hedonic indexes are the main practical alternative. The study uses extensive scanner data on a monthly basis over January 1998 to December 1999 for three consumer durables: washing machines, dishwashers, and vacuum cleaners covering the changing quality features of about 43,000 observations representing 10.3 million transactions. In a novel development the study employs meta-analysis on the 216 results to better establish how different index number formulations differ.

Keywords: HEDONIC REGRESSIONS; COLI; CONSUMER PRICE INDEX; PARAMETER STABILITY; SCANNER DATA; META-ANALYSIS.

JEL classification: C43, C82, E31.

1. INTRODUCTION

Measurement bias in the U.S. consumer price index (CPI) has been the subject of three major reports, the Stigler Committee (1961), Boskin Commission (1996) and the report by the Committee on National Statistics (2002), the Schultze panel. A major concern of all three reports was bias due to an inability of the CPI to properly incorporate the effects of changes in the quality of goods and services consumed. The primary mechanism in CPI methodology for controlling for the effects on price of quality changes is the matched model method. A sample of items is selected in a price reference (base) period, and their prices are recorded in that period and matched in subsequent periods so that the resulting price changes are untainted by quality changes; like is compared with like. Two sources of bias may arise with this method. The first is that the matched sample can ignore the prices of unmatched varieties, particularly new varieties introduced after the base period – what Triplett (2002) calls *out-of-sample bias*. As the matched sample becomes increasingly unrepresentative of the universe of varieties, such bias may increase (Silver and Heravi, 2002). The second arises when items from the matched sample are no longer sold in subsequent periods. The price changes can be imputed by assuming they are the same as other goods in their class, or replacement items' prices may be used with or without an explicit adjustment for any difference in its quality, depending on its perceived comparability. If such assumptions or adjustments are wrong, this gives rise to Triplett's *in-sample bias* (Moulton and Moses, 1998 and Triplett, 2002). Hedonic regressions have been considered best-suited for quality adjustments by the Stigler, Boskin and Schultze reports, though a more cautious stance was taken by the latter:

> "Hedonic techniques currently offer the most promising approach for explicitly adjusting observed prices to account for changing product quality. But our analysis suggests that there are still substantial unresolved econometric, data, and other measurement issues that need further attention." (Committee on National Statistics, 2002: 6).

This paper examines alternative approaches to the use of hedonic *indexes* for quality adjusting CPIs in dynamic markets to explicitly adjust for in-sample and out-of-sample bias: when both matched and unmatched data are used. The need for such an evaluation requires emphasis. Many product markets are highly differentiated by brand and characteristics with rapid turnover of models. Monitoring the matched prices of, for example, near obsolete models of personal computers while ignoring new models is unsuitable. Hedonic indexes are based on (representative samples of) prices of models in each period, some of which will be matched, but some will reflect the dynamic nature of the market. There are a host of such methods and relatively little work on their nature and evidence on their differences (though see Berndt and Rappaport (2001), Pakes (2002) and Aizcorbe (2003) on parameter instability).

The study is an extensive examination of the alternative methods for this important area where the matched models method breaks down. The broad nature of hedonic indexes is outlined in Section 2. Section 3 outlines *thirty six* alternative methods and discusses their relative merits. These methods fall under three general approaches: (i) *Hedonic imputation indexes* (hereafter HI indexes) which rely on parameter instability for the measurement of price changes, (ii) *Dummy time (variable) hedonic indexes* (hereafter DTH indexes) which paradoxically constrains parameters between the periods to be the same and (iii) *fixed effects model indexes* (hereafter FE indexes) which are similar to DTH indexes, but use dummy variables for individual models, as opposed to their characteristics, to control for quality changes. The breadth of the empirical work allows us to consider a number of research questions. We comment on the use of chaining, weighting, arithmetic versus geometric aggregation, parameter instability, base-current period spread and the differences between and relative merits of the three approaches. Research issues and formulae are summarised in section 4. Many of the issues are empirical ones and section 5 outlines the data for the study: monthly scanner data for three electrical consumer durables; washing machines, vacuum cleaners and dishwashers. The data includes details of prices, sales and quality characteristics on about 43 thousand observations representing over 10 million transactions. Section 6 discusses the results from the 36 measures for 3 products over 2 years, i.e., 216 resulting index numbers. It employs a meta-analysis of this data to better establish the patterns from employing different index number formulations. This extends to an analysis of the spread of base-current period HI indexes, an issue of interest given a recommendation by Pakes (2002) for the use of 'Paasche-type' current period HI indexes which require hedonic estimates in only the base period.

2. THE HEDONIC APPROACH

a) Theory

The hedonic approach involves the estimation of the implicit, shadow prices of the quality characteristics of a product. A set of ($z_k = 1,\ldots.K$) price-determining characteristics of the models are identified and data over i=1,…N 'models' are collected. A hedonic regression equation of the price of model i, p_i, on its set of quality characteristics z_{ki} is given by $\boldsymbol{h_i}(z_i)$:

$$\ln \boldsymbol{p_i} = \gamma_0 + \sum_{k=1}^{K} \boldsymbol{\beta_k} \boldsymbol{z_{ki}} + \boldsymbol{\varepsilon_i} \tag{1}$$

The β_k are estimates of the marginal valuations the data ascribes to each characteristic. Rosen (1974) showed that they can be equated in economic theory to a mapping of the equilibria in characteristic space of production possibility curves and indifference curves of specific distributions of optimising consumers and producers with respective varying tastes and technologies. Rosen (1974), Griliches (1988) and Triplett (1988) have argued that the derivatives of a hedonic regression should not be interpreted as either one of estimates of willingness to pay derivatives or cost derivatives, but arise from equilibria processes (though see Diewert (2003) for a demand-based framework). Griliches (1988: 120) noted that:

> "My own view is that what the hedonic approach tries to do is to estimate aspects of the budget constraint facing

consumers, allowing thereby the estimation of "missing" prices when quality changes. It is not in the business of estimating utility functions *per se*, though it can also be useful for these purposes…what is being estimated is the actual locus of intersection of the demand curves of different consumers with varying tastes and the supply curves of different producers with possible varying technologies of production. One is unlikely, therefore to be able to recover the underlying utility and cost functions from such data alone, except in very special circumstances."

Pakes (2002) identified the hedonic price function as the sum of the marginal cost function and a function that summarizes the relationship between mark-ups and characteristics. The coefficients can thus change when the characteristics of products or the distribution of consumer preferences change. Two implications arise; that coefficients may change over time – new products will be directed to parts of characteristic space where mark-ups had been high driving down the mark-up – thus being 'unstable'. Second, and more contentiously, that there is no reason to expect the coefficients to be positive on desirable characteristics.[1]

Econometric issues are surveyed in Griliches (1990), Triplett (1990) and Gordon (1990), but for examples of empirical work and further discussion of econometric issues see also Griliches (1971), Cole (1986), Dulberger (1989), Berndt and Griliches (1993), Arguea, Hsiao and Taylor (1994), Berry, Levinsohn and Pakes (1995), Berndt, Griliches and Rappaport. (1995), Silver and Heravi (2001), Kokoski *et al*. (2001) and Diewert (2002).

b) Alternative methods and the scope of the study

Statistical offices use the matched models method for CPI measurement whereby price collectors select a sample of models in a price reference period 0, and then continue to collect prices of these same matched models in subsequent periods so that the prices of like are compared with like. When a model is missing, because it is obsolete, the price collector may find a replacement of a comparable quality, in which case a direct price comparison may be made. If the replacement model is not directly comparable in quality, then the coefficients (or predicted value) from a hedonic regression may be used to make a quality adjustment, so that the old and new (non-comparable) unmatched prices can be compared. Silver and Heravi (2001) refer to this as 'patching' and Pakes (2002) as hybrid indexes. However, patching can only make use of data outside of the matched sample when an item is missing. It may be that several new varieties are introduced in a month when there are few, if any, replacements. The likely atypical price changes of the new varieties will be ignored with patching. The needs of quality adjustment, in dynamic markets such as personal computers, is to resample each month to cover a representative sample of what is purchased. The concern of *hedonic*

[1] When development costs are a function of the characteristics of a product, product development strategies may involve trading off one vertically characteristic against another, leading to a mark-up with the 'wrong' sign. Furthermore, averages of characteristics are used in regressions and these assume that given inputs of such characteristics 'produce' the same utility to all consumers. A positive coefficient on a vertical characteristic requires that we can order the utility generated by the 'input' of a characteristic and that this ordering is the same for all consumers. Yet consumers with differing social, economic or demographic attributes will differ in the way that more utility is generated for given inputs of characteristics and there is then no reason to expect that a product that produces more of a vertical characteristic than a competitor will have a higher price (see also Tauchen and Witte, 2001). Given such complexities Diewert's (2002) has argued that there is much that be gleaned from a simpler demand side approach that is applicable in product markets characterised as such.

indexes is to ensure changes in the average quality of the models purchased do not taint measured changes in their average price.

This paper is concerned with different methods for hedonic indexes. We consider three such approaches and their relative merits: HI indexes, DTH indexes and FE indexes.[2] It will be seen that the three approaches, which are outlined below, while using the same data, have quite different conceptual bases and properties. For example, the essence of HI indexes is parameter instability while, paradoxically, the essence of the DTH indexes is to constrain the parameters on quality characteristics to be the same. The three approaches are each used in this study, first, as direct comparisons between periods 0 and *t*, and second, as chained indexes, with individual links being calculated between periods 0 and 1, 1 and 2,…, *t*-1 and *t,* the results being combined by successive multiplication. Third, they are further compiled using a geometric aggregator and then, fourth, an arithmetic one. They are fifth, then compiled in their simplest form – as unweighted indexes – and sixth, as weighted indexes for comparison. It is stressed that indexes based on data using weights are no doubt preferable, but in practice statistical offices do not generally have access to data on weights,[3] drawing information on prices and characteristics from observed display prices in outlets, web sites and magazines. The research question asked is that: given the realistic use of such unweighted data, does it matter? These and further issues are considered below.

3. THE METHODS

a). Hedonic imputation indexes – unweighted geometric means

Four methods are outlined here. Base and current period direct HI indexes (each requiring hedonic regressions in both periods), a geometric mean of the two, and an indirect current period hedonic index requiring only a base period regression. All methods outlined here use geometric means. The BLS use the geometric mean – the Jevons index – at this elementary aggregation for much of the U.S. CPI (Dalton *et al*., 1998). The Jevons index is also the recommended formula at this level in the forthcoming ILO *Manual* on Consumer Price Indexes. A semi-logarithmic formulation of the DTH method is used below which is consistent with a geometric mean.[4]

♣ ***unweighted geometric (Jevons) hedonic base period index*** holds *base* period 0 characteristics

[2] Kokoski *et al*. (1999) and Silver and Heravi (2001 and 2003) use a superlative framework, the latter being an adaptation of Feenstra (1995). In this adaptation weighted mean prices are compared for strata or cells of core characteristics, say televisions of particular brands and screen sizes. Hedonic regressions are used to control for quality changes for price changes within individual cells.

[3] Balk (2002) has shown that if the items are selected with probability proportionate to (quantity or value share) size (pps), then the sample unweighted estimator is of a population weighted target index, for which economic theory applies. For example, if sampling is with probability proportionate to base period value shares, then the expected value of a Carli index is a Laspeyres index. A Laspeyres index restricts consumer substitution to be zero and overstates inflation since items with above average price changes are not given less weight since any fall in quantity is not reflected in the weights. However, the expected value of a Jevons index under the same sampling scheme produces a base period weighted geometric mean which Balk (2002) has shown to correspond to consumer substitution behavior consistent with an elasticity of substitution of unity. The incorporation of such substitution effects was the main justification for the BLS switch to the Jevons index

[4] Silver (2002a) has shown that influence effects in the regression of outliers may distort the representativity of such indiexes.

constant under both base and current period prices. Consider a semi-logarithmic hedonic function $\hat{p}^0 = h^0(z^0)$ estimated in period 0 with period 0 quality characteristics and N^0 observations using (1). The resulting unweighted (or more precisely, equally weighted) *Jevons hedonic base* period index, P_{JHB}, is given by:

$$P_{JHB} = \frac{\left[\prod_{i=1}^{N^o} h_i^t\left(z_i^0\right)\right]^{1/N^o}}{\left[\prod_{i=1}^{N^o} h_i^0\left(z_i^0\right)\right]^{1/N^o}} = \frac{\left[\prod_{i=1}^{N^o} h_i^t\left(z_i^0\right)\right]^{1/N^o}}{\left[\prod_{i=1}^{N^o} \hat{p}_i^0\right]^{1/N^o}} = \frac{\left[\prod_{i=1}^{N^o} h_i^t\left(z_i^0\right)\right]^{1/N^o}}{\left[\prod_{i=1}^{N^o} p_i^0\right]^{1/N^o}} \tag{2}$$

It is a *hedonic* price comparison because the characteristics are held constant and a *base* period one because they are held constant in this period. Some authors refer to this as Laspeyres or Laspeyres-type index. The terminology is misleading since weights have yet to be applied and these weights may be current or base period. We refer to base (current) period HI indexes, when the characteristic set being valued is a base (current) period one. Since HI indexes make use of all observations in each period, the mean of $\hat{p}_i^0$ in the denominator of (2) is equal to the mean of p_i^0. Thus the hedonic regression has only to be estimated in period *t*. This need not hold had a patched or hybrid index[5] been calculated.

Consider the first term of (2). The prices in (2) can be considered as those predicted from a period 0 bundle of characteristics using both period t and period 0 hedonic equations and then compared. The denominator is the geometric mean of predicted prices in period 0. The numerator is hypothetical: it is the geometric mean of prices of tied bundles of period 0 characteristics evaluated at the characteristic prices estimated in period t. Of course a utility maximising consumer in period t would not purchase a period 0 bundle of characteristics, but choose more of those characteristics whose relative prices had fallen. The base period HI index thus overstates, or is an upper bound on, its true theoretical cost-of-living index (COLI), since by measuring the cost of a fixed *base* period basket of characteristics, it does not allow for consumers substituting towards items/characteristics with below average price changes.[6] Consumers are not going to be worse off under a base period imputation since they can always substitute away from the base period bundle of characteristics, and may be better off from doing so.

♣ ***unweighted geometric (Jevons) hedonic current period index*** with constant *current* period characteristics given by:

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[5] Wherein only unmatched observations use hedonic estimates from the wider sample, then $\left[\prod_{i=1}^{N} \hat{p}_i^0\right]^{1/N} \neq \left[\prod_{i=1}^{N} p_i^0\right]^{1/N}$ if $E\left[\hat{p}_i^0\right]$ differ for *i* from matched and unmatched samples, for which there is some evidence (Silver and Heravi, 2002).

[6] Hedonic *base*-period indexes are defined in economic theory as the ratio of the minimum expenditures required to maintain a base period level of utility when the consumer faces p_t and p_{t-1} prices and tied bundles of quality characteristics z_t and z_{t-1} (Triplett, 1988, Zieschang and Fixler, 1992, Feenstra, 1995 and Diewert, 2002).

$$P_{JHC} = \frac{\left[\prod_{i=1}^{N^t} h_i^t\left(z_i^t\right)\right]^{1/N^t}}{\left[\prod_{i=1}^{N^t} h_i^0\left(z_i^t\right)\right]^{1/N^t}} = \frac{\left[\prod_{i=1}^{N^t} \hat{p}_i^t\right]^{1/N^t}}{\left[\prod_{i=1}^{N^t} h_i^0\left(z_i^t\right)\right]^{1/N^t}} = \frac{\left[\prod_{i=1}^{N^t} p_i^t\right]^{1/N^t}}{\left[\prod_{i=1}^{N^t} h_i^0\left(z_i^t\right)\right]^{1/N^t}} \tag{3}$$

What is apparent from the first terms of equations (2) and (3) is that parameter instability is the essence of quality-adjusted price change measurement using HI indexes. All that changes are the estimated coefficients. It is also apparent from (3) that by holding the basket of characteristics constant in the current period t, the hedonic imputation will give too little emphasis to above average price changes of characteristics. It will understate its theoretical COLI while (2) will overstate it. However, since the mean of predicted values will equal that of the observations, a hedonic regression equation need only be estimated for the base period 0.

♣ ***geometric mean of base and current period hedonic imputation indexes*** argued by Diewert (2002) to be a suitable symmetric mean in this (and many other) context:

$$P_{JHBC} = \sqrt{P_{JHB} P_{JHC}} \tag{4}$$

♣ ***indirect current period hedonic imputation*** method is calculated as a Jevons hedonic imputed *quantity* index divided into an index measuring the change in price to derive a *Jevons hedonic current* period *indirect* price index:

$$P_{JHCI} = \frac{\left[\prod_{i=1}^{N^t} p_i^t\right]^{1/N^t}}{\left[\prod_{i=1}^{N^0} p_i^0\right]^{1/N^0}} \div \frac{\left[\prod_{i=1}^{N^t} h_i^o\left(z_i^t\right)\right]^{1/N^t}}{\left[\prod_{i=1}^{N^0} h_i^0\left(z_i^0\right)\right]^{1/N^0}} = \frac{\left[\prod_{i=1}^{N^t} h_i^t\left(z_i^t\right)\right]^{1/N^t}}{\left[\prod_{i=1}^{N^t} h_i^0\left(z_i^t\right)\right]^{1/N^t}} = P_{JHC} \tag{5}$$

(5) is of course equivalent to (3) and has no immediately apparent application, at least for geometric means.

(b) Hedonic imputation indexes – weighted geometric means

Equations (2), (3), (4) and (5) are unweighted indexes. In the compilation of a CPI weights are not used at the lowest level of aggregation, say for individual models of washing machines, due to lack of data on expenditure shares, though as Balk (2002) has argued they may be implicit in the sample design. However, it is axiomatic that were data on expenditure shares available they should be used to weight the price changes. Since scanner data provides current and base period expenditure share weights (s_i^t and s_i^0) and allows regressions to be run on current and base period data, the unweighted HI indexes can be compared with their weighted counterparts. Since (2) and (3) are ratios of geometric means, their weighted counterparts use a geometric aggregator for consistency so that the effects of weights can be determined without being confused by functional form. The weighted indexes in the base and current periods are geometric-Laspeyres and geometric-Paasche indexes and these are applied to Jevons base and current period HI indexes respectively:

♣ ***geometric-Laspeyres base period hedonic index***

$$P_{HB-GLas} = \frac{\left[\prod_{i=1}^{N^0} h_i^t\left(z_i^0\right)\right]^{s_i^0}}{\left[\prod_{i=1}^{N^0} h_i^0\left(z_i^0\right)\right]^{s_i^0}} \qquad (6)$$

♣ ***geometric-Paasche current period hedonic index***:

$$P_{HC-GPas} = \frac{\left[\prod_{i=1}^{N^t} h_i^t\left(z_i^t\right)\right]^{s_i^t}}{\left[\prod_{i=1}^{N^t} h_i^0\left(z_i^t\right)\right]^{s_i^t}} \qquad (7)$$

and the counterpart to (4):

♣ ***Törnqvist HI index***

$$P_{HBC-Tornq} = \sqrt{P_{HB-GLas} P_{HC-GPas}} \qquad (8)$$

c) Hedonic imputation indexes – unweighted arithmetic means of relatives[7]

We compare the unweighted and weighted geometric aggregators in equations (2) to (8) with their arithmetic relatives counterparts.[8]

♣ **unweighted arithmetic (Carli) hedonic base period index:**

$$P_{CaHB} = \sum_{i=1}^{N^0} \frac{h_i^t\left(z_i^0\right)}{h_i^0\left(z_i^0\right)} / N^0 \qquad (9)$$

♣ **unweighted arithmetic (Carli) hedonic current period index:**

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[7] There is a further set of arithmetic hedonic indexes based on the ratio of arithmetic averages, i.e. Dutot hedonic indexes as there are other formulations including harmonic mean hedonic indexes not considered here.

[8] For a *Carli hedonic base* index, separate (linear) hedonic estimates would be required for *each* period since $P_{CaHB} = \sum_{i=1}^{N} h_i^t\left(z_i^0\right) / h_i^0\left(z_i^0\right) = \sum_{i=1}^{N} h_i^t\left(z_i^0\right) / \hat{p}_i^0 \neq \sum_{i=1}^{N} h_i^t\left(z_i^0\right) / p_i^0$. Diewert (2002) and Silver and Heravi (2003) have argued that $\hat{p}_i^0$ should be used and not p_i^0 since any misspecification error that removes a price from the hedonic surface would then be included in the numerator, but not in the denominator, thus leading to bias.

$$P_{CaHC} = \sum_{i=1}^{N^t} \frac{h_i^t(z_i^t)}{h_i^0(z_i^t)} / N^t \qquad (10)$$

♣ **geometric mean of unweighted Carli hedonic base and current period indexes:**

$$P_{CaHBC-GM} = [P_{CaHB} \times P_{CaHC}]^{\frac{1}{2}} \qquad (11)$$

d) Hedonic imputation indexes – weighted arithmetic means of relatives

We can also compare the weighted geometric indexes in section (b), equations (6) to (8), to their arithmetic counterparts:

♣ ***Laspeyres hedonic base period index:***

$$P_{HB-Las} = \sum_{i=1}^{N^0} s_i^0 \left(\frac{h_i^t(z_i^0)}{h_i^0(z_i^0)} \right) \qquad (12)$$

♣ ***Paasche hedonic current period index:***

$$P_{HC-Pas} = \sum_{i=1}^{N^t} s_i^t \left(\frac{h_i^t(z_i^t)}{h_i^0(z_i^t)} \right) \qquad (13)$$

♣ ***Fisher hedonic index:***

$$P_{HBC-Fisher} = \sqrt{P_{HB-Las} P_{HC-Pas}} \qquad (14)$$

As regards the preferred weighting, s_i^0 or s_i^t, both baskets and indexes are equally justifiable from a conceptual point of view. Laspeyres (s_i^0) is widely used for the pragmatic reason that base period expenditure weights are readily available. Laspeyres is likely to overstate price changes since its fixed base period weights do not reflect the substitution of items with below average price increases for those with above average price increases. Similarly Paasche understates its theoretical COLI counterpart. However, there exists a class of superlative indexes, to which the Fisher (8) and Törnqvist (14) indexes belong which use symmetric averages of both base and current period quantity information (Diewert, 1990). Such indexes do not suffer from substitution bias and, moreover, can also be justified from an axiomatic and average fixed basket approach (Diewert, 1997). Following Boskin *et al*. (1996) the BLS is introducing a trailing Fisher index in recognition of its superiority as a measure of a cost-of-living index (COLI).[9]

All of the above methods can be used as **fixed** or **chained** base indexes. A fixed base Laspeyres HI index, for example, would compare prices in the base period 0 and current period t, while a chained version would form binary links between succeeding periods combining them using successive multiplication.

[9] Though the Schultze panel could not reach agreement as whether COLI or a cost of goods index (COGI) should be the preferred target (Committee on National Statistics, 2002).

e) Mean value function for hedonic indexes

Though not the subject of the empirical work, an understanding of the differences between the hedonic approaches benefits from an outline of some further HI indexes. Assume $z_i^0 = z_i^t$ and $N^t = N^0 = N$, i.e. the sample is matched. In this case for (2) and (3) (and similarly for other base and current period indexes):

$$P_{JHB} = P_{JHC} = \frac{\left[\prod_{i=1}^{N} h_i^t\left(z_i^t\right)\right]^{1/N}}{\left[\prod_{i=1}^{N} h_i^0\left(z_i^0\right)\right]^{1/N}} = \frac{\left[\prod_{i=1}^{N} p_i^t\right]^{1/N}}{\left[\prod_{i=1}^{N} p_i^0\right]^{1/N}} \qquad (15)$$

the hedonic base and current period indexes for the matched samples of items with identical characteristics require no quality adjustment; they are the ratio of average prices (or average of relatives).[10] But a constant characteristics HI index may be based on a mean value of the base and current period characteristics, say $\bar{z}_i = \left[z_i^0 z_i^t\right]^{1/2}$. Equations (2) and (3) would be:[11]

$$\frac{\left[\prod_{i=1}^{N} h_i^t\left(\bar{z}_i\right)\right]^{1/N}}{\left[\prod_{i=1}^{N} h_i^0\left(\bar{z}_i\right)\right]^{1/N}} = \frac{\left[\prod_{i=1}^{N} p_i^t\right]^{1/N}}{\left[\prod_{i=1}^{N} p_i^0\right]^{1/N}} \qquad (16)$$

but this would only hold for matched samples. If items exist in period *t* but not in 0, and *vice-versa,* then the left-hand-side of (16) is a hybrid measure the matched items being evaluated at $\bar{z}_i$ while the unmatched ones may be at z_i^0 or z_i^t in the denominator and numerator respectively. The equality in (16) would then not hold.[12]

f) Dummy time hedonic (DTH) indexes

A second approach is the DTH variable method which, as with HI indexes, does not require a matched sample.[13] The formulation is similar to equation (1) except that a single regression is estimated on the data in the two time periods compared, $i \in N^t \cap N^0$, the equation also including a dummy variable D^t being 1 in period *t*, zero otherwise:

[10] Diewert (2002) establishes similar results for weighted versions of these indexes.

[11] Similarly defined unweighted arithmetic and weighted geometric and weighted arithmetic baskets of characteristics can be defined. These can be placed in similarly defined unweighted and weighted HI indexes, (akin to Walsh and Marshall-Edgeworth formulae). A HI index is a family of indexes and can be defined for any average basket, such indexes differing from averages of the base and current period indexes.

[12] We can conceive of a measure which extrapolates z_i^t or z_i^0 using $\bar{z}_j / z_j^t$ or $\bar{z}_j / z_j^0$ for *j* matched items expected to have similar changes in characteristics.

[13] See De Haan (2003) for a variant that uses matched data when available and the time dummy only for unmatched data – his double imputation method.

$$\ln p_i^t = \gamma_0 + \gamma_1 D^t + \sum_{k=1}^{K} \beta_k z_{ki}^t + \varepsilon_i^t \quad (17)$$

The coefficient γ_1 is an estimate of the quality-adjusted price change between period 0 and period *t*. It is an estimate of the change in (the logarithm of) price, having controlled for the effects of variation in quality via $\sum_{k=1}^{K} \beta_k \, z_{ki}$.

Three versions of equation (17) are considered for both weighted and unweighted indexes. The weighted versions use a weighted least squares estimator (WLS) the weights being expenditure shares. Diewert (2002) shows the form the weights should take for the estimates to correspond to particular index numbers and Silver (2002) shows how observations with undue influence affects the representativity of the weights.

♣ ***fixed base dummy (time) variable hedonic regression*** comparing January with December, for example, would use data only for these two months, the coefficient on the dummy variable taking a value of 1 in March and zero in January.

♣ ***rolling, chained base dummy (time) variable hedonic regression*** for a January-December comparison would estimate separate fixed base dummy variable indexes for the January-February index, the February-March index, March-April index….November -December index, and combine these 'links' by successive multiplication.

♣ ***fully constrained dummy (time) variable hedonic regression*** is a single constrained regression for say January to December with dummy variables for each month, though this is impractical in real time since it requires data on future observations.

The regressions constrain each of the quality β_k coefficients to be the same across months. In restricting the slopes to be the same, the (log of the) price change between say periods 0 and *t* can be measured at any value of *z*. Bear in mind the HI indexes outlined above estimate the difference between price surfaces with different slopes. As such the estimates have to be conditioned on particular values of *z*, which gives rise to the two estimates considered: the base hedonic imputation using z^0 and the current period hedonic imputation using z^t. For the DTH method the very core of the method is to constrain the coefficients to be the same, so there is no need to condition on particular values of *z*. The estimate usefully and implicitly makes symmetric use of base and current period data.[14]

g) Fixed effects (panel) estimator

[14] It is worth noting that Pakes (2002: 29-30) is critical of the method on this very ground since he considers a proper index to be one which is a (upper) bound on the true price index, rather than an estimate of it. He argues that the coefficients might be expected to be unstable over time and thus restricting the coefficients to be the same does not provide an estimate which is an [upper] bound. Yet it is well accepted that neither Laspeyres nor Paasche are conceptually superior,[14] and a Fisher or other superlative index is preferable. The Paasche only has an advantage because it requires a single base period hedonic equation to be estimated. But this is not only conceptually unjustified, it is out of kilter with the

A fixed effects dummy (time) period regression (suggested by Diewert, 2001 in an earlier draft of Diewert, 2003) treats the data as if it is unbalanced panel data – the observations are on cross-sections of models over time. The regression equation effectively has on its right-hand-side the usual dummy variables for time, but also dummy variables for each of the models in any month, instead of quality characteristics, thus allowing us to control more directly for model heterogeneity (see Aizcorbe, 2003 for an application). In practice the panel estimation procedure is much simpler; each variable for model *i* in period *t* is subtracted from its mean over all periods *t*. The price deviations $\left(p_i^t - \overline{p}_i\right)$ for each model are regressed on the deviations of the explanatory dummy variables $(\mathbf{x}_i^t - \overline{\mathbf{x}}_i)$ for each model for all *t* with an adjustment for degrees of freedom (Davidson and Mackinnon, 1993: 323). The fixed effect panel estimator is effectively based on data of deviations of price and deviations of the dummy variables on the models from their respective means for a model over time.

♣ ***Fixed base fixed effects indexes*** are estimated comparing say January data directly with December for a December index based on January. However, if a model is unmatched in either month, its price $\boldsymbol{p}_i^t$ subtracted from $\overline{p}_i$, and its dummy explanatory variable, are zero. The estimator effectively estimates indexes for only matched data. For an index that compares January with December; a large number of models will not be available in December (January) than were in January (December). As shown by Silver and Heravi (2001) less data is lost in the matching if chained indexes are estimated.

♣ ***Chained base fixed effects index*** compares January with February, February with March……November with December , the results being combined by successive multiplication. A chained fixed effect index would not necessarily include all of the data, but is likely to include very much more than a fixed base one. For example, for a model available from January to March, the chained index for April would include its price change for the January to February and February to March links, but exclude it for the March to April link. The direct fixed based index for January to April would exclude it (Silver and Heravi, 2002).

♣ ***Fully constrained fixed effects index*** may well utilize more data than the chained version since models may appear and reappear in subsequent periods, allowing $\left(\boldsymbol{p}_i^t - \overline{\boldsymbol{p}}_i\right) \neq 0$ slightly more frequently.[15]

4. RESEARCH METHODS AND ISSUES

a. Methods and research questions

Table 1 summarises the formulae used in this study for all three approaches.

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base Laspeyres formulation used. A Paasche imputation is neither a fixed base period cost of goods index (COGI), which forms the conceptual basis of many European CPIs, nor a good approximation to a Fisher COLI index, which is the conceptual base for the US CPI.

[15] We follow Kennedy (1998: 227) in a preference for the fixed effect over the random effect model due to the context of the data exhausting the population.

Table 1, Alternative formulae for hedonic indexes

	Direct fixed base	**Chained base**
HI indexes – unweighted geometric		
Jevons hedonic base imputation	P_{JHB}	CP_{JHB}
Jevons hedonic current imputation	P_{JHC}	CP_{JHC}
Geometric mean of above	$P_{JHBC}=\sqrt{P_{JHB}P_{JHC}}$	CP_{JHBC}
HI indexes – weighted geometric		
Geometric-Laspeyres - hedonic base imputation	$P_{HB-GLas}$	$CP_{HB-GLas}$
Geometric-Paasche - hedonic current imputation	$P_{HC-GPas}$	$CP_{HC-GPas}$
Törnqvist geo-mean – hedonic base/current imputation	$P_{HBC-Tornq}$	$CP_{HBC-Tornq}$
HI indexes – unweighted arithmetic		
Carli hedonic base imputation	P_{CoHB}	CP_{CaHB}
Carli hedonic current imputation	P_{CaHC}	CP_{CaHC}
Geometric mean of above	$PC_{aHBC-GM}$	$CP_{CaHBC-GM}$
HI indexes – weighted arithmetic		
Laspeyres hedonic base imputation	P_{HB-Las}	CP_{HB-Las}
Paasche hedonic current imputation	P_{HC-Pas}	CP_{HC-Pa}
Geometric mean of above (Fisher)	P_{HBC-F}	CP_{HBC-F}
Time dummy variable – unweighted		
Unweighted binary comparisons	P_{TD}	CP_{TD}
Unweighted fully constrained	P_{TD-FC}	
Time dummy variable – weighted		
Weighted binary comparisons	P_{TDW}	$\boldsymbol{CP_{TDW}}$
Weighted fully constrained	P_{TDW-FC}	
Fixed effects – unweighted		
Unweighted binary comparisons	$\boldsymbol{P_{FE}}$	$\boldsymbol{CP_{FE}}$
Unweighted fully constrained	$\boldsymbol{P_{FE-FC}}$	
Fixed effects – weighted		
weighted binary comparisons	P_{FEW}	CP_{FEW}
Weighted fully constrained	P_{FEW-FC}	

The research questions are:

1. Is the spread of the base to current period HI indexes (say P_{JHB} to P_{JHC}) large? If so either current period HI indexes or base period HI indexes are not justifiable?
2. Does chaining minimise the spread?
3. Does weighting matter?
4. Does the use of a geometric aggregator over an arithmetic one matter?
5. What governs the base-current period hedonic spread?
6. Are the results from the DTH approach similar to those of the HI approach?
7. Does weighting for the DTH approach matter?
8. What benefits, if any, are there from using a fixed effects (panel) estimator and how do the above results compare with matched model indexes?

b. Formula choice, changes in the characteristic mix and parameter instability.

(i) In general, we take it as axiomatic that weighted indexes are preferred to unweighted ones. Indexes which make symmetric use of information are preferred to those that do not (Diewert, 1997). So for weighted HI indexes (Törnqvist) Fisher is preferred to (geometric) Laspeyres and Paasche and for unweighted hedonic indexes geometric means of base and current period HI indexes are preferred to their constituent elements. It is apparent from equations (2) and (3) (and similar such formulae) that such differences are primarily dictated by the extent to which the characteristics change over time; i.e. $(z_i^0 - z_i^t)$. But the further hedonic base and current period estimates are apart, the less justifiable is the use of an individual estimate and the less faith there is in a compromise geometric mean.[16]

For unweighted indexes a geometric mean (Jevons) is preferred to an arithmetic mean (Carli) of price relatives. The latter is upwards biased in its failure of the time reversal test while the former has more reasonable implicit assumptions of unitary elasticity of substitution (Dalton *et al*., 1998). Chained base indexes are preferred to fixed base ones especially when samples degrade rapidly and their use reduces spread. Some caution is advised when prices 'bounce' since chained indexes can drift (Forsyth and Fowler, 1981 and Szulc, 1983). We consider below the relative merits of HI indexes as against DTH indexes, though note here that the equivalence of the fixed (panel) effect method to matched data makes it less desirable (Silver and Heravi, 2002).

(ii) On parameter stability and hedonic imputation indexes. The issue of parameter stability has been raised as an area of concern to the application of hedonic indexes. There is some empirical evidence of such instability. Berndt and Rappaport (2001) found, for example, from 1987 to 1999 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. Stability tests can also be undertaken within product areas (Berndt and Rappaport (2001) compared and found parameter instability between mobile and desktop PCs) and across countries (Heravi, Heston and Silver (2001) tested and found parameter stability for *cross-country* price comparisons and estimated Laspeyres, Paasche and Fisher hedonic indexes). Aizcorbe (2003) shows for a study of Intel's microprocessor chips the parameters to be unstable over time (annual data 1993-1999) and the use of different period's constrained parameters to lead in some periods to quite different indexes, though the parameters used were estimated from data that extended outside of the periods of the price comparisons. This would argue for our only constraining parameters within the sample comparison, unlike the fully constrained model outlined in 3(f) above.

[16] As an estimate of a COLI index the spread is irrelevant since the need is to include substitution effects and Fisher meets this need. However, Laspeyres and Paasche answer meaningful question and act as bounds on models of economic behaviour that different consumer might pursue. The Fisher estimate with less dispersion is more satisfactory.

It should be noted that parameter 'instability', i.e. from $h_i^0\left(z_i^0\right)$ to $h_i^t\left(z_i^0\right)$ in, for example, equation (2), is the essence of the measure of price change in both formulae; it is not the cause of spread. If the coefficients were stable there would be no price change in equations (2) and (3). Yet it has entered the debate for specific reasons. Pakes (2002) had as his target index a *base period* one and, using quarterly data on PCs between 1995 and 1999, found very slight differences between base and current period hedonic indexes. He concluded that it might be reasonable to use a *current period* HI index for the initial publications.[17] Parameter instability is thus identified as a problem for one-sided bound estimation on the grounds that were the base period parameters stable, they could serve as current period estimates. But were they stable, the basis of the measure would have no useful meaning – it would denote no price change. Thus for a target index which uses an average of base and current period information, we caution against the use of either estimate alone if the spread is large, something dictated by the change in characteristics.

(iii) On the dummy time hedonic index compared to an average of base and current period hedonic imputed indexes? While the change in the coefficients are the essence of price measurement for HI indexes, the DTH method paradoxically constrains the coefficients from the two periods to be the same. The problem with HI indexes is that they are conditioned on a given basket of characteristics, say base or current period, resulting in more than one possible index. An index which is invariant to the choice of basket would be one whose parameters on the characteristics were the same (parallel) over the ranges of z in multivariate space. Since, it can be argued, there is no reason to prefer period 0 estimates of the (marginal) valuations of the characteristics to period t ones, constraining the parameters to be the same as in (17), is not unreasonable. Thus the intuition of averaging baskets, aside from having a physical manifestation, is no less restrictive than one of averaging (constraining to be the same) marginal valuations. Both HI indexes and DTH indexes rely on hedonic regressions for quality adjustment and both make use of an averaging process, of base and current indexes in the former case and constrained parameters in the latter, to achieve a desired measure. There is, at least in these broad conceptual terms,[18] little to choose between the two approaches.

The two approaches can be considered from economic theory and their satisfaction of axioms. Economic theory lends itself to the analysis of the change over time in the composition of a basket of goods/characteristics in the face of relative price changes. It allows substitution effects to be distinguished from 'pure' price changes. A hedonic imputed fixed basket approach is consistent with established index number theory. The approach has the further advantage of giving an insight into the spread of the two estimates so that the reliability of an individual average estimate can be gauged.[19] It so happens that such

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[17] Pakes (2002) also found evidence of severe instability for PCs with the null of equality of coefficients for a general model in which the fourth year, when Pentium II was launched, was constrained to be the same as the preceding three years being rejected with a $\div^2$ of *61,000* for í =18 df.

[18] Some care is needed in the specification of the regressions for a correspondence of the approaches. For example, Diewert (2002) shows that for matched data an average of revenue shares over the two periods should be used as weights in a WLS estimator and for unmatched data the square root of the revenue share in the relevant period, if a correspondence with a Törnqvist index is desired.

[19] Diewert (2002) points out that the main advantage of HI indexes is that it they are more flexible; i.e., changes in tastes between periods can readily be accommodated. Yet hedonic imputations are argued to have a *disadvantage* that *two* distinct estimates will be generated and it is

averages can be devised with good axiomatic properties. But functional forms for time dummy hedonic regressions, particularly the semi-logarithmic, have been shown (Diewert, 2002) to possess good axiomatic properties

Diewert (2002) and Aizcorbe (2003) show while the DTH and HI indexes will be the same for matched models, they differ in their treatment of unmatched data. Consider hedonic functions $h_i^t\left(z_i^t\right)$ and $h_i^0\left(z_i^0\right)$ for periods t and 0 respectively:

$$\ln p_i^t = \gamma_0^t + \sum_{k=1}^{K} \beta_k^t z_{ki}^t + \varepsilon_i^t \qquad (18)$$

$$\ln p_i^0 = \gamma_0^0 + \sum_{k=1}^{K} \beta_k^0 z_{ki}^0 + \varepsilon_i^0 \qquad (19)$$

and a constrained version for the time dummy method

$$\ln p_i^{0,t} = \gamma_0^{*0} + \gamma_1^* D^{0,t} + \sum_{k=1}^{K} \beta_k^* z_{ki}^{0,t} + \varepsilon_i^{0,t} \qquad (20)$$

where $\gamma_1^* = (\gamma_0^{*t} - \gamma_0^{*0})$ for $D^t = 1$ if period t, 0 otherwise and γ^* and β_k^* are constrained estimates. Consider an unmatched observation only available in period t. A base period HI index such as (2) would exclude it, while a current period HI index such as (3) would include it and a geometric mean of the two (4) would give it half the weight in the calculation of that of a matched observation. For a DTH index such as (20) it would appear only once in period t in the estimation of constrained parameters, as opposed to twice for matched data. We would therefore expect averages of base and current period HI indexes such as (4) to be closer to DTH indexes than their constituent elements, (2) and (3). Yet (4) would include the unmatched item by way of its (possibly) actual period t price in the numerator of (3) and an estimate using (19) in the denominator of (3). A DTH index would (simultaneously be determined by and) value the characteristics of unmatched items at the constrained coefficient's prices. Thus the two methods will give different results because of the way they value/impute unmatched data.

Thus for unmatched data the characteristics will by definition change and this we argued above would give rise to spread for HI indexes. But HI and DTH index methods differ because they give different imputations to the characteristics of unmatched data. It follows that the more unmatched data there is as the sample

somewhat arbitrary how these two estimates are to be averaged to form a single estimate of price change. Yet a Fisher average is generally supported axiomatic grounds and the averaging in the time dummy index is arbitrary. Diewert (2002) rightly identifies the main advantages of the dummy variable method are that it conserves degrees of freedom and is less subject to multicollinearity problems. In this study we are fortunate that df are not an issue given the relatively large sample size. We are careful to make our quality adjustments using predicted values rather than individual coefficients to avoid bias from multicollinearity.

degrades, the larger the change in characteristics, and the more the spread. The more spread the greater the differences between the imputations accorded by the different methods and, thus, the results from the two index number approaches.

Silver (2002) has shown that while HI indexes explicitly incorporates weights, they are implicitly incorporated in the OLS or WLS estimator used for DTH. The latter may not be fully representative being subject to influence effects from observations with high leverage and residuals.

The two approaches thus differ with regard to the averaging of indexes as opposed, to constraining of coefficients, their valuations of unmatched items and the weighting employed. We now turn to empirical evidence on the differences between the formulae summarized in Table 1 above.

5. EMPIRICAL ANALYSIS

(a) Data: scope and coverage

This study uses scanner UK data on a *monthly* basis for the two year period 1998 and 1999 for three consumer durables: washing machines, vacuum cleaners and dishwashers. Hedonic regressions are estimated to derive, for each month, coefficients on *brands*, *characteristics* and *outlet-types.* 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 model number code for the item sold which is linked to a file on the characteristics of the model. The transactions are counted and prices aggregated for each model sold in each outlet-type in each month (the data being supplemented by visits to independent outlets without scanners) to yield the volume, total value of sales and thus the unit value or 'price' of each model in each month/outlet -type. The observations are for a model of the product in a given month in one of four different outlet types: multiples (chains), mass merchandisers, independents and catalogue.

The coverage of the data is impressive both in terms of transactions and features. For the UK for example in 1998, Table 2 shows the data to cover about 3 million transactions for vacuum cleaners. The coverage of outlets is estimated (by GfK Marketing Services) to be "...well over 90%" with scanner data being supplemented by data from price collectors in outlets that do not possess bar-code readers. The number of observations is given for each product in Table 2 for 1998 and 1999, 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. From Table 2 the data for the three products can be seen to amount to *43,000 such observations representing 10.3 million transactions valued at £2.27 billion*.

[Table 2 about here]

(b) Data: the variables

The set of *performance characteristics* naturally varies between products. They are given in Annex 1 and, in their dummy variable representation, can be seen to be particularly extensive. Common to just about all products are: *price* which is the unit value of a model in a month/outlet across all transactions (see Balk, 1999 for the statistical properties of unit values) and *volume* which is the sum of the transactions during the period. Many of the models sold in any month have relatively low sales.

(c) The hedonic regressions

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. The choice of 30 was based on some experimentation.[20] 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 and vacuum cleaners 9,043 to 5,367 observations, 3.077 million to 3.036 million sales. As should be apparent from the above, many of the models had often only a single transaction, being the end of an old line.

The OLS estimated regressions all fitted well by the standards of such things with F-tests rejecting the null hypothesis of all coefficients equalling zero, $\overline{R}^2$s of around 0.85 and individual coefficients having the expected signs and magnitudes (results available from authors). The details of each of the estimated regression equations in each month are not presented here for reasons of space.[21]

There is a technical issues to consider. Estimates from a semi-logarithmic regression are biased and an adjustment of the subtraction of ½ variance of the residuals is required—Van Garderen and Shah (2002), though see also Berndt and Rappaport (2002). The effect was found to be minimal in this study, the standard errors being very small. For example the effect for 1998 estimates using a fixed base time dummy method was to lower the estimated monthly price fall by 0.001 percentage point.

6. RESULTS

Table 3 presents the results for the 36 formulae for 3 products for 1998 and 1999, 216 indexes in all. Choice of formula does matter. The standard deviations of monthly inflation rates for 1998 and 1999 are,

[20] The results were qualitatively similar for weaker constraints.

respectively, -0.210 and -0.242, about half of their respective means of -0.391 and -0.473. The multitude of measures and influences makes it not straightforward to evaluate the results. Table 4 presents the results of a meta-analysis from a linear OLS regression of the hedonic indexes on dummy variables of distinguishing factors.

[Tables 3 & 4 about here]

a. Why hedonic indexes differ

The coefficient on the year 1999 in Table 4 shows the compound monthly fall in hedonic-adjusted prices for 1999 fell on average by a further 0.082 percentage points, than for 1998, this fall being after controlling for the different index number formulations. Dishwasher prices fell by on average 0.087 percentage points more than vacuum cleaners and washing machines even further—by 0.186 percentage points more than vacuum cleaners. Chained indexes fell by on average 10.5 percentage points less than fixed base ones, and weighted ones had no statistically significant difference to unweighted ones, after controlling for other features. We emphasise that these findings are for the overall average effect and that weighting can matter for some products (less so in 1998); for example, for washing machines in 1999 the unweighted geometric mean of geometric base and current period HI indexes fell by 0.449 percent, compared with a weighted Törnqvist index falling by 0.256 percent.

The use of geometric aggregation, as opposed to arithmetic aggregation led to an on average further fall of 0.063 percentage points. The Fisher and Törnqvist hedonic indexes can be seen from Table 3 to be fairly close in their fixed base weighted form, but less so in their chained form and even less so in their unweighted formulations. [22]

The fixed effects (FE) estimator was argued above to be implicitly constrained to matched samples and its use had a more pronounced effect—a further fall of 0.327 percentage points against other approaches. As identified earlier, the FE, fixed base index implicitly only considers *matched* data between January and December and the chained base index is based only matched successive binary comparisons. The chain base indexes have clearly fallen more than their fixed base counterparts, possibly due to the exclusion in the latter of many unmatched new models with relatively low quality-adjusted prices. We noted in section 3 that when there are only a low proportion of unmatched comparisons, then FE indexes are preferable to DTH indexes since the latter require a satisfactory specification of the hedonic function. However, consumer durables of the type studied here have been found to suffer from severe sample degradation (Silver and Heravi, 2002).

There was no overall statistically significant difference between the DTH and HI indexes, except in its chained form which fell on average by a statistically significant, and quite substantial, further 0.16 percentage points. Table 3 finds substantial variation in the results for different DTH formulations; the chained form, for example, fell faster, by and large, (or at a roughly equivalent rate) than the fixed base

[21] Though are available from the authors on request.

index. The decision to use either of these three DTH formulations, given the discrepancies in results, argues for a clear idea of purpose. If it is to compare prices in a comparative static manner, not influenced by what went on in-between, the fixed base is appropriate, otherwise the chained path-dependency or constrained aggregation is preferred.

It must be borne in mind that some of the HI indexes in the data are geometric means of other indexes, though their impact, others things being equal is not statistically significant. A more important concern is the dummy for current period hedonic imputations as against their base-period counterparts. Other things controlled for, this difference or spread is not statistically significant, but this is on average for a meta-analysis and we consider it further.

b. The spread between base and current period hedonic imputation indexes

The spread of *individual* results can be seen in Table 3 to quite substantial for policy purposes. We employed a similar meta-analysis to that used for all the index results, but on the (24 absolute values of the) spread between the 48 current and base weighted formulae. The mean spread was 0.17 with a standard deviation of 0.027 percentage points. The distribution was highly skewed since differences were more substantial than expected: for dishwashers in 1999, for example, the monthly average fall for the fixed base HI index was 0.241 percent compared with 0.662 percent for the current period HI index, although other indexes had relatively small spread: the monthly average fall for washing machines was 0.453 compared with 0.446 in 1999 for base and current HI indexes respectively. A regression (Table 4) of the 24 differences found the (absolute) spread can change over time, in 1999 it was on average a substantial 0.255 percentage points more than its monthly rate in 1998. A minimal spread in one period should not be expected to hold for the next. Chaining reduced the (absolute) spread by a considerable 0.156 percentage points on average and the use of a geometric mean aggregator further reduced such spread by 0.085 percentage points (though this was borderline statistically significant at the 5% level).

c. Differences between hedonic imputation (HI) indexes and dummy time variable (DTH) indexes.

The mean and standard deviation of the absolute differences between the two methods was 0.09 and 0.018 percentage points respectively. Table 3 shows that the results from the DTH approach often fell outside of the base-current period HI index bounds. Any differences between the approaches was argued in section 4(iii) to be in part positively associated with spread. Since spread was itself determined via the dummy variables that characterise the formulae (Table 4), we regressed the difference between the DTH and HI indexes on such characteristics. Chaining and weighted were both found to increase the absolute value of the difference between the DTH results as against the HI ones (Table 4). Chaining can be seen to be influential in all the regressions in Table 4: it helps explain variation in hedonic indexes, spread and the difference between DTH and HI indexes. The interaction TD*chained variable finds a significant larger fall for such

[22] A Fisher HI index differs from the Törnqvist HI index not only in the functional form of the weighted aggregator, but also in linear as against semi-log functional form used for the hedonic imputations.

indexes as against the benchmark fixed-base TD indexes and HI indexes, while the significant coefficient on chaining in explaining the absolute difference between HI and DTH indexes finds chaining increases the extent of the absolute difference. On both grounds we find against chaining given our difficulty in section 4(ii) in preferring DTH over HI indexes. The difference arising from weighting is more problematic since on grounds of representativity we cannot argue for unweighted indexes. In Table 4 it can be seen to have influence only with regard to the difference between DTH and HI indexes and this may be due to the manner in which weights are used in the two formulations, in DTH indexes via WLS and explicitly in HI indexes.[23]

7. SUMMARY

The need for hedonic indexes in for the measurement of quality-adjusted prices was argued in section 2 for differentiated products subject to a high turnover in models. We distinguished between three approaches and 36 methods in all and conducted an extensive empirical study benefiting from the use of scanner data (Table 3). Using the results from these 36 methods on three products over two years we undertook a meta-analysis of the 216 results (Table 4) to examine the extent of variation between methods and to try to explain such variability. We found that choice of method did matter; the standard deviations of monthly inflation rates for 1998 and 1999 were -0.210 and -0.242 respectively, about half of their respective means of -0.391 and -0.473. We found, for example, smaller overall falls from chaining, larger falls from geometric aggregation and from the (matched) fixed effect approach. Differences were found within the different formulations of each approach. Differences within DTH index methods were found to be quite substantial and attention was drawn to the need to relate method to purpose in such choice. Particular attention was given to the quite substantial base-current period spread found in HI indexes. Such spread was found to be unstable over time, but could be reduced by chaining and the use of a geometric aggregator. Attention was also focussed on the differences between HI indexes and DTH indexes. The discussion in section 4(ii) and 4(iii) found little to choose between these approaches on theoretical grounds which is cause for concern given the extent of the differences found. In particular chaining was found to increase such differences arguing against its use from this standpoint.

Annex 1 – Characteristic sets included in regression formulations.

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) free standing, built-under and integrated; built-

[23] Silver (2002) showed that the weights implicit in a WLS estimator need not correspond to those explicitly used in a HI index because of influence effects.

under not integrated; built-in and integrated; (xi) vintage; (xii) outlet-types: multiples, mass merchandisers, independents, multiples; (xiii) vintage is the year in which the first transaction of the model took place.

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; (xiv) vintage is the year in which the first transaction of the model took place.

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.

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Table 2: Details of the data, 1998 and 1999

	Number of transactions (millions)		Number of models by outlet-type (observations)		Total sales value (£ millions)	
	1998	1999	1998	1999	1998	1999
Dishwashers	0.382	0.436	4,621	4,483	140	140
Vacuum cleaners	3.077	3.174	9,043	9,378	420	420
Washing machines	1.517	1.732	7,750	7,728	550	600

Table 3, Results from hedonic index numbers formulae

Unweighted					Weighted			
Monthly compound growth rates % *								
		Washing Machines	**Dishwashers**	**Vacuum cleaners**	**Hedonic imputations weighted**	**Washing Machines**	**Dishwashers**	**Vacuum cleaners**
HI indexes – geometric means								
Jevons base hedonic P_{JHB} CP_{JHB}	**Fixed** base **Chain** base	**98:-0.533** 99:-0.453 **98:-0.736** 99:-0.409	**98:-0.640** 99:-0.241 **98:-0.712** 99:-0.324	**98:-0.152** 99:-0.387 **98:-0.249** 99:-0.485	Geo-Laspeyre hedonic base $P_{HB-GLas}$ $CP_{HB-GLas}$	**98:-0.522** 99:-0.210 **98:-0.689** **99:-0.216**	**98:-0.501** 99:-0.207 **98:-0.502** 99:-0.361	**98:-0.305** 99:-0.389 **98:-0.225** 99:-0.243
Jevons current hedonic P_{JHC} CP_{JHC}	**Fixed** base **Chain** base	**98:-0.480** 99:-0.446 **98:-0.625** **99:-0.429**	**98: -0.519** 99:-0.662 **98:-0.326** 99:-0.123	**98:-0.266** 99:-0.490 **98: -0.248** 99:-0.384	Geo-Paasche hedonic current $P_{HC-GLas}$ $CP_{HC-GLas}$	**98:-0.568** 99:-0.302 **98:-0.710** 99:-0.259	**98: -0.399** 99:-0.555 **98:-0.326** 99:-0.198	**98:-0.236** 99:-0.318 **98: -0.201** 99:-0.185
Geo-mean $P_{JHBC} = \sqrt{P_{JHB}P_{JHC}}$ CP_{JHBC}	**Fixed** base **Chain** base	**98:-0.507** 99:-0.449 **98:-0.681** 99:-0.419	**98:-0.579** 99:-0.452 **98:-0.519** 99:-0.223	**98:-0.209** 99:-0.438 **98:-0.249** 99:-0.435	Törnqvist $P_{HBC-Tornq}$ $CP_{HBC-Tornq}$	**98:-0.545** 99:-0.256 **98:-0.700** 99:-0.238	**98:-0.450** 99:-0.381 **98:-0.414** 99:-0.280	**98:-0.270** 99:-0.353 **98:-0.213** 99:-0.214
HI indexes – arithmetic means of relatives								
Unweighted base hedonic $P_{HB-Carli}$ $CP_{HB-Carli}$	**Fixed** base **Chain** base	**98:-0.507** 99:-0.423 **98:-0.673** 99:-0.329	**98:-0.569** 99:-0.189 **98:-0.497** 99:-0.058	**98:-0.113** 99:-0.343 **98:-0.096** 99:-0.303	Laspeyres base hedonic P_{HB-Las} CP_{HB-Las}	**98:-0.498** 99:-0.401 **98:-0.650** 99:-0.174	**98: -0.463** 99:-0.181 **98:-0.336** 99:-0.187	**98:-0.290** 99:-0.367 **98:-0.167** 99:-0.161
Unweighted Paasche current hedonic $P_{HC-Carli}$ $CP_{HC-Carli}$	**Fixed** base **Chain** base	**98:-0.455** 99:-0.401 **98:-0.571** 99:-0.335	**98: -0.470** 99:-0.549 **98:-0.074** 99:-0.252	**98:-0.228** 99:-0.449 **98:-0.096** 99:-0.217	Paasche current hedonic P_{HC-Pas} CP_{HC-Pa}	**98:-0.539** 99:-0.277 **98:-0.673** 99:-0.211	**98: -0.365** 99:-0.477 **98:-0.890** 99:-0.011	**98:-0.216** 99:-0.291 **98:-0.139** 99:-0.103
Fisher $P_{HBC-Carli}$ $CP_{HBC-Carli}$	**Fixed** base **Chain** base	**98:-0.481** 99:-0.412 **98:-0.622** 99:-0.335	**98: -0.519** 99:-0.369 **98:-0.286** 99:0.096	**98:-0.170** 99:-0.396 **98:-0.096** 99:-0.260	Fisher $P_{HBC-Fisher}$ $CP_{HBC-Fisher}$	**98:-0.519** 99:-0.235 **98:-0.662** 99:-0.193	**98:-0.414** 99:-0.329 **98:-0.240** 99:-0.088	**98:-0.253** 99:-0.329 **98:-0.153** 99:-0.132
DTH indexes								
Binary P_{TD} CP_{TD}	**Fixed** base **Chain** base	**98:-0.531** 99:-0.453 **98:-0.778** 99:-0.452	**98: -0.586** 99:-0.281 **98:-0.637** 99:-0.274	**98:-0.265** 99:-0.374 **98:-0.256** 99:-0.394	Binary P_{TDW} CP_{TDW}	**98:-0.488** 99:-0.564 **98:-0.702** 99:-0.507	**98:-0.380** 99:-0.315 **98:-0.525** 99:-0.385	**98:-0.228** 99:-0.553 **98:-0.245** 99:-.450
Fully constrained unweighted: P_{TD-FC}	**Fixed** base	**98:-0.632** 99:-0.422	**98:-0.522** 99:-0.198	**98:-0.107** 99:-0.492	Fully constrained P_{TDW-FC}	**98:-0.549** 99:-0.484	**98:-0.431** 99:-0.228	**98: -0.255** 99:-0.555
Fixed effects (panel) regression indexes								
Binary $\boldsymbol{P_{FE}}$ $\boldsymbol{CP_{FE}}$	**Fixed** base **Chain** base	**98:-0.549** 99:-0.531 **98:-0.864** 99:-0.558	**98: -0.594** 99:-0.426 **98:-0.746** 99:-0.514	**98:-0.426** 99:-0.531 **98:-0.656** 99:-0.773	Binary $\boldsymbol{P_{FEW}}$ $\boldsymbol{CP_{FEW}}$	**98:-0.594** 99:-0.865 **98:-1.345** 99:-0.984	**98:-0.773** 99:-0.576 **98:-1.345** 99:-0.865	**98:-0.254** 99:-0.665 **98:-0.920** 99:-1.530
Fully constrained unweighted: $\boldsymbol{P_{FE-FC}}$	**Fixed** base	**98:-0.782** 99:-0.558	**98:-0.629** 99:-0.435	**98:-0.558** 99:-0.674	Fully constrained $\boldsymbol{P_{FEW-FC}}$	**98:-0.938** 99:-0.855	**98:-0.801** 99:-0.531	**98: -0.210** 99:-0.674

* Calculated for January to December as r in: January index$(1+r)^{12}$ =December index for monthly compound rate.

Table 4, Analysis of monthly compound hedonic inflation rates

Regression of:	**hedonic indexes:**		**spread:** †		**Time dummy less hedonic imputation index:** †	
	Coefficients	*t*-statistic‡	Coefficients	*t*-statistic‡	Coefficients	*t*-statistic‡
Intercept	-0.252	-6.58***	0.123	2.30**	0.001	0.02
1999	-0.082	-3.63***	0.255	3.83***	0.003	0.07
Washing machines	-0.186	-6.69***	0.048	0.89	0.027	0.76
Dishwashers	-0.087	-3.12***	0.046	0.87	0.003	0.08
Chained	0.105	4.17***	-0.156	-2.31**	0.099	2.21**
Weighted	-0.008	-0.34	0.007	0.16	0.061	2.11**
Geometric-aggregation	-0.063	-2.28**	-0.085	-1.96*	0.005	0.19
Fixed effect (FE)	-0.327	-8.26***				
Time dummy hedonic (TD)	0.041	0.75				
TD*Chained	-0.160	-2.49**				
TD*Weighted	-0.002	-0.04				
Geo-mean of indexes	0.013	0.37				
current weighted	0.003	0.07				
	n=216, $\overline{\boldsymbol{R}}^2 = 0.47$		n=24, $\overline{\boldsymbol{R}}^2 = 0.38$		n=24, $\overline{\boldsymbol{R}}^2 = 0.35$	

† Absolute values.

‡Denotes statistically significant in two-tailed tests at the *** 1%, **5% and *10% levels.