Quality Adjustment, Sample Rotation and CPI Practice: An Experiment

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Abstract

This paper considers the methods of quality adjustment in the compilation of consumer price indices (CPIs) which arises when a variety is no longer available and a matched comparison of like with like cannot take place. In such cases an implicit or explicit quality adjustment is necessary so that the price comparison of the new variety with the old variety is not marred by quality differences. A replication of CPI procedures is attempted on scanner data. This uses implicit and explicit quality adjustment procedures for non-comparable replacements, fifteen different methods in all, and compares the results. Implicit imputations have the effect of degrading the sample as price changes in the existing sample are used to impute price changes of missing varieties. The related issue of more frequent sample rotation is thus also explored. The limitations of the data for this analysis are recognised, but it is nonetheless hoped that it will be useful exploratory device for gaining insights into the relative merits of different approaches to quality adjustment.

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1. INTRODUCTION

A major source of bias in the measurement of inflation is held to be its inability to properly incorporate quality changes (Boskin *et al.*, 1996 and 1998; Diewert, 1996; Cunningham, 1996; Hoffmann, 1998; Abraham *et al.*, 1998). This is not to say statistical offices are unaware of the problem. Price collectors attempt to match the prices of 'like with like' to minimise such bias. However, comparable items are often unavailable and methods of implicit and explicit quality adjustment are not always considered satisfactory (Reinsdorf *et al.*, 1995, Armknecht *et al.*, 1997 and Moulton *et al.*, 1998). Alternative approaches using matching and hedonic indexes on scanner and CPI data include Silver (1995 and 1999), Saglio (1995), Reinsdorf (1996), Bradley *et al.*, (1998), Haan (1998), Dalen (1998), Lowe (1999), Moulton *et al.* (1999), Hawkes and Smith (1999), Moulton *et al.* (1999), Kokoski *et al.* (1999) and Silver and Heravi (2001).

These studies are primarily 'desk studies', taking an existing data set and employing the best techniques available to measure quality adjusted price changes. Yet the problems of quality adjustment for the practical compilations of CPIs by statistical offices are quite different. In general display prices are recorded by price collectors on a monthly basis for matched product varieties in a sample of individual stores. When a variety is missing in a month, the replacement may be of a different quality and 'like' may no longer be compared with 'like'. Its quality adjusted price change has to be imputed by the statistical office. There is no problem of quality adjustment when varieties are matched. It is only when one is unavailable and its price change has to be imputed that there is a problem. The purpose of this experiment is to attempt to replicate the practices used by statistical offices in CPI compilation using scanner data. The effects of different quality adjustment techniques and sample rotation can then be simulated.

It should be borne in mind that the price quotes may be unavailable because they are missing on a temporary – seasonal or out-of-stock- or permanent basis. In the former case our concern is with imputations for the missing prices. These may include the simple 'carry over' of the previous price quote, until the variety returns, use of an overlap price or 'overall mean' or 'class mean' imputation based on assumptions of similar price movements of existing varieties (Armknecht and Maitland-Smith, 1999 and Feenstra and Diewert, 2000). For permanently 'missing' prices comparable substitutes may be available. If not, non-comparable substitutes may be used with explicit, direct quality adjustments. Such explict, direct methods are preferred, though often imputation techniques similar to those used for temporary missing price quotes are used. In this study, using scanner data, all missing prices will be treated in the same way irrespective of whether they are permanently or temporarily missing, as will be discussed later.

Missing varieties are not a trivial matter. Moulton *et al*. (1999) examined the extent to which price collectors were faced with unavailable varieties of TVs in the U.S. CPI. Between 1993 and 1997, 10,553 prices on TVs were used of which 1,614 (15%) were replacements of which, in turn, 680 (42%) were judged to be not directly comparable. Canadian experience for TVs over an almost identical period found 750 of the 10,050 (7.5%), to be replacements of which 572 (76%) were judged to be not directly comparable. For international price comparisons the problem is much more severe (Feenstra and Diewert, 2000).

Valuable insights into the validity of quality adjustment methods can of course be gained by using a number of such methods *on actual CPI data* and comparing the results – seminal work in this area includes Moulton *et al*. (1999) and Lowe (1999). So why do we use scanner data? First, the results arise from well-defined experiments not subject to the procedures of individual statistical offices. Second, the experiment can allow simulations of different, for example, sample designs and rules for item substitution to be considered alongside quality adjustment procedures, whereupon the use of real data would be more seriously constrained in this respect. Finally, scanner data provides insights into the consequences of our actions on the rest of the sample; for example how more frequent item substitution would eat into the population of transactions. Studies based on real data and procedures of course benefit from the availability of benchmark estimates of results from current methods for the CPI as actually applied and for alternative methods as could actually be used.

The experimental framework and initial results were outlined in Silver and Heravi (2000). The study demonstrated how scanner data might be used to simulate CPI practices to help judge the veracity of alternative quality adjustment procedures. The results here are extended to consider the use of the modified short run Laspeyres and sample rotation alongside a host of quality adjustment procedures. We outline the results for the indices and coverage of the sample implied by these methods using:

- long run Laspeyres with overall mean imputation;
- long run Laspeyres with targeted (class) mean imputation;
- long run Laspeyres with comparable replacements;

- short run modified Laspeyres with overall mean imputation;
- short run modified Laspeyres with targeted (class) mean imputation;
- nine formulations of direct hedonic quality adjustment procedures;
- six month sample rotation (long run Laspeyres);
- three month sample rotation (long run Laspeyres);
- annual, chained Laspeyres, Paasche and Fisher.

In section 2 alternative quality adjustment procedures are reviewed followed in section 3 by an account of the data used and the experimental set up. Results on quality adjustment methods are presented in section 4 and on sample rotation in section 5, shortcomings of the experiment being considered in 6.

2. QUALITY ADJUSTMENT AND SAMPLE ROTATION FOR CPIs

I Quality adjustment

A number of well-documented options are available and outlined in Turvey *et al.* (1989), Reinsdorf *et al*. (1995), Moulton and Moses (1997), Armknecht *et al.* (1997 and 1999) and Moulton *et al.* (1999), though the terminology differ; they include:

- *Imputation* – where no information is available to allow reasonable estimates to be made of the effect on price of a quality change, the price change in the elementary aggregate group as a whole, to which the variety belongs, is assumed to be the same as that for the variety.
- *Direct comparison* – if another variety is directly comparable, that is it so similar it can be assumed to have the same base price, its price replaces the missing price. Any difference in price level between the new and old is assumed to be due to price changes and not quality differences.
- *Direct quality adjustment* – where there is a substantial difference in the quality of the missing and replacement varieties, estimates of the quality differences are made to enable quality adjusted price comparisons to be made.

For illustration, consider a product variety with a price of £100 in January. In October, a replacement version with a widget attached is priced at £115. The direct comparison would use the price of an essentially identical variety. The direct quality adjustment method requires an estimate of the 'worth' of the widget. For example, if it was found that the widget increased the product's flow of services by 5%, the £115 in October could be compared with an adjusted base period price of £100 (1.05) = £105. The imputation approach would use the index for the relevant product group. If this was 110.0 in October (January = 100.0), the replacement item would have a revised base period price of £115/1.10 = £104.55 to compare with the new price of £115, i.e., 115/104.55 x 100 = 110.0, a 10% increase in price, the residual 5% being assumed to be due to quality differences.

The methods used in this study include:

(a) overall mean implicit imputation: long run – price comparisons were only used when January prices could be matched with the month in question. In our example the January to March comparisons were based on varieties 1 and 5 only, the price changes of varieties 2 and 6 being assumed to be the same as these remaining varieties. The weights for varieties 1 and 5 would be $w_1 / (w_1 + w_5)$ and $w_5 / (w_1 + w_5)$ respectively. Feenstra and Diewert (2000:2) ask whether this should be the end of the story?

> "The answer is *yes* if all price relatives have the same mean whether they are in the current sample or not. The answer is *no* if the pattern of price movements for commodities that are always in the sample is different from the pattern of price changes for commodities that do not have reported price quotes for every period. In our empirical work [International Price Program of the Bureau of Labor Statistics, January 1997 to December 1999], we find the answer is no rather than yes."

One way to improve the estimates is to target the imputations towards price changes of those varieties likely to experience similar price changes, following principles akin class mean imputation used by the U.S. Bureau of Labor Statistics (Armknecht and Maitland-Smith, 1999).

(b) targeted implicit imputation: long run – the price changes of missing varieties for a specific make within an outlet type were assumed to be the same as for the remaining active sample for that make within its outlet type. If we assumed varieties 1 and 2 and 5 and 6 are of the same make, then the weights for varieties 1 and 5 would be $(w_1 + w_2)/W$ and $(w_5 + w_6)/W$ respectively where $W = (w_1 + w_2 + w_5 + w_6)$.

(c) direct comparison: long run – in practice price collectors may choose a replacement variety if a variety is believed to be permanently missing. The price collector should attempt to find a comparable variety of a similar quality. The price of the new variety in period *t* acts as a surrogate for the price of the missing variety and takes its place in that and future periods. , The implicit assumption is that any difference between the prices of the two varieties is due to price and not quality. We attempted to replicate this procedure: *within each outlet type* a search was made for the best match first, by matching brand, then in turn by type and then by individual characteristics, for example in the case of washing machines in this study, by width and spin speed. If more than one variety was found, the selection was according to the highest value of transactions (expenditure). In our example, varieties 1, 3 or 4 and 5 or 7 would replace varieties 2 and 6 in March respectively.

(d) Overall mean imputation: modified short run - the imputation is based on the short run price movements using the overall price change between the current and preceding period, as opposed to the long run comparison above between the base and current period. For a comparison between period 0 and *t*, the index is first calculated using period 0 weights between period 0 and *t*-1. It is then calculated again between period *t*-1 and *t* for varieties available in period 0. Any variety available in period 0 and *t*-1, but unavailable in period *t*, has its price movements implicitly imputed using the overall price changes between periods *t*-1 and *t,* as opposed to periods 0 and *t* outlined in (a) above. It is given in the example here for March by:

$(w_1(p_{12}/p_{11}) + w_2(p_{22}/p_{21})+w_5(p_{52}/p_{51})+w_6(p_{62}/p_{61}))/W^*(w_1(p_{13}/p_{12})+w_5(p_{53}/p_{52})/W^1$

where $W= (w_1+w_2+w_5+w_6)$ and $W^1=(w_1+w_2)$

The intuition is that assumptions of similar short run price movements are more likely to hold than long run ones. The method also makes use of the data on prices for varieties that exist in periods 0 and *t* –1, as well as those coexisting in periods *t* and *t*-1, in contrast to the long run approach which is confined to those available only in both period and 0 and *t.* This would only be varieties 1 and 5 in our example.

(e) targeted implicit imputation: modified short run – the imputation is again based on short run price movements. However, the short run price changes of missing varieties for a specific make within an outlet type were assumed to be the same as for the remaining active sample for that make within its outlet type. In this case the assumption of similar price changes for the missing variety and the targeted group is required to hold for the short run, between periods *t* and *t*-1, as opposed to the targeted long run between periods 0 and *t*.

These approaches have involved direct imputations of the missing prices, as opposed to a direct estimate. These are now considered using hedonic adjustments. There are of course other direct approaches including the use of quantity adjustments, if the size of, for example, a packet of breakfast cereal is replaced by a bigger packet. Alternatively, option costs may be used whereby a replacement is found which is identical to the missing variety, usually being the same brand, except for its possession of some options. The manufacturer (or retailer) may have data on the cost (or retail value) of such options. The manufacturer's cost would have to include an estimate of the retail mark up, distribution costs and taxes. Hedonic approaches may be applicable when the replacement variety differs with regard to a number of dimensions and estimates of the value of these dimensions are derived using data on the prices of varieties in the market and their price determining characteristics

(f) explicit hedonic: predicted versus actual – a hedonic regression (see Triplett, 1987 and 1990) of the (log of the) price of model i in period t on its characteristics set z_{tki} was estimated *for each month*, given by:

$$1np_{ti} = \beta_{0t} + \sum_{k=1}^{K} \beta_{kt} z_{kit} + \varepsilon_{it} \qquad (1)$$

Say the price of a variety m goes missing in March, period $t + 2$. The price of variety m can be predicted for March by inserting the characteristics of variety m into the estimated regression equation for March and similarly for successive months. The predicted price for this 'old' unavailable variety m in March and its price comparison with January (period t) are respectively given by:

$$\hat{p}_{m,t+2} = \exp\left[\hat{\beta}_{0,t+2} + \sum \beta_{k,t+2}\, z_{k,m}\right] \qquad \text{for } \hat{p}_{m,t+2} / p_{m,t} \text{ - old} \qquad (2)$$

The 'old' denotes the comparison is based on a prediction of the price of the unavailable variety in the current period rather than the (new) replacement variety's price in the base period. In our example we would estimate $\hat{p}_{23}, \hat{p}_{24}$ etc. and $\hat{p}_{6,3}$, $\hat{p}_{64}$ etc. and compare them with p_{21} and p_{61} respectively. We would effectively fill in the blanks for varieties 2 and 6.

An alternative procedure is to select for each missing m variety a replacement n variety using the routine described in (c) above. In this case the price of n in period $t + 2$, for example, is known, and we require a predicted price for n in period t. The predicted price for the 'new' variety and required price comparison are:

$$\hat{p}_{n,t} = \exp\left[\beta_{0,t} + \sum \beta_{k,t}\, z_{k,n}\right] \qquad \text{for } p_{n,t+2} / \hat{p}_{n,t} \text{ - new} \qquad (3)$$

i.e. the characteristics of variety n are inserted into the right-hand-side of an estimated regression for period t. The price comparisons of equation (2) would be weighted by $w_{m,t}$ as would those of its replaced price comparison in equation (3).

A final alternative is to take the geometric mean of the formulations in equations (2) and (3) on grounds akin to those discussed by Diewert (1990) for similar index number issues.

(g) explicit hedonic:predicted versus predicted - A further approach was the use of predicted values for say, variety n in *both* periods, e.g., $\hat{p}_{n,t+2} / \hat{p}_{n,t}$. Consider a mis-specification problem in the hedonic equation. For example, there may be an interaction effect between a brand dummy and a characteristic – say a Sony television set and Nicam stereo sound. Possession of both characteristics may be worth 5% more on price (from a semi-logarithmic form) than their separate individual components (for evidence of interaction effects see Curry *et. al.*, 2001). The use of $p_{n,t+2} / \hat{p}_{n,t}$ would be misleading since the actual price in the numerator would incorporate the 5% premium while the one predicted from a straightforward semi-logarithmic form would not. A more realistic approach to this issue might be to use predicted values for *both* periods. It is stressed that in adopting this approach we are substituting a recorded, actual price for an imputation. This is not desirable, but neither would be the form of bias discussed above.

The comparisons using predicted values in both periods are given as:

$\hat{p}_{n,t+2} / \hat{p}_{n,t}$ for the 'new' variety

$\hat{p}_{m,t+2} / \hat{p}_{m,t}$ for the disappearing or 'old' variety or

$$\left[\left(\hat{p}_{n,t+2} / \hat{p}_{n,t}\right)\left(\hat{p}_{m,t+2} / \hat{p}_{m,t}\right)\right]^{0.5} \tag{4}$$

as a (geometric) mean of the two.

(h) explicit hedonic:adjustments using coefficients – in this approach a replacement variety was found using the routine in (c) above and any differences between the characteristics of the replacement n in, for example, t+2 and m in period t ascertained. A predicted price for n in period t, i.e. $\hat{p}_{n,t}$ was determined and compared with the actual $p_{n,t+2}$. However, unlike the formulation in equation (3) $\hat{p}_{n,t}$ was estimated by applying the subset of the k characteristics that distinguished m from n, to their respective marginal values in period t estimated from the hedonic regression, and adjusting the price of $p_{m,t}$. For our illustration if the nearest replacement for variety 2 was variety 3, then the characteristics that differentiate variety 3 from variety 2 were identified and the price in the base period, p_{31} is estimated by adjusting p_{21} using the appropriate coefficients from the hedonic regression in that month. For example, if variety 2 of a washing machine had an 800rpm spin speed and variety 3 an 1100 rpm, other things being equal, the marginal value of the 300 rpm differential would be estimated from the hedonic regression and p_{21} would be adjusted for comparison with p_{33}. Note that if the z variables in the characteristic set are orthogonal to each other the results from this approach will be identical to those from equation (3). A similar approach to equation (2) was also undertaken which only used the salient distinguishing characteristics and the geometric mean of the two calculated. This provided in all 12 different measures of quality adjusted price changes.

II Sample Rotation

In the previous section the sample was taken in January and long run comparisons were undertaken for those varieties for which matched prices existed in the current period, with a number of implicit and explicit quality adjustments being undertaken. As the current period moves further from the base period, the coverage of the sample suffers. In addition the veracity of the implicit assumptions become less tenable. The short run Laspeyres was designed to help overcome this very problem. Yet this approach confines itself to the January sample. With sample rotation a fresh sample is selected. The practice of sample rotation varies between statistical offices. In some cases a fresh sample is taken every year and new weights applied – the index is rebased and chained annually, as in the U.K. and France for example. In other cases the sample of varieties selected may be rotated but the weights remain the same – as in the U.S. The weighting at this elementary aggregate level may be the proportion of items selected of different varieties, or be based on the relative prices in the base period comparison, depending on the formula used in the aggregation at this level. More frequent sample rotation is a costly business and its effects on the coverage of the sample, as well as the outcome of the index is thus of some interest. In this study long run Laspeyres formulae were used with overall mean imputation for:

(a) sample rotation on a biannual month basis – the sample in this experiment is composed of all observations weighted by their base period expenditures. In this case the index for July to December 1998 was recalculated on a long run June 1998=100 weighted base month and the results spliced onto the January 1998=100 weighted base month index for January 1998 to June 1998.

(b) sample rotation on quarterly basis – four sets of indices were calculated: January to March (January 1998=100); March to June (March 1998=100); June to September (June 1998=100) and September to December (September 1998=100) and the succeeding results spliced together.

© chained monthly indices – using a Laspeyres formula matched price quotes were calcultaed between the current and preceeding period: January with February 1998; February with March 1998, March with April 1998 and the 'links' combined using successive multiplication. Results are presented for Laspeyres, Paasche and Fisher chained indices.

3. DATA AND IMPLEMENTATION

a) Data: Scope and coverage

The study is for monthly price indices for washing machines in 1998 using scanner data. Scanner data are compiled on a monthly basis 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. Manufacturers provide information on the quality characteristics, including year of launch, of each model that can then be linked to the model number. Retailers are naturally interested in analysing market share and pass on such data to market research agencies for analysis. By cumulating these records for all outlets (supplemented by visits to independent outlets without scanners) the agencies can provide, on a monthly basis, comprehensive data, for each model for which there is a transaction, on: price (unit value), volume of sales, quality characteristics, make, and outlet type. There is a reluctance for them to provide separate data for a given model in a given outlet. This would not only allow competitors to identify how each outlet is pricing a particular model, and the resulting sales, but also allow manufacturers, governmental and other bodies to check on anti-competitive pricing. Data are however identifiable by broad types of outlets and models codes often apply to specific outlets, though they are not identifiable.

It should be stressed that the data, unlike that collected by price collectors:

- covers all time periods during the month;
- captures the transaction price rather than then display price;
- are not concerned with a limited number of 'representative' items;
- are not from a sample of outlets;
- allow weighting systems to be used at an elementary level of aggregation;

- include data on quality characteristics;
- come in a readily usable electronic form with very slight potential for errors.

The data are not without problems in that the treatment of multi-buys and discounts varies between outlets and the coverage varies between product groups. For example, items such as cigarettes sold in a variety of small kiosks are problematic. Nonetheless, they provide a recognised alternative, first proposed by Diewert (1993) and used by Silver (1995) and Saglio (1995), though see also, for example, Lowe (1998) for Canada, Moulton, LaFleur and Moses (1998) and Boskin *et al*. (1995) for the US and, – as Astin and Sellwood (1998 p297-298) note in the context of Harmonised Indices of Consumer Prices (HICP) for the European Union:

> "Eurostat attaches considerable importance to the possible use of scanner data for improving the comparability and reliability of HICPs [(European Union) Harmonised Indices of Consumer Prices], and will be encouraging studies to this end. Such studies might consider the various ways in which scanner data might be used to investigate different issues in the compilation of HICPs for example………..provide independent estimates as a control or for detection of bias in HICP sub indices;…….analyse the impact of new items on the index; carry out research on procedures for quality control."

Our observations (observed values) are for a model of the product in a given month in one of four different outlet types: multiples, mass merchandisers, independents and catalogue. We stress that we differentiate models as being sold in different types of outlets. This is a very rich formulation since it allows us to estimate, for example, the marginal value of a characteristic in a particular month and a particular type of outlet and apply these to changes in the usage of such stores. Not all makes are sold in each type of outlet. In January 1998, for example, there were 266 models of washing machines with 500 observations, that is each model was sold on average in 1.88 types of outlets.

The coverage of the data is impressive both in terms of transactions and features. For the UK for example in 1998, there were 1.517 million transactions involving 7,750 observations (models/outlet types) worth £550 million. 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.

b. Data: variables

The variable set includes:

<u>Price</u> **-** the unit value = value of sales/quantity sold of all transactions for a model in an outlet

type in a month.

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/outlet 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. For example 823 observations - models of washing machines in a month (on average) differentiated by outlet type – each only sold 1 machine in 1998. There were 1,684 observations (models in outlet types) selling between 2 and 10 machines in a month (on average) selling about 8 thousand machines: so far a total of 2,407 observations managing a sales volume of about 8,800. Yet the 12 models achieving a sales volume of 5,000 or more in any outlet/month accounted for 71,600 transactions.

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; 1.1787 million of the about 1.517million washing machines sold in 1998 were first sold in 1997 or 1998 – about 77.7% leaving 22.3% of an earlier vintage coexisting in the market.

Makes: transactions occurred in 1998 for machines of 24 different makes. The market was, however, relatively concentrated with the three largest selling (by volume) makes accounting for between about 60% of the market. Hotpoint had a substantial 40% of sales volume in 1998. This was achieved with 15% of models (observations). Zannusi, Hoover and Bosch followed with not unsubstantial sales of around 10% each by volume.

The characteristics set includes:

Type of machine: 5 types – top-loader; twin tub; washing machine (WM) (about 90% of transactions); washer dryer (WD) with and without computer;

WD with /without condensors (about 10% with);

Drying capacity of WD – a mean 3.15kg and standard deviation of 8.2 KGs for a standard cotton load;

Height of machines in cms - about 90% of observations being 85cms tall;

Width - 94% being about 60cms. Depth - most observations taking values between 50 and 60 cms inclusive;

Spin speeds: 5 main - 800rpm, 1000rpm, 1100rpm, 1200rpm and 1400rpm accounting for 10%, 32%, 11%, 24%, and 7%v of the volume of sales respectively.

Water consumption which is advertised on the displays as "..not a measure of efficiency since it will vary according to the programme, washload and how the machine is used." It is highly variable with a mean of about 70 litres and standard deviation of 23 litres;

Load capacity is another such measure for"…a maximum load when loaded with cotton" - a mean about 50Kgs with a standard deviation of about 13 Kgs;

Energy consumption (kWh per cycle) is"…based on a standard load for a 60 degree cotton cycle - a mean of about 12kWh with again, a relatively large standard deviation of about 6kWh.;

Free standing, built-under and integrated; built-under not integrated; built-in and integrated.

Outlet-types include multiples, mass merchandisers, independents, multiples.

(c) The experiment

The purpose of this experiment is to replicate CPI data collection using scanner data to provide a means by which different CPI procedures can be emulated. The formulation here is relatively crude, being an initial attempt at the exercise. However, it is hoped it will be useful for illustrative purposes. We start by taking a January fixed basket of washing machines comprising all varieties for which there was a transaction in January. Our varieties are for a model in one of four outlet types; multiples, mass-merchandisers, catalogue and independents. Since many models are only sold in chains of particular outlets, the classification is in practice closer to a given model in a specific chain or even individual outlet, which is the price observed by a price collector. The unit value of each variety in January is treated as the average display price collected by the price collectors. Since the volume of transactions is known for each variety, the January sample is taken to be the universe of every transaction of each variety. This January universe is the base period active sample. We can of course subsequently modify this by using different sampling procedures and identify their effects on the index.

If the variety in each outlet type continues to exist over the remaining months of the year, matched comparisons are undertaken between the January prices and their counterparts in successive months. Consider again for illustration Table 1, the case of four varieties existing in January, each with relative expenditures of w_1, w_2, w_5 and w_6 and prices of p_{11}, p_{21}, p_{51} and p_{61}. A Laspeyres price index for February compared with January = 100.0 is straightforward. In March the prices for varieties 2 and 6 are missing. Each of these were collected from different outlet types, multiples and mass merchandisers in this example. To enable Laspeyres price comparisons to be undertaken in such instances the range of methods discussed in section 2 above were utilised.

4. RESULTS

(a) Quality adjustment and sample coverage

Table 2 provides a summary of the data used. In January 1998 there were 500 varieties (models in one of the four outlet types – multiples, mass merchandisers, catalogue and independents) of washing machines accounting for 126,171 transactions. The distribution was highly skewed with the top 5% and 10% of varieties (in an outlet type) accounting for

49% and 66% of transactions respectively in January. The indices compiled in this section fixed base January 1998 = 100.0 indices compiled over the period January to December 1998. Unlike chained indices they take no account of varieties introduced after January unless they replace a variety which is 'missing', that is, it no longer has any transactions. The imputation approach does not replace missing varieties. Table 2 shows that by December, only 53% of the January basket of varieties were used for the December/January index, though these accounted for 81.6% of January expenditure. Varieties with lower sales values dropped out quicker. However, the remaining 0.53 (500) = 265 varieties in December only accounted for 48.2% of the value of transactions *in December*. The active sample relating to the universe of transactions in December had deteriorated.

[Table 2 about here]

The fall in the coverage of the active sample is mitigated by the introduction of replacement varieties when using direct comparisons. This approach requires the price collector to find a comparable replacement to each of the missing varieties, as outlined in 2(c) above. The sample of information used in successive months is supplemented by the price information on the replacement varieties. The 'base' period price quotes and the weights used remain, of course, those in January 1998. In December 1998 for example, the use of replacements increased from 53% to 97.6 % the percent of January observations used, accounting for 99.8% of January expenditure. The search procedure outlined above for replacements for direct comparisons, and used in some of the hedonic methods, had a minimum condition – that the replacement must at least be of the same make in a given outlet type. This can be seen to have been generally met, the fall-off being negligible.

The short run modified Laspeyres as outlined in 2(d) and 2(e) above combines the long run comparison between the base period and the preceding month and the short run comparison between the current month and its preceding one. The short run modified approach was introduced not only because similar short run price changes were expected to be a more plausible assumption than similar long run ones. For a comparison between January and December, for example, the short run comparison is first based on the long run January to November comparison using 54% of January observations accounting for 83.5% of January expenditure, though only 49.4% of November expenditure. And second on the November to December comparison, which uses 47.9% of December expenditure. The short run comparisons always make a slightly less intrusion into current expenditure than the long run ones. This is because the long run comparison requires price data to exist for January and

December, while the short run one comparison is still based on the active January sample, but also requires November and December information on prices.

The hedonic approach benefited from use of information on the whole sample in each month for the estimation of the equations. The estimated regression equations were based on the whole sample in spite of the inclusion of varieties with limited transactions on the grounds that such varieties were more likely to be the ones going missing. The 12 regressions estimated in each month had a mean $\overline{R}^2$ of 0.80 and in each case, the null hypothesis of the individual coefficients being jointly equal to zero was rejected by an F-test. The average monthly sample size was 558.

(b) Quality adjustment and index results

Table 3 provides the results. The extent of any bias arising from the imputation approach is dictated by the ratio of missing price comparisons to the total number of comparisons, and the difference between *quality adjusted* price changes of the missing varieties had they continued to exist, and those of other varieties (see Annex 1). The bias from the class mean imputation approach should be smaller than the imputation approach, and these methods show the choice between the results matter – an approximately 2 percentage point difference over the year for a roughly 10 per cent fall.

[Table 3 about here]

The price fall measured using direct comparisons was found to be smaller than the class mean result – a fall of 8.2% compared with 11.1%. *A priori* there is no expectation of the direction of bias from the targeted imputation approach (see Annex 1), though for direct comparisons the replacements in varieties are more likely to be priced higher than the missing ones, the smaller fall in price thus being expected. However, given the selection of replacement is not governed by the judicious selection of price collectors, but by a computational procedure, the extent of the difference is smaller than expected.

The use of hedonic adjustment methods provide an explicit basis for the quality adjustments. The results for the predicted *vs*. actual have a smaller fall for the 'old' (equation (2)) than 'new' (equation (3)) comparison (Table 3). The actual old, disappearing varieties could be argued to be more likely to be below the hedonic surface as they price to clear the market, while the actual new varieties are more likely to be above the hedonic surface as they price skim segments of consumers with higher price elasticities. However, the effect of both are to increase the price change. The geometric mean of an 8.6% fall is slightly higher than the other results as expected.

The above estimates were also undertaken using a subset of the regression coefficients applied to only the characteristic differences that took place. If the variables for the characteristics are orthogonal to each other, the results will be the same as those for equations (2) and (3) discussed above. The adjustments are affected by multicollinearity as imprecise estimates of individual marginal values are utilised for the adjustment. Multicollinearity occurs when characteristics are bundled together and it is not clear whether the differences between the results of the two formulations are some measure of this. Nonetheless, the results for the two geometric means are quite similar - a fall of 8.8% for the adjustment via coefficients.

The final set of estimates are the predicted *vs.* predicted. The 'old' and 'new' estimates are very close with a geometric mean and a fall of 8.4%. This compares with the geometric mean of the predicted *vs.* actual of 8.6% implying the results, when averaged using the geometric mean, are not subject to serious misspecification error.

Thus in summary, different hedonic adjustment techniques provide similar results, though the 'old' and 'new' predicted to actual appear to work best as a geometric mean. This similarity is encouraging given the plethora of such approaches. These results are also similar to those from a computational, direct replacement method, but both imputation approaches lead to larger falls in prices, a result with no immediate explanation given the analysis in Annex 1.

(c) Sample rotation

In the context of this experiment each transaction is sampled, so a sample rotation has the effect of re-weighting the index. The design of the experiment allows for sampling to be used; though our concern here is to not confound the results with sampling errors.

Table 5 presents results for Laspeyres long run comparisons using overall mean imputation with reweighted sample rotation conducted on a biannual, quarterly and then monthly basis. The coverage figures relate to the percentage of the current month's expenditure captured in the matching of prices between the base and current period. For example in the biannual comparison in October (compared with June 1998) 75.25% of expenditure in October was covered by the matching procedure, the remaining being implicitly imputed using the overall mean. The use of biannual sample rotation improves the coverage of the matching to at worst, a little over 70%, compared with 48.2% in Table 2 when rotating annually: a substantial improvement. Table 5 shows the upgrading of the rotation to a quarterly basis to further improve coverage to an at worst, 76.71% (September) and annual chaining to 83.33% (July). The average coverage over the 12 months for the biannual, quarterly and monthly chained procedures were 73.5%, 79.8% and 86.8 % respectively compared with 48.2% for the annual sample rotation.

[Table 5 about here]

The more regular sample rotation affects the results of the indices. In Table 2 the overall mean imputations are given with no sample rotation, the results for the first six months of the biannual rotation being of course identical. However, the results soon diverge: with no imputation the index in July 1998 (January=100) has fallen to 93.14 compared with 94.32 (January =100 – spliced) when the sample is rotated biannually. A massive difference given the June figures were identical. However, there does not seem to be any drift between the results in successive months with the December figures being quite similar. The Laspeyres results for quarterly and monthly sample rotation are very similar, the indices not falling as fast as the previous results. The increased sample coverage argues for biannual rotation, though the index results are not close to the quarterly and monthly results arguing for a frequency of rotation beyond the means of normal price collection methods.

An initial expectation might be that these results would be closer to the short run modified index, since the imputation for the latter is the same as the chained index in the current month. However, the modified index carries with it the long run comparison for preceding months, which, especially in later months, can be especially problematic. For example, the December short run modified Laspeyres index relies on the long run comparison between January and November 1998, a fall to 91.52 (January 1998=100) – Table 2. The chained index for December relies on the chained index to November 1998, a fall to 93.39 (January 1998 =100) – Table 5. It might of course be argued that the chained results are affected by a tendency to drift and are not a reliable guide. Yet the quarterly rotated sample provides similar results to the monthly chained one.

A final point worth noting is how these results compare with those from the full data set when compiled on a chained basis using Paasche and Fisher indices (Table 5). The results are, as expected from economic theory, lower than their Laspeyres counterparts.

5. CONCLUSIONS

The results are exploratory in the sense that they arise from an experimental formulation that is subject to some limitations that cannot be easily remedied as well as some restrictions that can. A major limitation is that the observations are for a product variety in a specific outlet type, as opposed to in a specific outlet (in a geographical place). That some models are specific to some outlet chains helps, but we cannot distinguish here between the locations of the outlets, though in principle this is possible with scanner data. This in itself may not be problematic for price comparisons since there is still some debate over the validity of using the aggregated unit values over outlets for price comparisons (Balk, 1999, Diewert, 1990 and de Haan and Opperdoes, 1998). However, the concept of 'missing' prices used here is not appropriate since a price collector may, for example, find a price missing for a variety in an outlet in Cardiff while other price collectors may find price quotes for the same variety in different stores/locations. The experiment would only treat prices as missing if there were no transactions anywhere for the product variety. Furthermore all missing prices were treated in the same way irrespective of whether they were permanently or temporarily missing. Scanner data does allow a search to see if the variety returns, though our data is aggregated at the outlet type level and 'missing' in our sense refers to no further transactions being conducted for that model in one of four store types. Something that returns on aggregate may not do so in an individual store. Scanner data provides a proxy variable on the extent to which each variety is sold in different outlets and use of this is being considered to develop the experiment.

Further work might also include consideration of the effects of:

- different sampling schemes for the January selection as opposed to the use of the universe of transactions;
- more frequent item selection (rebasing) on the need for quality adjustments;
- more frequent item selection (rebasing) on the coverage of the universe of transactions;
- variations in the specification and sample used for the hedonic regressions;
- different selection criteria for replacements;
- use of different formulae;
- different rules for deciding when a variety is 'missing';
- more refined class imputation procedures;
- missing market innovations;
- extension to other products.

Summary conclusions from the results indicate that:

- long run Laspeyres comparisons over the period of 12 months can seriously degrade the active base period sample and its coverage of the current population of transactions;

- long run and short, run modified Laspeyres can give quite different results as is the case with
- targeted (class) means and overall class means;

- short run, modified Laspeyres does little to ameliorate the poor coverage of the sample;

- the variety of hedonic approaches investigated provide similar results;

- the hedonic and comparable replacement results are similar and the fall in prices from these explicit approaches is generally less than from the implicit imputations – imputations may be missing out on relatively large (quality adjusted) price increases from new varieties;

- biannual, quarterly and monthly sample rotation does much to improve the coverage of the tranasaction;

- biannual rotation provides similar indices to long run Laspeyres, though with quarterly and monthly (chained) rotation the results are similar to those using explicit adjustments;

- Laspeyres and Paasche provide upper and lower bounds to a Fisher long run index.

Annex 1

Jack Triplett in a draft OECD Manual has been responsible for a detailed analysis of the implicit bias from imputations and while the formulation here is quite different, there is much that has been usefully applied from his analysis. For $i = 1 ... m$ varieties where $P_{m,t}$ is the price of variety *m* in period *t*, $P_{n,t+1}$ is the price of a replacement variety *n* in period *t* + 1, A(*h*) is a quality adjustment to $P_{n,t+1}$ which equates its quality services to $P_{m,t+1}$ such that the quality adjusted price $P^*_{m,t+1} = A(h)P_{n,t+1}$ and Q is the implicit adjustment which allows the method to work then the arithmetic formulation for one missing variety is given by:

$$\frac{1}{m}\left[\frac{P^*_{m,t+1}}{P_{m,t}} + \sum_{i=1}^{m-1}\frac{P_{i,t+1}}{P_{i,t}}\right] = \left[\frac{1}{(m-1)}\sum_{i=1}^{m-1}\frac{P_{i,t+1}}{P_{i,t}}\right] + Q \qquad \text{(A1)}$$

$$Q = \frac{1}{m}\frac{P^*_{m,t+1}}{P_{m,t}} - \frac{1}{m(m-1)}\sum_{i=1}^{m-1}\frac{P_{i,t+1}}{P_{i,t}} \qquad \text{(A2)}$$

and for *x* missing varieties by:

$$Q = \frac{1}{m}\sum_{i=1}^{x}\frac{P^*_{m,t+1}}{P_{m,t}} - \frac{x}{m(m-x)}\sum_{i=1}^{m-x}\frac{P_{i,t+1}}{P_{i,t}} \qquad \text{(A3)}$$

The relationships are readily visualised if r_1 is defined as the respective geometric or arithmetic means of price changes of varieties that continue to be recorded and r_2 of quality-adjusted missing varieties, i.e., for the arithmetic case:

where $r_1 = \left[\sum_{i=1}^{m-x} P_{i,t+1} / P_{i,t}\right] \div (m-x)$

$$r_2 = \left[\sum_{i=1}^{x} P^*_{i,t+1} / P_{i,t}\right] \div x \qquad \text{(A4)}$$

then the ratio of arithmetic mean biases from substituting equations (A4) in (A3) are:

$$Q_g = \frac{x}{m}(r_2 - r_1) \qquad \text{(A6)}$$

which equal zero when $r_1 = r_2$. The bias depends on the ratio of missing values and the difference between the mean of price changes for existing varieties and the mean of quality-adjusted replacement to missing price changes. Note that the bias is small if *either* (x/m) *or* the difference between r_1 and r_2 is small. Furthermore, note that the method is reliant on a comparison between price changes for existing varieties and *quality-adjusted* price changes for the replacement/missing comparison. This is more likely to be justified than a comparison without the quality adjustment. For example, if we had *m* = 3 varieties, each with a price of 100 in period *t*. Let the *t* + 1 prices be 120 for two varieties, but assume the third is missing, i.e., *x* = 1 and is replaced by a variety with a price of 140, 20 of which is due to quality differences. Then the arithmetic bias as given in equation (A6) where

$x = 1$, *m* = 3 and $r_2 = \left[\left(A(h) + P_{n,t+1}\right)/ P_{m,t}\right]$ is:

$$\tfrac{1}{3}\left[(140-20)/100 - \left(\tfrac{240}{2}\right)/100\right] = 0$$

Had the bias depended on the *unadjusted price* of 140 compared with 100, the method would be prone to serious error. In this calculation the direction of the bias is given by $(r_2 - r_1)$ and does not depend on whether quality is improving or deteriorating, i.e., whether $A(h) > P_{n,t+1}$ or $A(h) < P_{n,t+1}$. If $A(h) > P_{n,t+1}$, a quality improvement, it is still possible that $r_2 < r_1$ and for the bias to be negative, a point stressed by Jack Triplett.

References

Abraham K, Greenless J and Moulton, B (1998) Working to Improve the Consumer Price Index, *Journal of Economic Perspectives*, 12 (1), 23-36.

Armknecht, P.A., Lane, W.F. and Stewart K.J. (1997). 'New products and the US consumer price index'. In *The Economic of New Goods*, *Studies in Income and Wealth*, (eds. T.F. Bresnaham and R.J. Gordon), Vol.58, pp. 375-396, NBER Chicago and London: University of Chicago Press.

Armknecht, PA and Maitland-Smith, F. (1999), Price Imputation and Other Techniques for Dealing with Missing Observations, Seasonality and Quality Changes in Price Indices, *IMF Working Paper 99/78*, Statistics Department, International Monetary Fund, Washington, D.C.

Astin, JA and Sellwood DJ (1998), Harmonization in the European Union: A Review of Some Technical Issues, *Proceedings* of the Third Meeting of the International Working Group on Price Indices, edited by B. Balk. Research Paper no. 9806, Statistics Netherlands, 291-308.

Balk, B. (1998). 'On the use of unit value indices as consumer price sub-indices'. In Proceedings of the Fourth International Working Group on Price Indices (ed. W. Lane), pp.112-120, Washington DC: Bureau of Labor Statistics.

Blow L and Crawford I (1999), *Cost of Living Indices and Revealed Preference*, London: The Institute of Fiscal Studies.

Boskin MS (Chair) Advisory Commission to Study the Consumer Price Index (1996), Towards a More Accurate Measure of the Cost of Living, *Interim Report to the Senate Finance Committee*, Washington DC.

Boskin MS, Delberger ER, Gordon RJ, Griliches Z, Jorgenson DW (1998) Consumer Prices in the Consumer Price Index and the Cost of Living, *Journal of Economic Perspectives*, 12 (1), 3-26.

Bradley, R Cook, B, Leaver, SG and Moulton, BR (1998) An Overview of Research on Potential Uses of Scanner Data in the U.S. CPI, *Proceedings* of the Third Meeting of the International Working Group on Price Indices, edited by B. Balk. Research Paper no. 9806, Statistics Netherlands, 169-182.

Cunningham, A, (1996), Measurement bias in price indices: an application to the UK's RPI, *Bank of England Working Paper Series,* No. 47, London: Bank of England.

Dalen, J. (1998) Experiments with Swedish Scanner Data, *Proceedings* of the Third Meeting of the International Working Group on Price Indices, edited by B. Balk. Research Paper no. 9806, Statistics Netherlands, 163-168.

Diewert, W.E. (1980), Aggregation Problems in the Measurement of Capital. In *The Measurement of Capital*, edited by Dan Usher, Studies in Income and Wealth, Vol 45, National Bureau of Economics Research, Chicago: University of Chicago Press, pp.433-528.

Diewert, W.E. (1993), The Early History of Price Index Number Research. In WE Diewert and AO Nakamura (editors), Essays in Index Number Theory, volume I, North Holland: Amsterdam, 33-65.

Diewert, WE (1996) Sources of Bias in Consumer Price Indices, *Discussion Paper No: DP-96-04*, School of Economics, University of New South Wales.

Eurostat (1999) Meeting of the Working Party on Harmonisation of Consumer Prices, Quality Adjustment, HCPI 98/227, Luxembourg: Eurostat B-3.

Feenstra, R.C. and Diewert, E.W.(2000), Imputation and Price Indices: Theory and Evidence from the International Price Program, *National Bureau of Economic Research Working Paper*, forthcoming.

Haan, J de and Opperdoes, E (1998) Estimation of the Coffee Price Index Using Scanner Data: the Choice of the Micro Index, *Proceedings* of the Third Meeting of the International Working

Group on Price Indices, edited by B. Balk. Research Paper no. 9806, Statistics Netherlands, 191-202.

Hawkes, W. and Smith, R. (1999). 'Improving consumer price measurements through the use of scanner data and market segmentation'. In *Proceedings* of the Measurement of Inflation conference, (eds. M. Silver and D. Fenwick), pp.283-299, Eurostat/ONS/Cardiff University: Cardiff Business School.

Hoffmann, J (1998) Problems of Inflation Measurement in Germany, *Economic Research Group of Deutsche Bundesbank,* Discussion Paper 1/98, Frankfurt: Deutsche Bundesbank.

Ioannidis C and Silver, M (1999) Estimating Hedonic Indices: an Application to UK Television Sets, *Journal of Economics, Zeitschrift fur Nationalokonomie*, 69,1, 71-94.

Kokoski, M., Waehrer, K. and Rozaklis, P. (1999). 'Using hedonic methods for quality adjustment in the CPI: The consumer audio products component'. Paper presented at the Measurement of Inflation Conference, Eurostat/ONS/Cardiff University: Cardiff Business School.

Lowe, R. (1998). 'Televisions: quality changes and scanner data'. In *Proceedings* of the Fourth Meeting of the International Working Group on Price Indices, (ed. W. Lane), pp.5-20, Washington DC: Bureau of Labor Statistics.

Moulton, B, Moses, KE (1997), "Addressing the Quality Change Issue in the Consumer Price Index", *Brookings Papers on Economic Activity* 0(1): 305-49.

Moulton, B., LaFleur, T.J., Moses, K.E. (1998). 'Research on improved quality adjustments in the CPI: the case televisions'. In Proceedings of the Fourth Meeting of the International Working Group on Price Indices (ed. W. Lane), pp.77-99, Washington DC: Bureau of Labor Statistics.

Reinsdorf M (1996) Constructing Basic Components for the U.S. CPI from Scanner Data: A Test Using Data on Coffee, Working Paper 277, Bureau of Labor Statistics, Washington, D.C.

Reinsdorf, M. (1998). Divisia indices and the representative consumer problem', In *Proceedings of the Fourth Meeting of the International Working Group on Price Indices*, (ed. W. Lane), pp.210-235. Washington DC: Bureau of Labor Statistics.

Reinsdorf, Marshall, and Brent R Moulton, The Construction of Basic Components of Cost of Living Indices. In Bresnahan, TF and RJ Gordon, Eds *The Economics of New Goods*, Chicago: University of Chicago Press, 1997, 397-423.

Reinsdorf, Marshall, Paul Liegey and Kenneth Stewart, New Ways of Handling Quality Change in the US Consumer Price Index. *Working Paper* No.276, Bureau of Labor Statistics, 1995.

Saglio, A (1995), Comparative Changes in Average Price and a Price Index: Two Case Studies, L.M. Duchare (editor), *Proceedings of the First Meeting of the International Working Group on Price Indices*, Ottawa: Statistics Canada.

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

Silver, M (1999) An Evaluation of the Use of Hedonic Regressions for Basic Components of Consumer Price Indices, *Review of Income and Wealth*, 45, 1, 41-56.

Triplett JE, (1987), Hedonic Functions and Hedonic Indices, in *The New Palgraves Dictionary of Economics,* 630-634.

Triplett, J.E. (1990). 'Hedonic methods in statistical agency environments: an intellectual biopsy'. In *Fifty Years of Economic Measurement: The Jubilee Conference on Research in Income and Wealth, Studies in Income and Wealth*, Vol 56, NBER (eds. E.R. Berndt and J.E Triplett), pp.207-238. Chicago: University of Chicago Press.

Turvey R. *et al.* (1989), *Consumer Price Indices*, Geneva: International Labour Organisation.

Table 1: Illustration of matching and approaches to quality adjustment

Outlet-type	Variety	Weight	January	February	March	April
Multiple	1	w_1	p_{11}	p_{12}	p_{13}	p_{14}
	2	w_2	p_{21}	p_{22}		
	3				p_{33}	p_{34}
	4			p_{42}	p_{43}	p_{44}
Mass merchandiser	5	w_5	p_{51}	p_{52}	p_{53}	p_{54}
	6	w_6	p_{61}	p_{62}		
	7				p_{73}	p_{74}

Table 2: Number of observations and expenditure shares used by different methods

				Imputation - no replacements				Direct comparisons	
				Long run			Short run		
	Number of observations models in outlets	Number of transactions thousands	Expenditure, £'000s	% of January observations used	% of January expenditure used	% of current expenditure used	% of current expenditure used	% of January observations used	% of January expenditure used
January	500	126,171	45,727						
February	488	111,358	39,938	85.8	97.2	97.1	97.1	99.8	100.0
March	605	134,049	48,877	83.0	99.1	91.1	89.8	99.2	100.0
April	625	113,338	41,841	81.0	98.7	81.8	81.7	99.4	100.0
May	647	112,549	41,623	77.6	98.3	76.6	76.6	98.2	99.9
June	711	137,070	49,721	78.6	98.0	72.9	72.8	99.2	100.0
July	744	116,273	42,924	76.0	97.1	64.2	64.2	99.0	100.0
August	711	122,977	45,139	69.6	93.5	57.5	57.5	98.8	99.9
September	717	150,422	54,665	66.2	86.4	54.2	54.2	99.0	99.9
October	695	129,235	47,620	59.8	87.1	51.6	51.6	98.0	99.9
November	643	124,845	45,196	54.0	83.5	49.4	49.2	97.0	99.8
December	664	138,634	49,707	53.0	81.6	48.2	47.9	97.6	99.8

Table 3: Laspeyres indices

	Long run Overall mean Imputation	Targeted Imputation	Direct comparison	Short run modified Overall mean Imputation	Targeted Imputation
January	100.00	100.00	100.00	100.00	100.00
February	99.49	99.50	99.30	99.49	99.50
March	99.29	99.29	99.26	99.50	99.35
April	98.30	98.29	98.45	98.42	98.24
May	97.06	96.89	97.30	97.32	96.75
June	94.98	94.97	95.09	95.52	94.64
July	93.14	92.97	93.13	94.30	94.00
August	93.64	92.62	94.49	92.60	91.51
September	93.55	92.01	94.03	93.18	90.79
October	91.84	90.74	91.75	93.25	90.29
November	91.52	90.20	91.47	91.38	88.06
December	90.87	88.94	91.81	90.35	87.55

Table 4: Hedonic quality adjustments

	Predicted vs. actual			Adjustment via coefficients			Predicted vs. predicted		
	Old	new	geometric mean	old	new	geometric mean	old	new	geometric mean
January	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
February	99.75	99.16	99.45	99.41	99.38	99.40	99.49	99.48	99.49
March	99.35	99.17	99.26	99.23	99.20	99.22	99.27	99.29	99.28
April	98.23	98.29	98.26	98.21	98.38	98.30	98.09	98.31	98.20
May	96.95	97.10	97.02	96.94	97.18	97.06	96.75	97.09	96.92
June	95.00	94.95	94.98	94.92	95.05	94.98	94.91	95.07	94.99
July	93.44	93.08	93.26	93.28	93.10	93.19	93.40	93.22	93.31
August	94.64	93.83	94.24	94.28	94.07	94.18	94.09	93.87	93.98
September	94.91	92.26	93.58	93.37	93.29	93.33	94.06	93.96	94.01
October	92.99	90.48	91.73	91.49	91.30	91.40	92.13	92.14	92.13
November	93.26	89.94	91.59	90.85	90.83	90.84	91.75	92.17	91.96
December	92.74	90.09	91.41	91.26	91.19	91.23	91.63	91.66	91.65

Table 5: Coverage and indices with sample rotation

	Sample rotation Biannual		Sample rotation quarterly		Sample rotation monthly chained			
	Long run Laspeyres Index	% of current periods expenditure used	Long run Laspeyres index	% of current periods expenditure used	Laspeyres Index	% of current periods expenditure used	Paasche index	Fisher index
January	100.00		100.00		100.00		100.00	100.00
February	99.49	97.06	99.49	97.06	99.49	97.06	99.02	99.25
March	99.29	91.06	99.29	91.06	99.52	91.88	98.77	99.15
April	98.30	81.79	98.59	94.86	98.82	94.86	98.08	98.45
May	97.06	76.62	97.43	91.11	97.91	97.59	97.05	97.48
June	94.98	72.90	95.78	86.34	96.46	96.83	95.13	95.79
July	94.32	83.33	94.70	83.33	95.78	83.33	94.21	94.99
August	93.86	80.31	94.65	80.31	94.97	98.80	92.89	93.92
September	92.98	76.71	94.18	76.71	94.24	98.56	91.95	93.09
October	92.45	75.25	94.00	86.62	94.06	86.62	91.71	92.88
November	91.70	75.74	93.37	87.09	93.39	98.85	90.70	92.03
December	90.56	71.08	92.05	83.13	92.06	97.72	89.34	90.69