Accounting for the Effects of New and Disappearing Goods Using Scanner Data

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Abstract: With the 'discovery' of scanner data by statistical agencies comes a wealth of new information upon which price index calculations can be based. But old problems, such as the appearance and disappearance of goods over time, are likely to be an important feature of such data. However, given that scanner data includes prices and quantities of the population of transactions, all the sales of goods in a particular store over a particular time period, we have more information than is traditionally available to deal with the new and disappearing goods problem. Recent theoretical developments show that using the Constant Elasticity of Substitution cost function it is possible to calculate the exact cost-of-living index even when the domain of goods is changing over time. We use this theoretical framework to provide a detailed empirical analysis of the effects of new and disappearing goods for an Australian scanner data set of supermarket products.

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1. Introduction.

In this paper we discuss and quantify the effects of new and disappearing goods on the cost-of-living index. This is done in the context of the rich information source of scanner data (sometimes called barcode or point-of-sale data). The availability of this new data source has the potential to greatly improve the way price change is measured as scanner data records the *population* of sales of items in a given store over a given time period. This means that both price and quantity data is available to index practitioners often at a very disaggregated level. This has led many authors to emphasize the advantages of scanner data over the data that is conventionally used by statistical agencies to compute price indexes (Bradley *et al*, 1997; Dalen, 1997; Schut, 2002; Richardson, 2000; Silver and Webb, 2002).

As well as being of great benefit for the compilation of official statistics scanner data can also be used to investigate enduring economic problems associated with index number such as the extent of substitution bias and also interestingly the effect of new and disappearing goods. In this paper we undertake a detailed empirical investigation using a large scanner data set of the effects of non-matched (i.e. new and disappeared) goods on the cost-of-living index. The fact that we have both price and quantity data at a disaggregated level allows us to accurately estimate the differences between indexes which do and do not properly account for the effects of changes in consumption opportunities from new and disappearing goods.

In the next section we discuss the basic problem of ‘quality change and new and disappearing goods’ in the context of supermarket products which is the focus of this study. Unfortunately little research has been undertaken on quantifying the effects of new and disappearing goods on these types of product areas. However a number of methods have been suggested in the economics literature to account for non-matched goods. We briefly discuss three main approaches; estimating reservation prices, hedonic regression and finally the CES Cost Function Approach. The most promising approach is the last of these, which uses the CES cost function over changing domains of goods to exactly account for new and disappearing goods. This method is outlined in more detail in Section 3 where we draw heavily on Balk (1999). As well as this primary approach we use a simplified version of the reservation price approach to provide a cross-check on these results. These two methods are applied to a large scanner data set in Section 4 which provides a discussion of the empirical effects of new and disappearing goods along a discussion of some other issues. Section 5 concludes.

2. The Quality Change and New and Disappearing Goods Problem.

One of the enduring problems of economic measurement is how to deal with changes in the quality and availability of goods over time. In fact the debate ranges back at least to Alfred Marshall in 1887 (Diewert, 2001, p.19, n.38) who advocated the use of chained indexes to mitigate the effects of new and disappearing goods.

From an economic perspective the ideal measure of price change is the cost-of-living index which compares the minimum cost of obtaining a given level of utility under two price regimes. If there are differences in the quality or availability of goods under the two price regimes then this has an effect on utility which must be accounted for in the cost-of-living index (Gordon and Griliches, 1997). This approach is by no means the only approach to price index construction however. For example the recent Schultze Report (Schultze and Mackie, 2002) which was drafted by an eminent committee of economists, statisticians and other experts distinguished between a cost-of-living index and a cost-of-goods index. In places the committee seems split on the advisability of accounting for the effects of new and disappearing goods in official price indexes.[1] Whether official statistics should reflect changes in the availability of goods seems contentious at present. However, regardless of whether the cost-of-living approach should be fully implemented by statistical agencies it seems important and useful to have an idea of the influence of new and disappearing goods on welfare. In this paper we adopt the cost-of-living approach and hope to advance empirical research in this area.

2.1. Estimates of the Bias from New and Disappearing Goods.

The most comprehensive project quantifying the biases in official price indexes is that of the Boskin Commission (Boskin *et al*, 1996; Gordon and Griliches, 1997) who looked at the US Consumer Price Index (CPI). The Commission estimated that quality change and new goods constituted the largest source of bias in the US CPI. In total they estimated that the US CPI was overestimated by 0.6 percentage points in 1996 due to the failure to adequately account for quality change and new goods.

In this paper we focus on one particular area of the CPI. We look at what we term ‘supermarket products’, in particular: *Biscuits*, *Bread*, *Butter*, *Cereal*, *Coffee*, *Detergent*, *Frozen Peas*, *Honey*, *Jams*, *Juices*, *Margarine*, *Oil*, *Pasta*, *Pet Food*, *Soft Drinks*, *Spreads*, *Sugar*, *Tin Tomatoes* and *Toilet Paper*. These products provide a selection of the goods available in supermarkets and mainly comprise *processed food* items. The Boskin Commission did not look at this product area in particular detail however they concluded that the “Food at Home other than Produce” category, which covers most of the products above, had an annual upward bias of 0.3 percentage points from 1967 to 1996. The justification given for this bias estimate by Boskin *et al* (1996) is interesting. They write,

> How much would a consumer pay to have the privilege of choosing from the variety of items available in today’s supermarket instead of being constrained to the much more limited variety available 30 years ago? A conservative estimate of the value of extra variety and convenience might be 10 percent [approx. 0.3 percent annualized] for food consumed at home other than produce…

The noteworthy aspect of the quote from the Boskin Commission is that the primary reason they give for the upward bias of official indexes is the failure to properly account for changes in the *variety* of products. What is important then is the fact that the range of products available in supermarkets has increased substantially over recent decades. As noted by Koskimaki and Yla-Jarkko (2003, p.11), this increase in the range of products is likely to be a consequence of monopolistic competitors endeavoring to produce differentiated products so that substitution occurs within brands rather than between brands. The result of this is that an increasingly large set of niche-marketed products is

[1] See for example Conclusion 5-1 of Schultze and Mackie (2002, p.5-5).

available to consumers which has an influence on welfare and the cost-of-living. In the following subsections we briefly discuss various ways of measuring the effects of new and disappearing goods on the cost-of-living index.

2.2. Estimating Reservation Prices.

A diverse range of approaches have appeared in the economics literature for dealing with new and disappearing goods. The classic approach to the problem is derived from Hicks (1940) who saw it as one of missing prices. His solution for *new goods* was to estimate the reservation (or choke) price which would have driven demand for the good to zero in the period prior to its introduction. The reservation price can be used to look at the effect on welfare of the introduction of the good and also in a price index calculation. Of course an analogous approach can be used for disappeared goods.

This 'reservation price' method is very appealing and has a rigorous economic justification. Hausman (1997) adopts this approach and econometrically estimates a (compensated) demand system (and hence the reservation price and cost function) for the introduction of a new brand of cereal in the US. Hausman (1997) finds that the price index for cereals was too high by about 20 to 25 percent due to the effect of new brands.[2]

While this approach is attractive it has the major disadvantage that it is technically very difficult to implement involving complex econometric estimation. These estimation methods are also contentious and as emphasized by Bresnahan (1997), the discussant on Hausman's (1997) paper, the assumptions made in motivating the estimation can be important in influencing the results. This has led to some suspicion of this approach. For example, the recent Schultze Commission (Schultze and Mackie, 2002, p.5-4) noted that, "…there is no clearly acceptable technique for consistently estimating demand curves for new goods or services in such a way that choke prices can be confidently ascertained." It appears that at present this method is quite controversial and not widely accepted. Moreover it may prove impractical to econometrically estimate the reservation price for each new (and disappeared) good for the often extremely large scanner data sets. For these reasons we do will not adopt this version of the approach.

Recently, however Hausman (2003) has suggested an alternative *Approximate Reservation Price Method*. This method is far simpler than the full econometric method and requires only the estimation of the price elasticity of demand, $\varepsilon_i^t \equiv -d\ln(x_i^t)/d\ln(p_i^t)$, where p_i^t and x_i^t are the price and quantity of good i in period t. Here, instead of using the compensated demand curve which is the theoretically correct approach, we take a linear approximation to the market demand curve. It can easily be shown that in this case the estimated reservation price, $\hat{p}_i$, can be calculated using the following formula.

$$\hat{p}_i = p_i^t(1+1/\varepsilon_i^t) \qquad (2.1)$$

[2] This means that if the price change was 2.0 percent per year then the index would be over estimated by between 0.4 and 0.5 percent per year.

It should be emphasized that we have used two sources of approximation in this method, firstly approximating the compensated demand curve by the market demand curve[3] and secondly taking a linear approximation to the market demand curve. However, Hausman (2003, p.27) argues that the estimate will typically be not too different from the theoretically ideal measure. In the empirical section that follows we will briefly look at this Approximate Reservation Price Method.

2.3. Hedonic Regression.

Another popular approach to dealing with changing varieties of products is hedonic regression. The hedonic approach regards goods as being 'packages' of various utility-yielding characteristics which determine the price. A hedonic regression exploits this market relationship between the prices and characteristics of the good (Rosen, 1974). This approach is useful as it is often the case that the characteristics of a good are more stable than the various varieties (bundles of characteristics) produced. The hedonic function can be used to estimate the price of a good for any particular combination of characteristics and hence there are a number of ways in which it can be used to calculate price indexes (Diewert, 2003; Silver, 1999). This approach has been widely adopted in the US in recent times with Moulton (2001, p.1) noting that, "…currently 18 percent of the final expenditures in gross domestic product [are] deflated using price indexes that use hedonic methods."

Hedonic methods have most frequently been applied to areas where prices have changed rapidly due to technological factors such as computers (Berndt, Griliches and Rappaport, 1995). It has not however (to the best of my knowledge) been applied to supermarket commodities like those listed above. This is likely to be because hedonic methods will not pick up the effects of interest.

The hedonic regression approach to quality change and new and disappearing goods focuses entirely on how changes in prices relate to changes in characteristics where the characteristics are relatively stable across time. In the first instance it would be a non-trivial task to determine exactly what the price determining characteristics of some of supermarket products are. However, a more serious problem in the case of supermarket products is that, as emphasized by the quote from the Boskin Commission above, it is not a problem of accounting for *improvements* in the characteristics of products but rather one of accounting for the expansion in the *range* of available characteristics. Hedonic methods (at least as presently constituted) are not able to reflect these changes. To see this consider the case where prices for different varieties and characteristics are unchanging through time but an ever expanding range or mix of varieties and characteristics is available. As long as some of these products are desirable then the cost-of-living index should fall even though prices have not changed. The hedonic method will clearly not account for these changes. For this reason we will not explore this method further here and will instead turn to our primary method of accounting for new and disappearing goods.

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[3] In this sense we are taking the Consumer Surplus (CS) as an estimate of the two conceptually ideal measures, Compensating Variation (CV) and Equivalent Variation (EV). This approximation is not too controversial given that CS is typically bounded by CV and EV.

2.4. The CES Cost Function Approach.

In this paper we adopt a method of more recent vintage than those discussed above. This method is able to rigorously account for the effects of new and disappearing goods in a relatively simple framework. Specifically, a CES cost function is hypothesized for a representative consumer over changing sets of goods. Using this framework it is possible to exactly calculate the overall effect of new and disappearing goods on the consumers' cost-of-living. Empirically there have been only limited applications of this approach; Feenstra and Shiells (1994), Haan (2001) and to some extent Opperdoes (2001). We outline this method in greater detail in Section 3 below and we apply the approach to a scanner data set in Section 4.

3. The CES Cost-of-Living Index with New and Disappearing Goods – A Review of Balk (1999):

Using a relatively new technique it is possible to exactly account for the effect on the cost-of-living index of changes in the availability of goods overtime. This method was initially proposed by Feenstra (1994) and developed, extended and refined by Nahm (1998) and Balk (1999). In this section we briefly review this theory drawing strongly on Balk (1999).

3.1. The CES Cost-of-Living Index with New and Disappearing Goods.

We consider the case of two periods, $t = 0,1$. The index sets of goods available for these periods is represented by I^0 and I^1 and where we will also make use of the index set of goods which is common to both periods, $I^{1,0} \equiv I^1 \cap I^0$, which we assume is non-empty. Also U is some reference utility level, p^1 and p^0 are the price vectors, b_n are quality or taste parameters and σ is the elasticity of substitution which is defined as $\sigma \equiv -d\ln(x_i^t / x_j^t)/d\ln(p_i^t / p_j^t)$ for some goods i and j. Both b_n and σ are assumed fixed across time. With this terminology we can introduce the CES cost function over a changing domain of goods.

$$C(p^t, U \mid I^t) = \left(\sum_{n \in I^t} b_n (p_n^t)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} U, \quad t = 0,1 \tag{3.1}$$

The most important feature of the CES function form is σ, the elasticity of substitution, which represents the extent to which consumers change their relative consumption of goods as relative prices change. It must be non-negative in order for consumers' (compensated) demand curves not to slope upwards.[4]

[4] To see this consult the Appendix.

The cost-of-living index over changing domains of goods for the CES cost function is shown below.

$$\frac{C(p^1,U \mid I^1)}{C(p^0,U \mid I^0)} \equiv \left(\frac{\sum_{n \in I^1} b_n (p_n^1)^{1-\sigma}}{\sum_{n \in I^0} b_n (p_n^0)^{1-\sigma}} \right)^{\frac{1}{1-\sigma}} \tag{3.2}$$

The interesting feature of this cost-of-living index is that it explicitly depends not only on prices but also on the available *consumption opportunities* represented by I^0 and I^1. What is important is that we can in fact calculate this index exactly.

Following Balk (1999) let us briefly show how the exact CES cost-of-living index can be calculated that explicitly takes account of new and disappearing goods. We will make use of Shephard's Lemma which, when applied to the CES cost function, gives the relationship shown in (3.3) between observable expenditure shares and the unobservable parameters of the cost function.

$$s_n^t \equiv \frac{p_n^t x_n^t}{\sum_{n \in I^t} p_n^t x_n^t} = \frac{b_n (p_n^t)^{1-\sigma}}{\sum_{n \in I^t} b_n (p_n^t)^{1-\sigma}}, \quad n \in I^t,\ t = 0,1 \tag{3.3}$$

Let us also define the expenditure shares over the set of matched goods, denoted by $\hat{s}_n^t$. Using (3.4) above it can be shown that the following relationship holds between the expenditure shares for matched goods and the parameters of the cost function.

$$\hat{s}_n^t \equiv \frac{p_n^t x_n^t}{\sum_{n \in I^{1,0}} p_n^t x_n^t} = \frac{b_n (p_n^t)^{1-\sigma}}{\sum_{n \in I^{1,0}} b_n (p_n^t)^{1-\sigma}}, \quad n \in I^{1,0},\ t = 0,1 \tag{3.4}$$

Using equations (3.1) – (3.4) we are now able to derive the exact cost-of-living index over a changing domain of goods.

$$\frac{C(p^1,U \mid I^1)}{C(p^0,U \mid I^0)} = \left(\frac{\sum_{n \in I^1} b_n (p_n^1)^{1-\sigma}}{\sum_{n \in I^{1,0}} b_n (p_n^1)^{1-\sigma}} \frac{\sum_{n \in I^{1,0}} b_n (p_n^1)^{1-\sigma}}{\sum_{n \in I^{1,0}} b_n (p_n^0)^{1-\sigma}} \frac{\sum_{n \in I^{1,0}} b_n (p_n^0)^{1-\sigma}}{\sum_{n \in I^0} b_n (p_n^0)^{1-\sigma}} \right)^{\frac{1}{1-\sigma}} \tag{3.5}$$

$$= \left(\frac{\sum_{n \in I^{1,0}} s_n^1}{\sum_{n \in I^{1,0}} s_n^0} \right)^{\frac{-1}{1-\sigma}} \left(\frac{\sum_{n \in I^{1,0}} b_n (p_n^1)^{1-\sigma}}{\sum_{n \in I^{1,0}} b_n (p_n^0)^{1-\sigma}} \right)^{\frac{1}{1-\sigma}} \tag{3.6}$$

In Equation (3.5) we simply multiply and divide the CES cost-of-living index by the same expressions. We can eliminate the first and third fractions in (3.5) by using (3.3) and we are left with a representation of the cost-of-living index which is a function of observable expenditure shares and unobservable parameters of the cost function relating to matched-goods. Balk (1999) shows that the second term on the RHS of (3.6) containing parameters of the cost function, we will call it $\hat{P}$, can be written in a number of different ways. In this paper we will use four different representations which we outline below.

(a). Various CES Price Indexes.

The first representation of $\hat{P}$ is the well known *Lloyd-Moulton Price Index* which we will call the *(CES) Base-Weighted Price Index* (BWPI), P^{BW}. This is shown in (3.7) below and follows by using (3.4) for $t = 0$. This index dates back to Lloyd (1975).

$$\hat{P} \equiv \left(\frac{\sum_{n \in I^{1,0}} b_n (p_n^1)^{1-\sigma}}{\sum_{n \in I^{1,0}} b_n (p_n^0)^{1-\sigma}} \right)^{\frac{1}{1-\sigma}} = \left(\sum_{n \in I^{1,0}} \hat{s}_n^0 \left(\frac{p_n^1}{p_n^0} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \equiv P^{BW} \tag{3.7}$$

The BWPI (or Lloyd-Moulton Price Index) has attracted attention for its ability to reflect consumer's substitution behavior while only requiring knowledge of base period expenditure shares. This index was used by Shapiro and Wilcox (1997), for US data, to investigate whether a real-time price index could be calculated which reflected substitution. Shapiro and Wilcox (1997, p.123) concluded that using the BWPI, "…it is possible to produce an approximation to the Tornqvist index that is both feasible in real time and quite accurate." Indeed if we more generally regard the BWPI simply as a function of independent variables it can be shown that it is monotonically decreasing in σ (Hardy, Littlewood and Polya, Th. 16, p. 26, 1964). Indeed by appropriate choice of σ the function can produce any number between and including the maximum and minimum price relatives.

Returning to our cost-of-living index we can also derive a current-weighted equivalent expression by substituting equation (3.4) for $t = 1$ into (3.6). This gives the (*CES) Current-Weighted Price Index* (CWPI), P^{CW}, shown in (3.8) again first discussed by Lloyd (1975).

$$\hat{P} = \left(\sum_{n \in I^{1,0}} \hat{s}_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-(1-\sigma)} \right)^{\frac{-1}{1-\sigma}} \equiv P^{CW} \tag{3.8}$$

As both (3.7) and (3.8) are exact for the CES functional form we can take their geometric mean to obtain another index that solves (3.6). This index is a member of the superlative 'quadratic mean of order r' family of indexes discussed by Diewert (1976) and hence we will call it the *(CES) Quadratic Price Index* (QPI), P^Q.

$$\hat{P} = (P^{LM} \times P^C)^{\frac{1}{2}} = \left(\sum_{n \in I^{1,0}} \hat{s}_n^0 \left(\frac{p_n^1}{p_n^0} \right)^{1-\sigma} \right)^{\frac{1}{2(1-\sigma)}} \left(\sum_{n \in I^{1,0}} \hat{s}_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-(1-\sigma)} \right)^{\frac{-1}{2(1-\sigma)}} \equiv P^Q \tag{3.9}$$

This is the index that is primarily used to calculate the matched-goods price index reported in the empirical results that follow. The reason we use this index is that it has a strong justification based upon more flexible representations of technology than the CES functional form (Diewert, 1976). Balk (1999) noted for $\sigma = 0$ the QPI is equal to the *Fisher Price Index* while for $\sigma \to 1$ it is equal to the *Tornqvist Price Index* (both of these indexes are defined in the next section).

Finally, the *Sato-Vartia Price Index* (SVPI), P^{SV}, can also be derived from the CES functional form and is shown in (3.10).[5] The weights for the SVPI are rather complex and involve the normalized logarithmic mean of the expenditure shares in each period.[6]

$$\hat{P} = \prod_{n \in I^{1,0}} \left(\frac{p_n^1}{p_n^0} \right)^{w_n^{1,0}} \equiv P^{SV}, \qquad w_n^{1,0} = \frac{L(\hat{s}_n^1, \hat{s}_n^0)}{\sum_{n \in I^{1,0}} L(\hat{s}_n^1, \hat{s}_n^0)} \tag{3.10}$$

Interestingly, note that the SVPI does not depend on the elasticity of substitution. This is important for later purposes.

(b). Some Other Price Indexes.

In the empirical section we will also calculate some more familiar price indexes. Here we introduce the *Laspeyres Price Index* (LPI), P^L, *Paasche Price Index* (PPI), P^P, *Fisher Price Index* (FPI), P^F, and finally the *Tornqvist Price Index* (TPI), P^T, shown in this order over matched-goods below.

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[5] For the methods used to derive the Sato-Vartia index see Balk (1999).

[6] The logarithmic mean $L(a,b)$ is defined as $L(a,b) = (a-b)/(\ln a - \ln b)$ where $a \neq b$ and $L(a,a) = a$. Clearly we must have $a, b > 0$.

$$P^{L} \equiv \left(\sum_{n \in I^{1,0}} \hat{s}_n^0 \left(\frac{p_n^1}{p_n^0} \right) \right) \tag{3.11}$$

$$P^{P} \equiv \left(\sum_{n \in I^{1,0}} \hat{s}_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-1} \right)^{-1} \tag{3.12}$$

$$P^{F} \equiv (P^{L} \times P^{P})^{\frac{1}{2}} \tag{3.13}$$

$$P^{T} \equiv \prod_{n \in I^{1,0}} \left(\frac{p_n^1}{p_n^0} \right)^{\frac{(\hat{s}_n^0 + \hat{s}_n^1)}{2}} \tag{3.14}$$

Note that the LPI and PPI have been written in such a way as to emphasize there similarity to some of the CES price indexes. The LPI is equal to the BWPI, or Lloyd-Moulton Price Index, in equation (3.7) when $\sigma = 0$ while the PPI is equal to the CWPI in equation (3.8) also when $\sigma = 0$.

3.3. Summary and Discussion of the Cost-of-Living Index.

The method detailed above allows us to calculate the cost-of-living index over a changing domain of goods. Moreover the cost-of-living index takes the simple form shown below where we multiply one of the matched-goods price indexes (3.7) – (3.10), represented by $\hat{P}$, by an adjustment factor reflecting relative expenditure shares on matched-goods. This is shown in (3.15) where for heuristic purposes we have written the adjustment factor in two equivalent ways.

$$\frac{C(p^1, U \mid I^1)}{C(p^0, U \mid I^0)} = \left(\frac{\sum_{n \in I^{1,0}} s_n^1}{\sum_{n \in I^{1,0}} s_n^0} \right)^{\frac{-1}{1-\sigma}} \hat{P} = \left(\frac{1 - \sum_{n \in I^1, n \notin I^{1,0}} s_n^1}{1 - \sum_{n \in I^0, n \notin I^{1,0}} s_n^0} \right)^{\frac{-1}{1-\sigma}} \hat{P} \tag{3.15}$$

The intuitive explanation for the form of the adjustment factor is that the expenditure shares for new and disappeared goods reflect there 'importance' to consumers. The adjustment factor then looks at the relative gain from new goods and the loss from disappeared goods. This ratio is then adjusted using the elasticity of substitution.

It is interesting to note that no adjustment to the matched-goods price index occurs when, firstly, the expenditure shares on new and disappeared goods are equal – indicating that relative gains in consumption opportunities were equivalent to the losses, and secondly, as $\sigma \to \infty$ in which case all goods are very close substitutes and whether new goods appear or old goods disappear does not matter in terms of consumption opportunities.

3.4. A Restriction on the Elasticity of Substitution.

A vital point to note regarding this approach to calculating the cost-of-living index is that the elasticity of substitution must be larger than one, $\sigma > 1$. Balk (1999) showed this by considering an example where $p_n^1 = p_n^0 \;\; \forall n \in I^{1,0}$ and where we have some newly appeared goods but no disappearing goods. Then using (3.15), and noting that as common goods have unchanged prices the matched price index will equal one, the cost-of-living index for this particular case is shown below.

$$\frac{C(p^1, U \mid I^1)}{C(p^0, U \mid I^0)} = \left(\sum_{n \in I^{1,0}} s_n^1 \right)^{\frac{-1}{1-\sigma}} \tag{3.16}$$

But this index must be no larger than 1 as the consumer now has a greater range of goods to choose from with prices for all the continuing goods unchanged by assumption. It can be seen that this implies that we must have $\sigma > 1$.

(a). A Discussion of the Restriction.

Why do we have this restriction on the elasticity of substitution? Consider the following optimization argument. The cost function, by definition, is the minimum expenditure required to achieve a given level of utility. However, in looking at the effect of new and disappearing goods we are defining a *restricted* cost function where the consumption of some goods is constrained to zero in some periods. We can then write the modified cost function for period $t = 0,1$ in the following way.

$$\begin{aligned} C(p^t, U \mid I^t) = \min_{x_1,\dots,x_N} \quad & \sum_{n \in I^1 \cup I^0} p_n^t x_n^t \\ s.t. \quad & U(x^t) = U \\ & x_n^t = 0, \; \forall n \notin I^t \end{aligned} \tag{3.17}$$

However, this definition may cause problems if there are some goods i which are essential to consumption but are not common to both periods (i.e. where $i \notin I^{1,0}$). In this case it may not be possible to reach the reference utility level without some consumption of these goods and the constraints in the optimization problem may define a feasible set which is empty. To see that this is indeed the case we can derive the utility function which is dual to the CES cost function.

$$U(x^t \mid I^t) = \left(\sum_{n \in I^t} b_n^{\frac{1}{\sigma}} (x_n^t)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad t = 1,0 \tag{3.18}$$

From inspection of this utility function if $\sigma \le 1$ then every good is essential to consumption, as was noted by Feenstra (1994). It is only when $\sigma > 1$ that the consumption of goods can equal zero.

Economically this means that if $\sigma > 1$ then consumers can be compensated for the restricted (zero) consumption of some goods by increases in the consumption of other goods. This ability to compensate the consumer for the loss of some goods is vital in obtaining sensible answers to the effect of new and disappearing goods on the cost-of-living. If no compensation is possible then the cost-of-living index will be infinite if one of these 'essential' goods is lost. It seems reasonable to me that at the elementary level of aggregation, such as for scanner data where this theory will be applied, that all goods are effectively replaceable. This is clearly not so plausible at higher levels of aggregation. Consider for example *food* and *clothing*. If our consumption of these goods were restricted to zero then this certainly would be catastrophic for utility.

3.5. Estimating the Elasticity of Substitution.

In all the matched-goods indexes (3.7) – (3.10) above except the SVPI we need to know the elasticity of substitution in order to calculate the indexes. More importantly we must know the elasticity of substitution in order to determine the adjustment for new and disappearing goods. Therefore, to implement this approach we must have an effective means of estimating the elasticity of substitution.

Fortunately Balk (1999) outlined various ways in which the elasticity of substitution could be estimated. The basic idea of his approach is that all the matched price indexes derived from the CES cost function, (3.7) – (3.10) above, should be equal. This gives us two types of methods for estimating the elasticity of substitution.

The first method used to obtain $\hat{\sigma}$, an estimate of σ, is to equate the BWPI (3.7) to the CWPI (3.8) as in (3.19) below.

$$\hat{P}^{BW} \equiv \left(\sum_{n \in I^{1,0}} \hat{s}_n^0 \left(\frac{p_n^1}{p_n^0} \right)^{1-\hat{\sigma}} \right)^{\frac{1}{1-\hat{\sigma}}} = \left(\sum_{n \in I^{1,0}} \hat{s}_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-(1-\hat{\sigma})} \right)^{\frac{-1}{1-\hat{\sigma}}} \equiv \hat{P}^{CW} \tag{3.19}$$

This method will prove to be particularly appealing and we will call it the *Current v Base* method. Balk (1999) indicates that we can obtain an iterative solution to this equation, and an estimate of σ, by starting from $\hat{\sigma} = 0$ in (3.19). This gives the LPI on the left-hand-side of (3.19) and the PPI on the right-hand-side. As previously noted we expect the LPI to be greater than the PPI so to find a solution to (3.19) we can increase $\hat{\sigma}$ which reduces the left-hand-side and increases the right-hand-side of (3.19) due to the properties of this function (Hardy, Littlewood and Polya, Th. 16, p.26, 1964).

A second set of methods suggested by Balk (1999) is to equate the BWPI and the CWPI, which both include the elasticity parameter, to the SVPI, which is independent of the elasticity of substitution.

$$\hat{P}^{BW} \equiv \left(\sum_{n \in I^{1,0}} \hat{s}_n^0 \left(\frac{p_n^1}{p_n^0} \right)^{1-\hat{\sigma}} \right)^{\frac{1}{1-\hat{\sigma}}} = P^{SV} \tag{3.20}$$

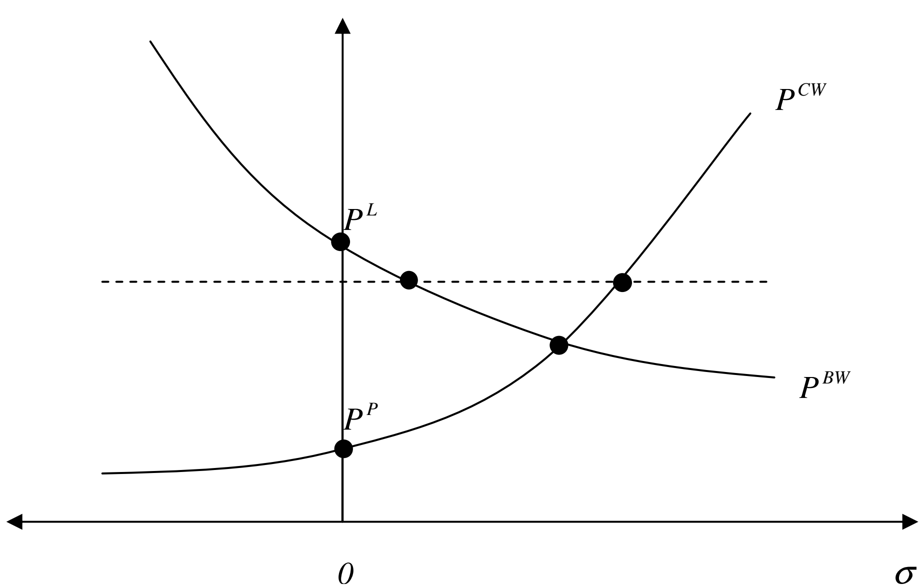
$$\hat{P}^{CW} \equiv \left(\sum_{n \in I^{1,0}} \hat{s}_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-(1-\hat{\sigma})} \right)^{\frac{-1}{1-\hat{\sigma}}} = P^{SV} \tag{3.21}$$

It seems warranted, as we will argue below, to take an average of these two estimates. We will call this the *Average Sato-Vartia* Method.

(a). A Discussion and Assessment of the Various Index Methods.

It should be noted that the various index methods for estimating the elasticity of substitution are closely related. A useful way of seeing this interrelationship is to consider Figure 1 below where we have taken prices and quantities as fixed and regarded the BWPI (P^{BW}) and CWPI (P^{CW}) as functions of σ alone. From Hardy, Littlewood and Polya (1964) we know that the BWPI slopes down while the CWPI slopes upward.

Figure 1: Estimation of the Elasticity of Substitution.



The *Current v Base* index method gives the value of the elasticity of substitution where the BWPI and CWPI intersect. As can be seen this has the appealing feature that the estimated elasticity will always be positive as long as the LPI exceeds the PPI. The other index method is a little different. To see this suppose that the horizontal dashed line in Figure 1 represents the SVPI which is independent of σ. Then equating this index to the BWPI and CWPI gives estimates of the elasticity of substitution which lie either side of the *Current v Base* estimate. In this sense each of the two individual estimates is a biased estimator of σ and for this reason we need to take an average of them. One problem this raises is that we need to make an essentially arbitrary choice about which averaging formula to use. The formula we choose however may influence our results. This problem can be avoided if we simply use the *Current v Base* method. Furthermore it is not clear that we are getting a superior estimate by using the *Average Sato-Vartia* method compared with the *Current v Base* method.

Another point to note from Figure 1 is that, in principle, negative estimates of the elasticity of substitution could arise from the Sato-Vartia Method even when the LPI lies above the PPI. This is because the SVPI is not bounded by the LPI and PPI. This is unlikely to be an important problem in practice however as we could typically expect the SVPI to lie between Paasche and Laspeyres Indexes.

Due to the factors we prefer the *Current v Base* approach to estimating the elasticity of substitution over the Average Sato-Vartia approach though we will compare both in the empirical section.

4. An Empirical Application to Scanner Data.

Now that we have revised some of the theory surrounding the primary approach we have chosen to new and disappearing goods we can proceed to the application of these ideas to our scanner data set. The focus of our application is in comparing price indexes which account for new and disappearing goods with those that do not. From Section 3 this involves comparing a matched-goods price index with and without the adjustment factor for new and disappearing. Before we proceed to this however let us discuss the data and some preliminary issues.

4.1. The Scanner Data Set and Data Issues.

The data used in this study was purchased by the Australian Bureau of Statistics (ABS) for the purpose of investigating the use of scanner data in the Australian CPI. It is the same data that has been used in studies undertaken by the ABS (Jain and Abello, 2001; Jain and Caddy, 2001).

The data set included a total of 100 stores, which were continuously present, belonging to four supermarket chains in one of the major cities of Australia. These stores accounted for around 80 percent of grocery sales in this city (Jain and Caddy, 2001, p.4).[7] The data set includes observations from the start of February 1997 to the end of April

[7] While we know that the data covered four different supermarket chains for commercial sensitivity reasons we were not told which supermarket came from which chain. This reduced the range of aggregation approaches that could be pursued.

1998, 65 weeks of data in total for 19 product categories. As detailed above the products are: *Biscuits*, *Bread*, *Butter*, *Cereal*, *Coffee*, *Detergent*, *Frozen Peas*, *Honey*, *Jams*, *Juices*, *Margarine*, *Oil*, *Pasta*, *Pet Food*, *Soft Drinks*, *Spreads*, *Sugar*, *Tin Tomatoes* and *Toilet Paper*. These products represent a selection of the goods available in supermarkets and mainly comprise processed food items. The total value of sales for these products over the 65 week period was just over AU$600 million.

(a). Aggregation Methods, Chain Price Indexes, and Other Preliminaries.

The data basic form of the data was weekly unit-value prices, and the corresponding sales volume, for a Product Code[8] in an Outlet. Various approaches to aggregation were applied to this very detailed data in order to derive the prices and quantities that were used in the index formulae above. In fact four different aggregation methods were used in order to ensure the robustness of the results to the aggregation approach. This is in the context of much research on scanner data where a number of researchers have shown that the method of aggregation is often very important (Dalen, 1997; Reinsdorf, 1999; Jain and Caddy, 2001; Silver and Webb, 2002; Triplett, 2003; Koskimaki and Yla-Jarkko, 2003).

We aggregated across time to a Monthly and Quarterly frequency. This is consistent with a recommendation in the draft ILO CPI manual (ILO, 2003, Chp. 20, p.6) that the, "…index number time period be at least 4 weeks or a month." Calculating indexes monthly or quarterly is standard international practice however it should be noted that one of the potential benefits of scanner data is that we could calculate more frequent price indexes.[9]

In addition to aggregation across time we experimented with, firstly taking a unique Product Code and Outlet combination as the definition of a good, and secondly using just the Product Code and aggregating across Outlets. The first approach can be justified on the basis that we are endeavouring to control for any differences in the quality of services from the various outlets. In practice these differences are likely to be minor furthermore it is often argued that aggregating across Outlets will help to mitigate the new and disappearing goods problem (Reinsdorf, 1999, p.153). In this case Diewert (1995, p.22) has suggested that aggregation across outlets for the same product seems acceptable.

Given our two time-aggregation and two product-aggregation methods we have a total of four aggregation approaches. At a monthly frequency we have *Month (Prod. Code, Outlet)*, which uses unique *Product Code* and *Outlet* combinations, as well as *Month (Prod. Code)* uses only the *Product Code* as the definition of a good and aggregates over *Outlets*. The corresponding quarterly indexes are *Quarter (Prod. Code, Outlet)* and *Quarter (Prod. Code)*. For each of these aggregation methods we calculate the price indexes discussed above where we take a chained index approach rather than calculate direct price indexes. The primary reason for this is that chained indexes are more likely to mitigate the effects of new and disappearing goods because there is greater

[8] Formally this is called the Australian Product Number (APN) which is the equivalent of the Universal Product Code (UPC) in the US or the European Article Number (EAN).

[9] In the not too distant future a weekly price index for some goods does not seem out of the question. Feenstra and Shapiro (2001) have made some progress in this regard.

overlap in the goods available for time-periods which are adjacent than those that are more distant.[10]

With these details out of the way we can proceed to the results of the empirical application. We start by discussing the results from estimating the elasticity of substitution which is an integral part of our approach to accounting for the effect of new and disappearing goods.

4.2. Estimating the Elasticity of Substitution.

In Section 3.5 we reviewed three methods which used price indexes to estimate the elasticity of substitution. In applying these methods we adopted a grid search approach using increments of 0.1 for $\hat{\sigma}$.

The index methods used for estimating the elasticity of substitution performed well. Table 3 in the Appendix presents the *average* and *standard deviation* of the estimated elasticities using the *Current v Base* method for each product and aggregation category. The results for the arithmetic average of the two Sato-Vartia methods, *Average Sato-Vartia*, were very similar to those for the *Current v Base* method. This can be seen in Table 3 where we have reported the average of absolute deviations of the *Average Sato-Vartia* method from the *Current v Base* method. These deviations are relatively small and on average well within the 0.1 degree of accuracy with which we are estimating the elasticities. It should be noted however, that while there was little difference between our methods for estimating the elasticity of substitution the estimates of the elasticity were rather volatile across time. This can be seen in the Figures in the Appendix for *Cereals*.

One interesting aspect of estimating the elasticity of substitution is the effect of aggregation. As we would have expected a priori, when we increase the level of aggregation the elasticity of substitution falls. One interesting feature however is that aggregation across time, from monthly to quarterly indexes, led to a far greater reduction in the elasticity than did aggregation across outlets. In a somewhat contradictory result a larger number of *negative*, and hence implausible, estimates of the elasticity of substitution occurred when we aggregated across outlets.

In applying the adjustment for new and disappearing goods discussed above we used an estimate of the elasticity of substitution derived from the *Current v Base* method for each time period. However, when the elasticity of substitution fell below one in a given time period for a good, which contradicts one of the implicit assumptions in the CES cost function approach, we instead used the average estimated elasticity of substitution over all time periods. In the usual case where the average estimated elasticity of substitution over all time periods was less than one for the *Current v Base* method we did not undertake the adjustment for new and disappearing goods. This only occurred for *Jams*, *Pasta* and *Sugar* for the *Quarter (Prod. Code)* aggregation method. With an estimate of the elasticity of substitution in hand we can now examine the effects of new and disappearing goods on the cost-of-living index.

[10] This is emphasized in ILO (Chp. 7 and 8). However, it should be noted that if there are seasonal products then adjacent periods may not be more similar than say periods separated by a year. Fortunately our data set does not include any products with strong seasonal patterns.

4.3. The Influence of New and Disappearing Goods on the Cost-of-Living.

The results of the application of the CES cost function approach to the problem of new and disappearing goods are startlingly. For each of the aggregation methods and for almost all of the goods there is a significant downward adjustment required to the basic matched-goods price index to reflect the effects of new and disappearing goods. The results are shown in Table 1 where of the 73 adjustments for new and disappearing goods that could be undertaken in total 69 of them were downward adjustments meaning that the matched-goods price index overstated the actual cost-of-living. On average the matched-goods index was upwardly biased by between around 1 and 3 percent over the 65 week period or around 0.8 to 2.4 percent annually. This is significantly larger than the estimate by the Boskin Commission (Boskin *et al*, 1996, Table 2) mentioned earlier of an upward bias of 0.3 percent each year for the "Food at Home other than Produce" category from 1967 to 1996.

It is important to note that the estimate of an upward bias is robust to the choice of aggregation method. All aggregation methods showed on average an upward bias for the matched-goods price index. Interestingly, the most aggregated category, Quarter (Prod. Code, Outlet), showed the greatest level of bias which seems to conflict with our expectation that greater aggregation serves to alleviate the new and disappearing goods problem. We now turn to a more detailed discussion of the reasons for the apparent bias in matched-goods indexes.

(a). Matched-Goods Index Bias, Expenditure Shares and Changes in the Availability of Goods.

The interesting feature of the results it that they imply a sizeable bias for the matched-goods method despite there being a large overlap of expenditures on common goods. As can be seen in Table 4 the average proportion of expenditure in the *current* ($t=1$) and *base* ($t=0$) periods is very high, usually at around 98 and 99 percent of total expenditure. However, from our discussion of the theory in Section 3.1 – 3.3 we noted that it was the relative not absolute size of expenditure shares that mattered. Remember that the matched-goods price index, $\hat{P}$, is multiplied by the adjustment factor $\hat{A}$ shown below.

$$\hat{A} = \left(\frac{\sum_{n \in I^{1,0}} s_n^1}{\sum_{n \in I^{1,0}} s_n^0} \right)^{\frac{-1}{1-\hat{\sigma}}} = \left(\frac{1 - \sum_{n \in I^1, n \notin I^{1,0}} s_n^1}{1 - \sum_{n \in I^0, n \notin I^{1,0}} s_n^0} \right)^{\frac{-1}{1-\hat{\sigma}}} \tag{4.1}$$

For $\hat{A}$ to be consistently less than one, as $\sigma > 1$, it must be the case that the expenditure on common goods in the current period is less than expenditure on these goods in the base period, or equivalently, the share of expenditure on new goods in the current period is larger than the share of disappeared goods in base expenditure. Indeed this seems to be a very strong empirical regularity in our scanner data set. In the final section of Table 4 we show the percentage change in the chained indexes of current relative to base expenditure shares. For all of our 76 comparisons except 3 these indexes fell and often quite significantly.

It is this empirical regularity which is the driver of our estimate of an upward bias from omitting new and disappearing goods. However, while this is a strong aspect of our data set it may not feature in all cases. For example, in Reinsdorf's coffee data (Reinsdorf, 1999, Table 3, p.155) where there seems to be no systematic difference between the current and base proportions of expenditure on common goods. In contrast in a scanner data study by Dalen (1997, p.2, Table 1) of four products we do in fact see strong evidence that the proportion of current expenditure shares on common goods is less than that for the base period.

An interesting question is, what is the driver of this disparity between base and current expenditure shares on common goods? One explanation of sorts could be that there is an ever increasing number of products so that the number of newly introduced goods exceeds the number of goods withdrawn. If this is the case then we would typically expect expenditure shares to follow a similar pattern. Table 5 compares the number of products available in each product category in the first and last of the time periods for each aggregation method. The results show that indeed for most of the product categories the number of goods available increased though there were often significant differences in growth rates. While this appears to be one of the reasons for our results it is likely that other factors are also at work. For example, *Soft Drinks* recorded a large fall in the size of the product range between the first and last time periods of the order of 10 percent for each aggregation method. However, it also recorded a downward adjustment to the matched-goods index in 3 out of 4 aggregation approaches due to the effects of new and disappearing goods. This perhaps indicates that rather complex factors, such as consumers' desire for variety, may be at play.

(b). A Comparison with the Approximate Reservation Price Method.

As outlined in Section 2.2 above an alternative approximate method for determining the influence of new and disappearing goods on the cost-of-living index is to estimate reservation prices. It is interesting to compare the results from the CES Cost Function Method with the Approximate Reservation Price Method. In order to apply this latter method we require an estimate of the price elasticity of demand, ε_i^t, from (2.1). In order to ensure comparability with the CES Cost Function Method we will use an estimate of ε_i^t derived from the CES functional form. It is easy to show that in the CES case, $\hat{\varepsilon}_i^t = \hat{\sigma}(s_i^t - 1)$ where $\hat{\sigma}$ is the elasticity of substitution which we have already estimated and s_i^t is the expenditure share of the good.[11] The estimated reservation price for new and disappearing goods can be used in an index formula in a conventional fashion. In determining the effect of new and disappearing goods we compared a matched-goods Fisher Price Index with an Augmented Fisher Price Index. This latter index is a geometric mean of the *Augmented Laspeyres* and *Paasche Price Indexes* which

[11] To see this consult the Appendix.

use the estimated reservation prices for non-matched goods. These indexes are defined below.

$$P^{AL} \equiv \left(\sum_{n \in I^{1,0}} s_n^0 \left(\frac{p_n^1}{p_n^0} \right) + \sum_{n \in I^0, n \notin I^{1,0}} s_n^0 \left(\frac{\hat{p}_n^1}{p_n^0} \right) \right) \tag{4.2}$$

$$P^{AP} \equiv \left(\sum_{n \in I^{1,0}} s_n^1 \left(\frac{p_n^1}{p_n^0} \right)^{-1} + \sum_{n \in I^1, n \notin I^{1,0}} s_n^1 \left(\frac{p_n^1}{\hat{p}_n^0} \right)^{-1} \right)^{-1} \tag{4.3}$$

$$P^{AF} \equiv (P^{AL} \times P^{AP})^{\frac{1}{2}} \tag{4.4}$$

The results of this exercise are informative and help to reinforce our strong suspicion that the matched-goods price index is upwardly biased. This method indicates that the matched-goods price index is upwardly biased by around 0.5 to 1 percent on average over the 65 weeks. This is still a relatively large bias estimate but is somewhat lower than that recorded using the CES Cost Function Approach.

Let us now briefly turn to a somewhat different topic before concluding the discussion – the issue of the effects of aggregation and index formula on the matched-goods price indexes.

4.4. Aggregation, Price Change and Index Formula.

One of the most interesting and challenging features of scanner data is the sensitivity of the index numbers to the index formula and the aggregation method. This feature of scanner data has been noted by many authors (Dalen, 1997; Reinsdorf, 1999) and while this has not been the primary focus of this exercise it is interesting to compare the various matched-goods price indexes that we have calculated.

One of the most notable features of scanner data is the often extremely large differences between the LPI and PPI. Because the data is so disaggregated there are often very large substitution effects which drives a wedge between Laspeyres and Paasche. The Paasche-Laspeyres Spread, the percentage difference between the LPI and PPI over the 65 week period, is shown in Table 2. There are often very large spreads with the biggest reaching almost 230 percent for *Margarine* using *Month (Prod. Code, Outlet)* aggregation. The Paasche-Laspeyres falls by around 3 times when we aggregate across outlets. However, what is most interesting is that it falls by a far larger factor when we aggregate across time. This helps to reinforce what we found for our estimates of the elasticity of substitution. It appears that aggregation across time is more important than aggregation across outlets in reducing substitution effects.

Given the fact that the Paasche–Laspeyres spread is large we emphasize, as have many other studies of scanner data (Dalen, 1997; Haan and Opperdoes, 1997; Reinsdorf, 1999), that the use of a superlative price indexes which treat the periods being compared symmetrically is essential. However, is the choice of superlative index important? In Table 2 we show the Fisher, Tornqvist and CES Quadratic Price Indexes all of which are superlative. It can be seen that these indexes approximate each other closely for a given aggregation method.[12] This indicates that once the type of aggregation is chosen the choice of superlative index formula is not likely to be too important. A more problematic question is, what is the appropriate form of aggregation? This question is difficult and depends in many ways on the use of the price index however we venture a suggestion on one way of looking at this question.

(a). A Criterion for Evaluating the Validity of an Aggregation Method.

At present there appears to be little consensus about the best method of aggregating the basic data into a form for use in an index formula. A number of researchers have pursued a variety of approaches with few definitive answers on the best method.

Here we argue that in undertaking aggregation one important criterion that should be considered in checking whether an aggregation method is valid is whether it produces economically meaningful results. That is, are the aggregated prices and quantities related in ways which are consistent with basic consumer theory. One example of this is ensuring that the estimated elasticity of substitution is non-negative as this would imply (compensated) demand curves slope upwards. In terms of our framework this is equivalent to ensuring that the LPI exceeds the PPI. Indeed this is a fairly general test as under the assumption of homothetic preferences and cost minimisation the (input) LPI should always exceed the (input) PPI. Moreover if this feature of the data is present prior to aggregation then it seems reasonable to require that it should also exist after aggregation.

This approach is useful in checking the plausibility of our aggregation methods as well as those used by others. Negative estimates of the elasticity of substitution arose in our study only when we aggregated across Outlets. This may indicate that the aggregation of Product Codes across different Outlets is not reasonable. Consumers may not regard the same Product Code in different stores as comparable products and hence the normal economic rules relating prices and quantities breakdown. One of the most comprehensive recent papers on aggregation is that of Koskimaki and Yla-Jarkko (2003) who use 16 different aggregation strategies in the calculation of Fisher and Laspeyres Price Indexes.[13] At the highest level of aggregation along both the product and spatial dimension the Fisher Price Index routinely exceeds the Laspeyres indicating that either very unusual economic behaviour is taking place or the aggregation strategy is inappropriate.

In summary checking whether normal economic behaviour is observed after aggregation seems like a minimal criterion for justifying an aggregation approach. One such test of conventional economic behaviour is to see whether the LPI exceeds the PPI, or equivalently in our framework, whether the elasticity of substitution is greater than zero. However, far more discussion of aggregation issues is needed however to more rigorously determine the appropriate level of aggregation.

[12] The Sato-Vartia Price Index was also calculated and recoded similar results.

[13] This paper has been recently cited and discussed in the draft ILO Manual (ILO, 2003, Chp. 20, pp.8-10).

5. Conclusion.

The main purpose of this paper has been to quantify the effects of new and disappearing goods on the cost-of-living index using a scanner data set. To this end we primarily adopted a particular approach to the measurement of this effect based on the CES cost function. This approach was outlined by Feenstra (1994), Feenstra and Shiells (1994), Nahm (1998) and developed by Balk (1999).

The advantage of this approach as opposed to alternative methods such as hedonic regression or the estimation of reservation prices is that very little has to in fact be estimated. Using the CES Cost Function Approach all that we require is an estimate of the elasticity of substitution which can be relatively easily obtained. These estimates were then used to determine the effects of new and disappearing goods on the cost-of-living index.

Most importantly our results show that the adjustment for the matched-goods to account for new and disappearing goods is invariably in the downward direction and likely to be larger than previously thought. The basic matched-goods price index was on average rated downwards by between 1 and 3 percent over the 65 week period under study, depending on the form of aggregation. In annualized terms this amounts to an upward bias of 0.8 to 2.4 percent. Our use of the Approximate Reservation Price Method confirmed these results though they indicated a smaller, but nevertheless still significant, bias. The magnitude of the effects of new and disappearing goods appears too large to ignore for those index practitioners interested in calculating a cost-of-living index. The results provide a strong caution against the belief that the simple matched-goods approach to index construction is entirely adequate.

6. References.

Balk, Bert (1999), "On Curing the CPI's Substitution and New Goods Bias", Paper Presented at the Fifth Meeting of the Ottawa Group, Reykjavik, Iceland.

Berndt, Ernst R., Zvi Griliches, Neal J. Rappaport (1995), "Econometric Estimates of Price Indexes for Personal Computers in the 1990's", *Journal of Econometrics*, Vol. 68, pp. 243 – 268.

Boskin, Michael J., Ellen Dulberger, Robert J. Gordon, Zvi Griliches and Dale Jorgenson (1996), *Toward a More Accurate Measure of the Cost of Living*, Final Report to the Senate Finance Committee from the Advisory Commission to Study the Consumer Price Index.

Bradley, Ralph, Bill Cook, Sylvia G. Leaver and Brent Moulton (1997), "An Overview of Research on Potential Uses of Scanner Data in the U.S. CPI", Paper Presented at the Third Meeting of the Ottawa Group, Voorburg, Netherlands.

Bresnahan, Timothy F. (1997), "Comment on Valuation of New Goods under Perfect and Imperfect Competition", in *The Economics of New Goods*, Timothy F. Bresnahan and Robert J. Gordon (eds.), pp.237 – 247.

Dalen, Jorgen (1997), "Experiments with Swedish Scanner Data", Paper Presented at the Third Meeting of the Ottawa Group, Voorburg, Netherlands.

Diewert Erwin W. (1976), "Exact and Superlative Index Numbers", *Journal of Econometrics*, Vol. 4, No. 2. Pp. 115-145.

Diewert, Erwin W. (1995), "Axiomatic and Economic Approaches to Elementary Price Indexes", *Department of Economics Discussion Paper No. 95-01*, University of British Columbia.

Diewert, Erwin W. (2001), "The Consumer Price Index and Index Number Theory: A Survey", *Department of Economics Discussion Paper No. 01-02*, University of British Columbia.

Diewert, Erwin (2003), "Hedonic Regressions: A Review of Some Unresolved Issues", Paper Presented at the Seventh Meeting of the Ottawa Group, Paris, France.

Feenstra, Robert (1994), "New Product Varieties and the Measurement of International Prices", *American Economic Review*, Vol. 84, No. 1.

Feenstra, Robert C. and Clinton R. Shiells (1994), "Bias in U.S. Import Prices and Demand", *NBER Working Paper*, No. 4841.

Feenstra, Robert C. and Matthew D. Shapiro (2001), "High Frequency Substitution and the Measurement of Price Indexes", Paper Prepared for the CRIW Conference *Scanner Data and Price Indexes*, September, 2000.

Gordon, Robert J. and Zvi Griliches (1997), "Quality Change and New Products", *The American Economic Review*, Vol. 87, No. 2.

Haan, Jan de and Eddy Opperdoes (1997), "Estimation of the Coffee Price Index Using Scanner Data: the Choice of Micro Index", Paper Presented at the Third Meeting of the Ottawa Group, Voorburg, Netherlands.

Haan, Jan de (2001), "Generalized Fisher Price Indexes and the Use of Scanner Data in the CPI", Paper Presented at the Sixth Meeting of the Ottawa Group, Canberra, Australia.

Hardy, G. H., J. E. Littlewood and G. Polya (1964), *Inequalities*.

Hausman, Jerry (1997), "Valuation of New Goods under Perfect and Imperfect Competition", in *The Economics of New Goods*, Timothy F. Bresnahan and Robert J. Gordon (eds.), pp. 209 – 237.

Hausman, Jerry (2003), "Sources of Bias and Solutions to Bias in the Consumer Price Index", *Journal of Economic Perspectives*, Vol. 17, No. 1. pp. 23 – 44.

Hicks, J. R. (1940), "The Valuation of the Social Income", *Economica*, Vol. 7.

International Labour Organisation (2003), *Revision of the International Guidelines on the CPI*. (http://www.ilo.org/public/english/bureau/stat/guides/cpi/).

Jain, Malti and Joanne Caddy (2001), "Using Scanner Data to Explore Unit Value Indexes", Room document at the Sixth Meeting of the Ottawa Group, Canberra Australia.

Jain, Malti and Ruel Abello (2001), "Construction of Price Indexes and Exploration of Biases Using Scanner Data", Room document at the Sixth Meeting of the Ottawa Group, Canberra, Australia.

Koskimaki, Timo and Mari Yla-Jarkko (2003), "Segmented Markets and CPI Elementary Classifications", Paper Presented at the Seventh Meeting of the Ottawa Group, Paris, France, 2003.

Lloyd, Peter (1975), "Substitution Effects and Biases in Nontrue Price Indices", *American Economic Review*, Vol. 65, pp. 301 – 313.

Moulton, Brent R. (2001), "The Expanding Role of Hedonic Methods in the Official Statistics of the United States". *Bureau of Economic Analysis Discussion Paper*.

Nahm, Daehoon (1998), "Incorporating the Effect of New and Disappearing Products into the Cost of Living: An Alternative Index Number Formula*", Seoul Journal of Economics*, Vol. 11, No. 3.

Opperdoes, Eddy (2001), "Some Empirical Experiments with CES Functions", *Statistics Netherlands*.

Reinsdorf, Marshall (1999), "Using Scanner Data to Construct CPI Basic Component Indexes", *Journal of Business and Economic Statistics*, Vol. 17, No. 2.

Richardson, David H. (2000), "Scanner Indexes for the CPI", Paper Presented at the Sixth Meeting of the Ottawa Group, Canberra, Australia.

Rosen, Sherwin (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition", *Journal of Political Economy*, April, pp.34 – 55.

Schultze, Charles and Christopher Mackie (eds.) (2002), *At What Price? Conceptualizing and Measuring Cost-of-Living and Price Indexes*. National Research Council.

Schut, C. M. (2002), "Using Scanner Data to Calculate Consumer Price Indices", *Statistics Netherlands*.

Shapiro, Matthew D. and David W. Wilcox (1997), "Alternative Strategies for Aggregating Prices in the CPI", *Review of the Federal Reserve Bank of St. Louis*.

Silver, Mick (1999), "An Evaluation of the Use of Hedonic Regressions for Basic Components of Consumer Price Indices", *Review of Income and Wealth*, Series 45, No. 1.

Silver, Mick and Bruce Webb (2002), "The Measurement of Inflation: Aggregation at the Basic Level", *Journal of Economic and Social Measurement*, Vol. 28, pp. 21 – 35.

Triplett, Jack (2003), "Using Scanner Data in Consumer Price Indexes: Some Neglected Conceptual Considerations", Chp. 6, *Scanner Data and Price Indexes*, Feenstra and Shapiro (eds.), pp. 151 – 164.

7. Appendix.

The elasticity of substitution and the (compensated) demand function.
Here we briefly show that for the CES functional form that we must have $\sigma \geq 0$ for the compensated demand function to not slope upward. Using Shephard's Lemma we can derive the compensated demand curve.

$$x_i^t(p^t, U \mid I^t) = \frac{\partial C(p^t, U \mid I^t)}{\partial p_i^t} = b_i \, (p_i^t)^{-\sigma} \left(\sum_{n \in I^t} b_n \, (p_n^t)^{1-\sigma} \right)^{\frac{\sigma}{1-\sigma}} U \qquad (7.1)$$

Let us differentiate $x_i^t(p^t, U \mid I^t)$ in order to determine the slope of the compensated demand function. With a bit of manipulation and using some of the definitions above we obtain the following expression.

$$\frac{\partial x_i^t(p^t, U \mid I^t)}{\partial p_i^t} = \sigma \frac{x_i^t}{p_i^t}(s_i^t - 1) \qquad (7.2)$$

Given that x_i^t, p_i^t and s_i^t are positive with $s_i^t \leq 1$ we see that for the derivative to be non-positive we must have $\sigma \geq 0$. Also from (7.2) we can also easily see the form of the price elasticity of demand for the CES functional form.

Table 1: The Effects of New and Disappearing Goods on the Cost-of-Living Index.

	CES Cost Function Method Adjustment for New and Disappearing Goods over 65 Weeks (%)				Approximate Reservation Price Method Adjustment for New and Disappearing Goods over 65 Weeks (%)			
Aggregation Method	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)
Biscuits	-2.04	-4.02	-0.51	-5.23	3.68	-1.28	1.05	-1.16
Bread	-0.61	-1.44	-3.56	-3.12	-0.38	-0.51	-1.10	-1.00
Butter	-0.87	-1.78	1.77	-0.84	-0.29	-0.68	0.45	-0.27
Cereal	-5.74	-5.56	-3.63	-5.32	-1.88	-1.83	-1.02	-1.32
Coffee	-1.02	-0.70	-1.13	-1.06	-0.43	-0.26	-0.52	-0.37
Detergent	-1.80	-1.30	-0.92	-5.72	-0.66	-0.48	-0.29	-1.09
Frozen Peas	-1.68	-1.43	-3.04	-5.20	-0.54	-0.46	-0.61	-0.78
Honey	-0.06	-0.35	-0.52	-1.50	-0.08	-0.13	-0.17	0.08
Jams	-1.42	-6.19	4.46	#	-0.43	-1.28	-0.21	-2.35
Juices	-3.17	-1.95	-2.82	-3.56	-0.96	-0.62	-0.78	-0.99
Margarine	-1.20	-1.23	-1.65	-0.75	-0.29	-0.42	-0.56	-0.24
Oil	-2.09	-0.73	-2.30	-1.15	-0.34	-0.26	-0.46	-0.31
Pasta	-3.24	-3.12	-3.74	#	-0.76	-0.58	-0.55	-1.93
Pet Food	-0.98	-2.70	-1.76	-5.10	-0.36	-0.91	-0.59	-2.18
Soft Drinks	-3.82	-1.29	0.40	-0.54	-1.29	-0.44	0.01	-0.15
Spreads	-8.03	-1.88	-0.82	-1.40	-2.74	-0.73	-0.42	-1.79
Sugar	0.59	-0.19	-0.50	#	0.14	-0.05	0.10	-0.14
Tin Tomatoes	-5.04	-2.28	-3.77	-4.91	-1.62	-0.97	-1.21	-1.11
Toilet Paper	-3.91	-2.74	-1.57	-2.23	-1.27	-0.75	-0.52	-0.73
Average	-2.43 [-2.63]	-2.15 [-1.96]	-1.35 [-1.61]	[-2.98]	-0.55	-0.67	-0.39	-0.94
Average (Exp. Wgt.)	-2.67 [-2.72]	-2.41 [-2.37]	-1.60 [-1.65]	[-3.15]	-0.42	-0.77	-0.37	-0.96

Note: # indicates that the average elasticity was less than one so the CES Approach is invalid. The average excluding these goods is in square brackets (i.e. [.]).

Table 2: Price Change, Index Formula and Aggregation.

	Fisher Price Index Change over 65 Weeks (%)				Paasche–Laspeyres Spread Difference over 65 Weeks (%)			
Aggregation Method	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)
Biscuits	-3.47	-4.94	-2.12	-3.67	42.60	13.68	5.37	-0.19
Bread	4.34	4.05	3.99	3.76	44.06	19.73	3.84	2.25
Butter	2.02	2.64	0.87	1.07	22.16	8.31	3.82	1.83
Cereal	0.46	0.42	0.09	-0.13	46.35	12.97	4.03	1.46
Coffee	10.59	11.13	10.16	10.08	90.88	28.04	6.02	2.59
Detergent	3.41	3.88	2.06	2.11	42.62	15.31	2.74	1.07
Frozen Peas	0.04	-0.27	0.52	0.42	35.81	15.24	2.65	1.07
Honey	4.93	4.82	4.20	4.12	10.98	4.66	1.53	0.53
Jams	-0.27	-0.26	-0.01	-0.42	31.74	11.81	2.89	1.04
Juices	-0.11	-0.50	0.68	0.50	51.09	21.24	5.22	2.72
Margarine	0.54	0.47	3.86	3.38	229.71	53.21	14.61	5.86
Oil	-12.32	-14.14	-8.73	-9.22	42.58	35.75	6.17	4.44
Pasta	-1.10	-0.45	-0.05	-0.25	53.09	20.20	3.40	1.06
Pet Food	-0.09	0.04	0.47	0.24	27.65	11.34	3.91	1.16
Soft Drinks	1.88	2.57	3.95	3.35	185.76	63.53	14.37	4.62
Spreads	6.19	6.67	4.33	4.22	17.78	7.56	2.12	0.90
Sugar	6.11	6.27	6.27	6.15	25.10	9.37	1.73	0.05
Tin Tomatoes	-1.25	-1.41	1.33	0.35	41.29	23.87	3.55	1.57
Toilet Paper	-3.05	-3.92	-0.14	-0.45	155.92	60.11	12.53	6.80
Average	0.99	0.90	1.67	1.35	63.01	22.94	5.29	2.15
Average (Exp. Wgt.)	0.69	0.55	1.60	1.17	79.89	28.42	6.81	2.53

Table 2 (contd): Price Change, Index Formula and Aggregation.

	Tornqvist Price Index Change over 65 Weeks (%)				CES Quadratic Price Index Change over 65 Weeks (%)			
Aggregation Method	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)	Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)
Biscuits	-3.71	-5.54	-2.21	-4.35	-7.47	-7.90	-2.91	-5.10
Bread	4.61	4.27	4.00	3.81	4.70	4.52	3.98	3.81
Butter	1.86	2.64	0.76	1.06	1.75	2.72	0.62	1.06
Cereal	0.57	0.52	0.07	-0.16	0.51	0.54	0.03	-0.20
Coffee	10.82	11.14	10.22	10.10	10.76	11.11	10.20	10.10
Detergent	3.54	3.91	2.04	2.06	3.26	3.78	1.94	2.03
Frozen Peas	0.15	-0.17	0.51	0.43	0.19	-0.05	0.46	0.42
Honey	4.87	4.76	4.18	4.09	4.66	4.66	4.11	4.05
Jams	-0.25	-0.36	0.03	-0.55	-1.21	-1.08	-0.07	-0.37
Juices	-0.07	-0.44	0.65	0.47	-0.26	-0.49	0.49	0.37
Margarine	1.10	0.46	3.72	3.23	1.73	0.04	3.52	3.02
Oil	-11.88	-13.47	-8.61	-9.11	-12.27	-12.30	-8.67	-9.07
Pasta	-0.95	-0.51	-0.07	-0.27	-1.13	-0.59	-0.11	-0.26
Pet Food	-0.02	0.04	0.48	0.20	-0.25	-0.05	0.42	0.14
Soft Drinks	2.12	2.52	3.85	3.31	3.47	2.57	3.65	3.25
Spreads	6.25	6.68	4.32	4.21	6.17	6.64	4.28	4.13
Sugar	6.42	6.28	6.22	6.11	6.91	6.16	5.99	6.18
Tin Tomatoes	-1.17	-1.18	1.31	0.31	-1.52	-0.06	1.22	0.21
Toilet Paper	-3.15	-3.96	-0.12	-0.54	-4.00	-4.00	-0.34	-0.92
Average	1.11	0.93	1.65	1.28	0.84	0.85	1.52	1.19
Average (Exp. Wgt.)	0.80	0.53	1.57	1.08	0.50	0.30	1.39	0.91

Table 3: Estimating the Elasticity of Substitution.

	Current v Base Method Average and Standard Deviation of Estimated Elasticity								Average Sato-Vartia Method Average Absolute Deviations from Current v Base Method			
Aggregation Method	Month (Prod. Code, Outlet)		Month (Prod. Code)		Quarter (Prod. Code, Outlet)		Quarter (Prod. Code)		Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)
Statistic	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.	Avg.	Std. Dev.				
Biscuits	3.46*	0.99	2.96+	1.63	2.63*	1.02	1.63+	2.77	0.05	0.06	0.16	0.18
Bread	3.39	0.69	3.58+	1.05	2.30	0.42	2.45	0.55	0.02	0.05	0.05	0.04
Butter	4.01	0.45	3.87	0.94	3.43	0.76	3.70	1.05	0.07	0.05	0.05	0.10
Cereal	3.25	0.23	2.70	0.53	2.50	0.20	2.10	0.43	0.03	0.03	0.04	0.08
Coffee	5.66	0.46	4.66	0.65	3.73	0.41	2.63	0.46	0.06	0.02	0.03	0.02
Detergent	3.88	0.34	3.41	0.45	2.18	0.13	1.35*	0.49	0.04	0.03	0.06	0.08
Frozen Peas	3.44	0.30	3.36	0.58	2.28	0.46	1.68*	0.85	0.02	0.02	0.01	0.04
Honey	4.04	0.79	4.31	2.10	3.03	0.85	2.13+	2.20	0.08	0.07	0.03	0.11
Jams	3.17	0.58	2.72+	1.17	1.65	0.47	0.70*	0.91	0.06	0.04	0.07	0.19
Juices	3.14	0.32	3.38	0.56	2.53	0.30	2.50	0.36	0.05	0.03	0.08	0.10
Margarine	4.63	0.42	3.99	0.61	3.63	0.39	3.60	0.75	0.03	0.02	0.01	0.03
Oil	4.59	0.71	5.47	0.83	3.13	0.38	2.88	0.51	0.20	0.52	0.04	0.03
Pasta	2.16	0.32	2.51	0.61	1.43	0.17	1.00*	0.84	0.02	0.03	0.03	0.06
Pet Food	3.64	0.35	3.29	0.42	2.95	0.17	1.75*	0.97	0.04	0.04	0.01	0.09
Soft Drinks	4.17	0.65	4.06	0.65	3.28	0.46	2.35	0.70	0.11	0.04	0.06	0.06
Spreads	3.71	0.70	3.61	0.86	2.75	0.60	2.33*	1.54	0.03	0.14	0.05	0.15
Sugar	4.16	1.58	3.31+	1.92	2.00*	1.13	0.73+	1.02	0.26	0.04	0.38	0.03
Tin Tomatoes	3.95	0.41	3.97*	1.02	2.70	0.14	1.98+	1.73	0.03	0.06	0.18	0.01
Toilet Paper	5.21	0.91	4.91	1.36	4.05	0.61	3.25	0.90	0.09	0.06	0.05	0.11
Average	3.88	0.59	3.69	0.94	2.73	0.44	2.14	1.00	0.07	0.07	0.09	0.08
Average (Exp. Wgt.)	3.81	0.57	3.61	0.84	2.63	0.71	2.23	0.92	0.06	0.05	0.07	0.08

Note: * (+) indicates that the elasticity of substitution fell below one (zero) in at least one period.

Table 4: Expenditure Shares.

	Average Proportion of Current and Base Expenditure Shares (%)								Changes in Current Relative to Base Expenditure Shares Change over 65 Weeks (%)			
Aggregation Method	Month (Prod. Code, Outlet)		Month (Prod. Code)		Quarter (Prod. Code, Outlet)		Quarter (Prod. Code)		Month (Prod. Code, Outlet)	Month (Prod. Code)	Quarter (Prod. Code, Outlet)	Quarter (Prod. Code)
Time Period	Base	Current	Base	Current	Base	Current	Base	Current				
Biscuits	98.34	97.80	99.94	99.24	96.03	95.42	99.71	97.62	-7.36	-9.41	-2.43	-8.14
Bread	99.50	99.23	99.89	99.64	99.22	97.88	99.66	98.34	-3.70	-3.57	-5.31	-5.20
Butter	99.41	99.23	99.99	99.59	98.53	98.95	99.88	99.57	-2.54	-5.52	1.73	-1.27
Cereal	98.85	97.93	99.99	99.22	98.33	97.05	99.92	98.51	-12.33	-10.43	-5.11	-5.55
Coffee	99.60	99.25	99.99	99.83	99.34	98.53	99.98	99.49	-4.86	-2.31	-3.24	-1.93
Detergent	99.25	98.85	99.98	99.72	98.18	97.87	99.96	99.28	-5.48	-3.66	-1.26	-2.68
Frozen Peas	99.25	98.96	99.98	99.77	98.43	97.86	99.90	99.30	-4.03	-2.89	-2.33	-2.41
Honey	99.47	99.39	99.98	99.88	98.92	98.85	99.89	99.43	-1.08	-1.34	-0.28	-1.84
Jams	98.67	98.44	99.97	99.46	97.54	97.15	99.92	98.67	-3.25	-6.84	-1.59	-4.90
Juices	99.19	98.76	99.98	99.71	98.27	97.37	99.83	98.68	-5.85	-3.68	-3.64	-4.55
Margarine	99.30	99.01	99.99	99.76	99.08	98.12	99.82	99.29	-4.07	-3.18	-3.85	-2.11
Oil	98.20	97.68	99.95	99.70	98.53	97.41	99.82	99.31	-7.23	-3.40	-4.50	-2.03
Pasta	98.88	98.60	99.92	99.75	97.77	97.32	99.73	99.10	-3.93	-2.46	-1.85	-2.47
Pet Food	98.86	98.63	99.91	99.48	97.73	96.83	99.77	98.26	-3.26	-5.97	-3.65	-5.91
Soft Drinks	97.97	97.25	99.98	99.74	97.98	98.07	99.91	99.76	-9.83	-3.34	0.34	-0.60
Spreads	99.09	97.83	99.99	99.63	98.79	98.17	99.90	99.17	-16.54	-5.05	-2.51	-2.93
Sugar	99.66	99.71	100.00	99.98	99.53	99.53	100.00	99.88	0.71	-0.26	-0.03	-0.46
Tin Tomatoes	98.67	97.69	99.98	99.46	96.94	95.36	99.84	97.88	-13.27	-7.12	-6.38	-7.63
Toilet Paper	98.63	97.42	99.99	99.47	97.75	96.51	99.94	98.49	-16.09	-7.11	-4.99	-5.72
Average	98.99	98.51	99.97	99.63	98.26	97.59	99.86	98.95	-6.53	-4.61	-2.68	-3.60
Average (Exp. Wgt.)	98.82	98.28	99.96	99.58	98.07	97.35	99.84	98.79	-7.29	-5.26	-2.92	-4.12

Table 5: Number of Products.

Numbers of Products in First and Last Time Periods and the Percentage Change												
Aggregation Method	Month (Prod. Code, Outlet)			Month (Prod. Code)			Quarter (Prod. Code, Outlet)			Quarter (Prod. Code)		
Time Period	First	Last	Chg. (%)	First	Last	Chg. (%)	First	Last	Chg. (%)	First	Last	Chg. (%)
Biscuits	38,408	39,220	2.11	918	883	-3.81	41,777	42,537	1.82	992	1,009	1.71
Bread	11,587	11,048	-4.65	308	335	8.77	12,085	12,175	0.74	325	355	9.23
Butter	3,174	3,422	7.81	61	65	6.56	3,321	3,495	5.24	64	66	3.13
Cereal	17,769	19,533	9.93	389	476	22.37	18,577	20,613	10.96	399	491	23.06
Coffee	7,958	8,937	12.30	152	168	10.53	8,412	9,408	11.84	162	176	8.64
Detergent	7,310	6,956	-4.84	147	142	-3.40	7,514	7,430	-1.12	151	154	1.99
Frozen Peas	8,163	8,300	1.68	189	186	-1.59	8,651	8,636	-0.17	201	196	-2.49
Honey	3,841	3,887	1.20	97	90	-7.22	4,018	4,013	-0.12	102	93	-8.82
Jams	10,857	10,329	-4.86	312	282	-9.62	11,626	11,125	-4.31	328	303	-7.62
Juices	41,800	42,426	1.50	862	894	3.71	43,577	44,769	2.74	899	963	7.12
Margarine	4,514	4,872	7.93	80	89	11.25	4,625	5,128	10.88	81	90	11.11
Oil	8,220	9,116	10.90	232	251	8.19	9,049	9,900	9.40	250	273	9.20
Pasta	16,256	18,207	12.00	465	544	16.99	17,453	19,552	12.03	523	578	10.52
Pet Food	39,697	41,605	4.81	786	876	11.45	41,229	44,628	8.24	806	935	16.00
Soft Drinks	37,277	32,043	-14.04	774	681	-12.02	40,067	34,758	-13.25	812	732	-9.85
Spreads	4,191	4,615	10.12	84	89	5.95	4,668	4,924	5.48	89	93	4.49
Sugar	4,190	4,200	0.24	96	103	7.29	4,355	4,439	1.93	101	106	4.95
Tin Tomatoes	3,646	3,867	6.06	90	91	1.11	3,931	4,210	7.10	98	97	-1.02
Toilet Paper	6,564	6,835	4.13	129	134	3.88	6,835	7,138	4.43	135	138	2.22
Average	---	---	3.39	---	---	4.23	---	---	3.89	---	---	4.40
Average (Exp. Wgt.)	---	---	0.99	---	---	3.99	---	---	2.20	---	---	5.52

Figure 2: Elasticity of Substitution (Cereal) – Month (Prod. Code, Outlet).

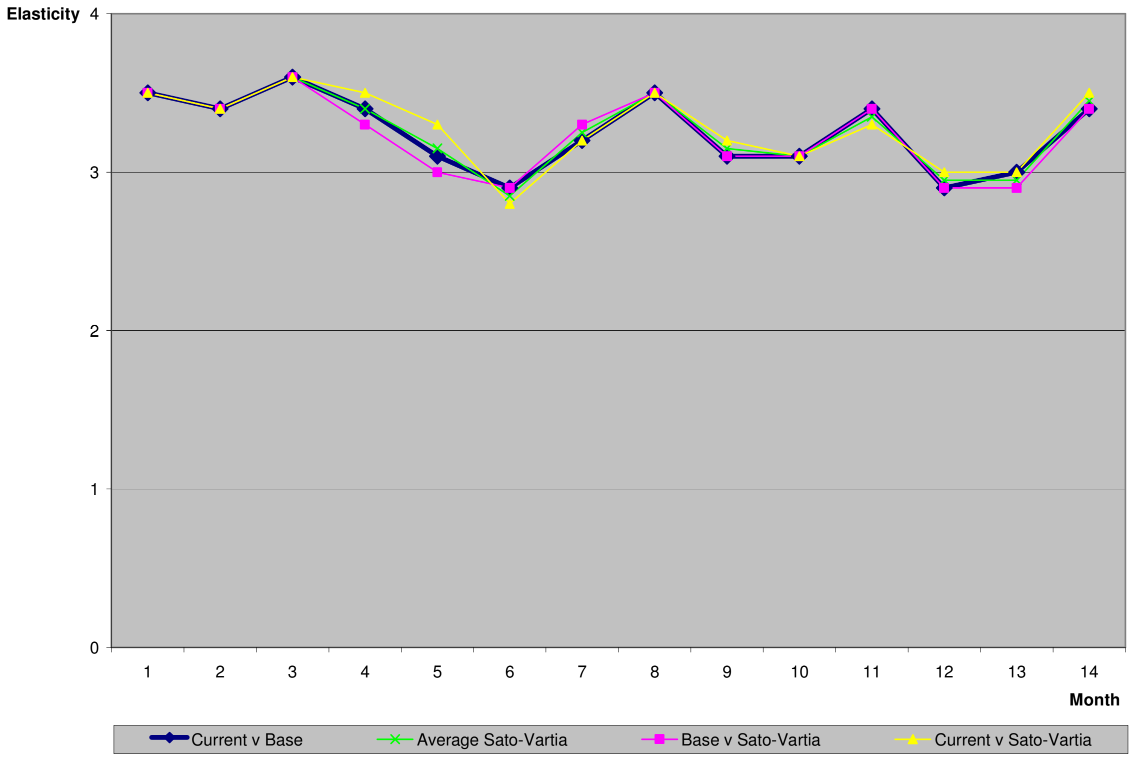


Figure 3: Price and Cost-of-Living Indexes (Cereal) – Month (Prod. Code, Outlet).

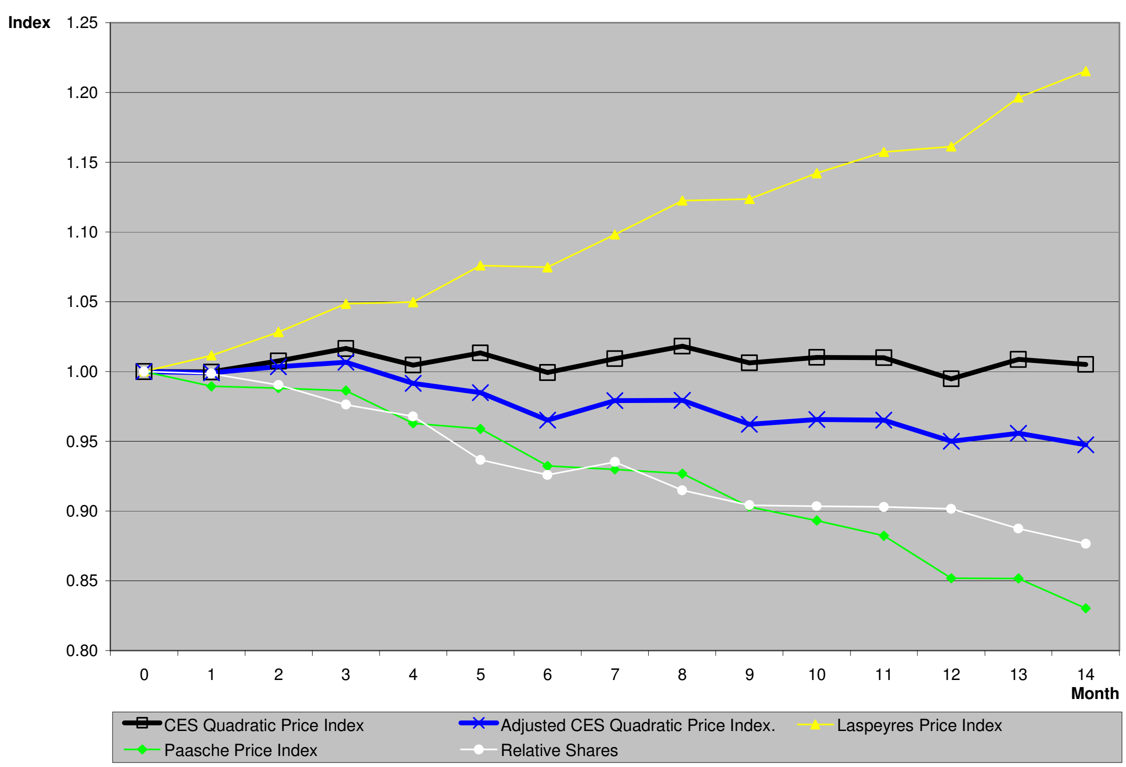


Figure 4: Elasticity of Substitution (Cereal) – Month (Prod. Code).

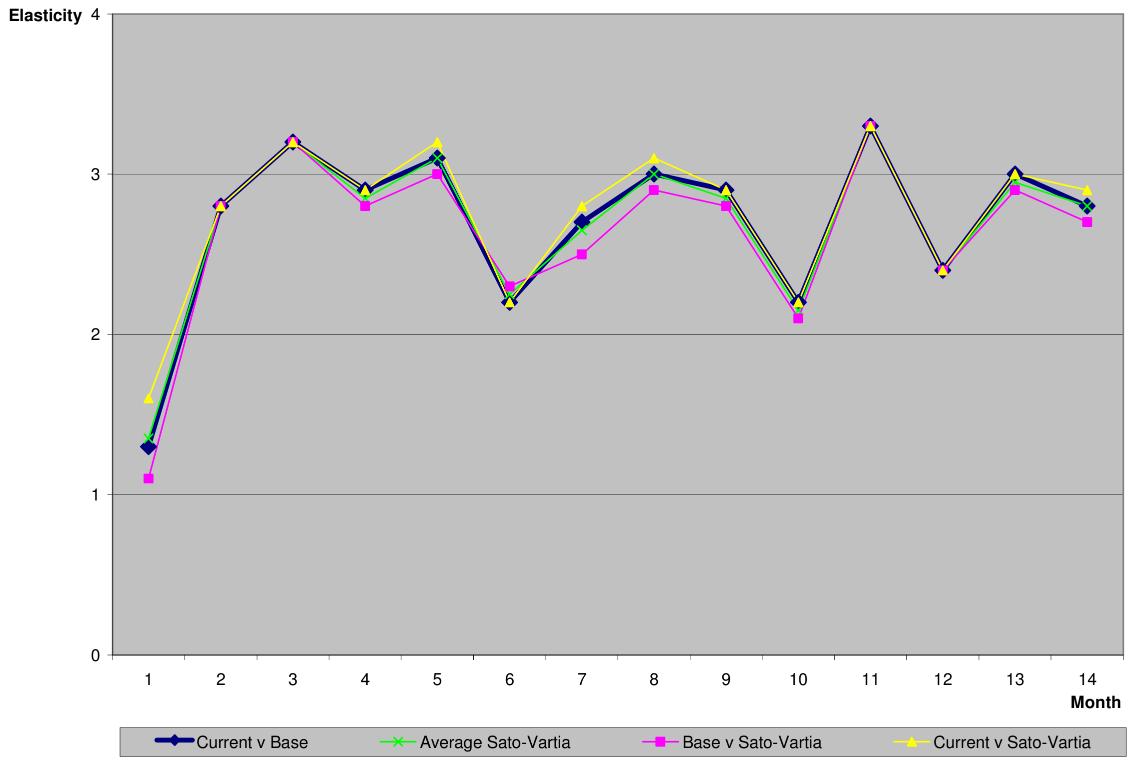


Figure 5: Price and Cost-of-Living Indexes (Cereal) – Month (Prod. Code).

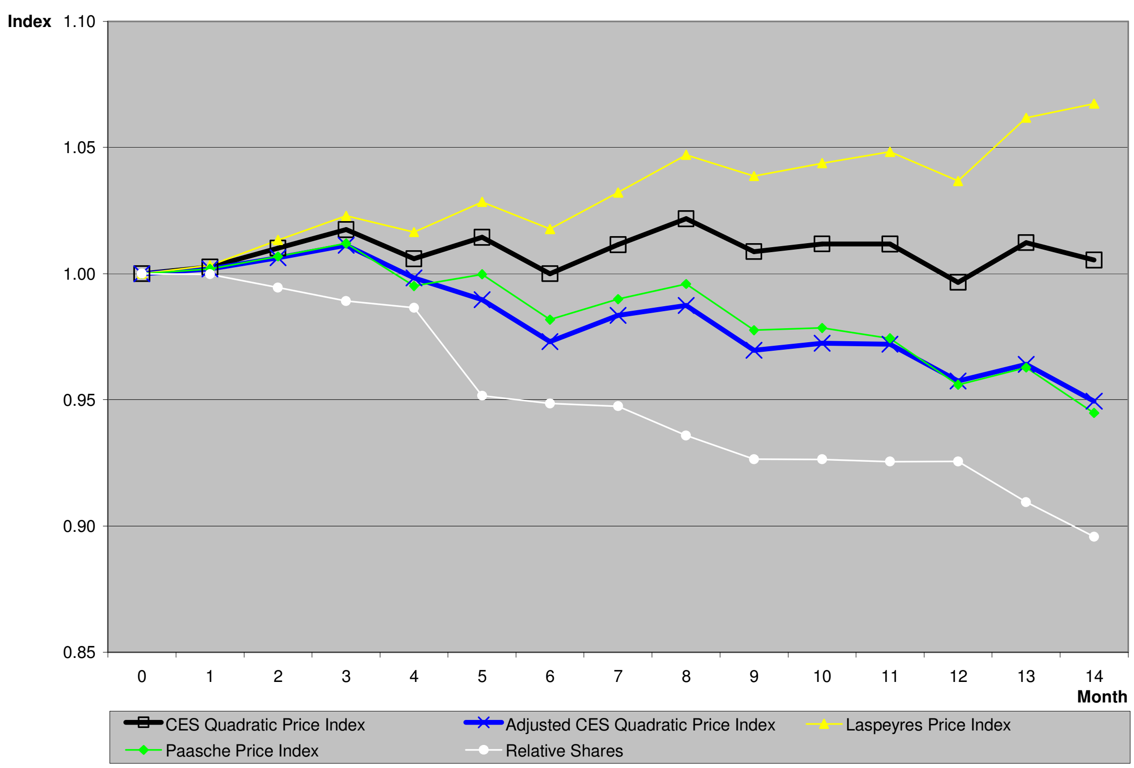


Figure 6: Elasticity of Substitution (Cereal) – Quarter (Prod. Code, Outlet).

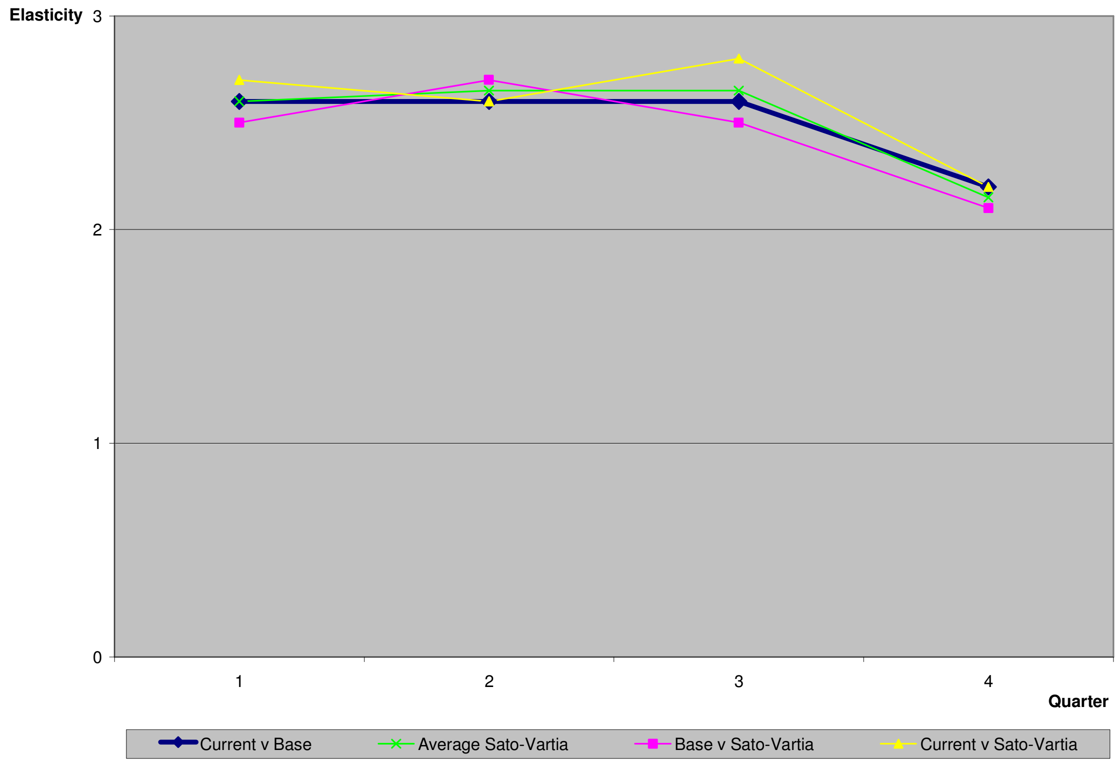


Figure 7: Price and Cost-of-Living Indexes (Cereal) – Quarter (Prod. Code, Outlet).

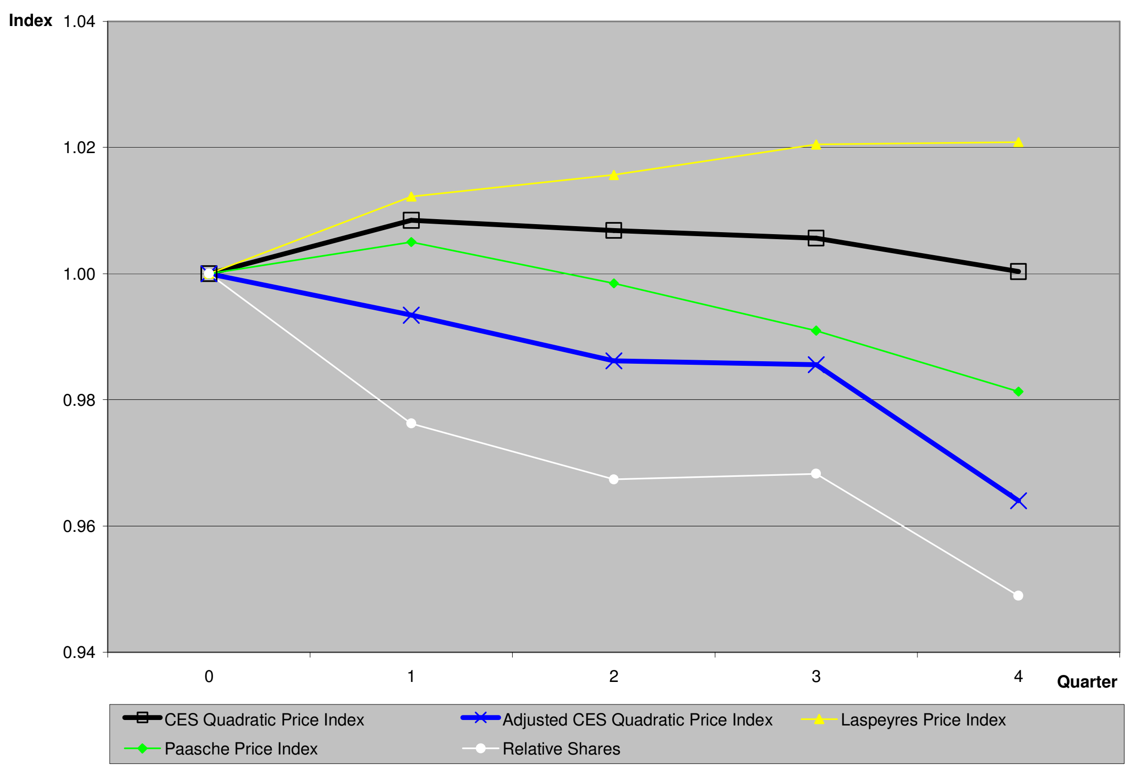


Figure 8: Elasticity of Substitution (Cereal) – Quarter (Prod. Code).

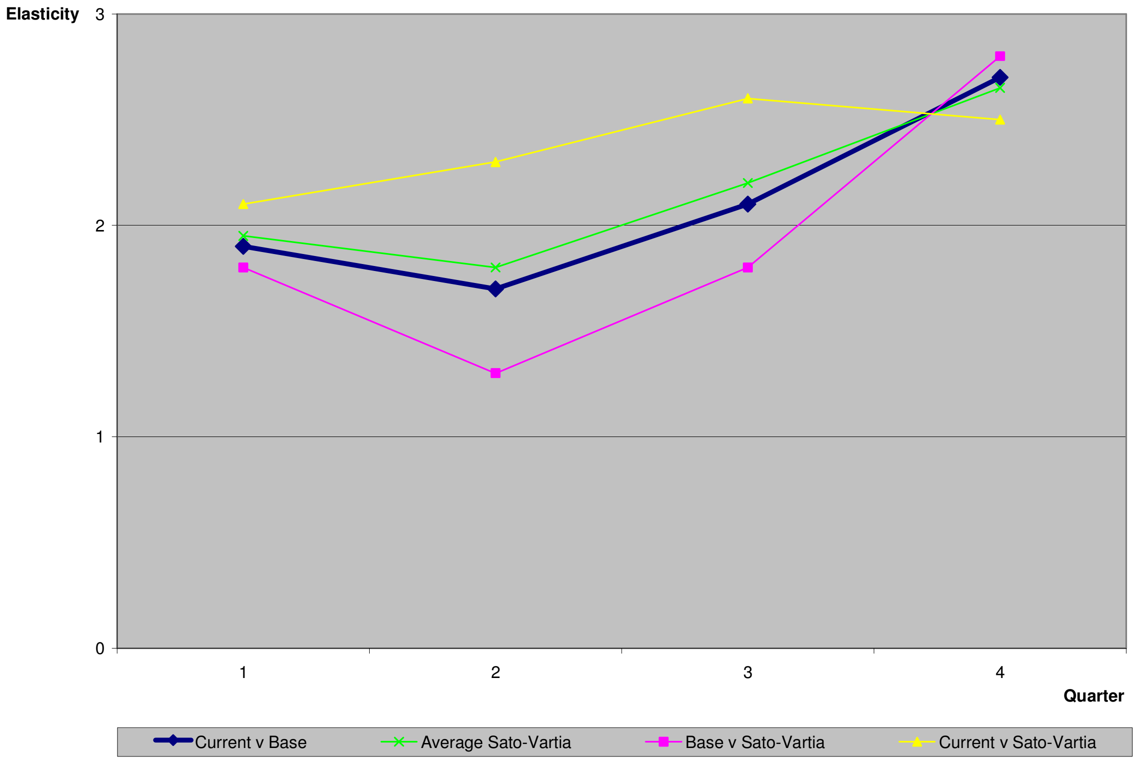


Figure 9: Price and Cost-of-Living Indexes (Cereal) – Quarter (Prod. Code).