Scanner Data, Time Aggregation and the Construction of Price Indexes

by

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Abstract

The impact of weekly, monthly and quarterly time aggregation on estimates of price change is examined for nineteen different supermarket item categories over a fifteen month period using scanner data. We find that time aggregation choices (the choice of a weekly, monthly or quarterly unit value concept for prices) have a considerable impact on estimates of price change. When chained indexes are used, the difference in price change estimates can be huge, ranging from 0.28% to 29.73% for a superlative (Fisher) index and an incredible 14.88% to 46,463.71% for a non-superlative (Laspeyres) index. The results suggest that traditional index number theory breaks down when weekly data with severe price bouncing are used, even for superlative indexes. Monthly and (in some cases even) quarterly time aggregation were found to be insufficient to eliminate downward drift in superlative indexes. In order to eliminate chain drift, multilateral index number methods are adapted to provide drift free measures of price change.

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1. Introduction

Aggregation of price and quantity information is fundamental to the construction of any price index. Prior to any index number calculation, decisions must be made as to how individual transaction price and quantity data are to be aggregated to obtain price and quantity vectors that can be inserted into a bilateral price or quantity index number formula. Aggregation decisions are generally limited by the use of regular but infrequent surveys to collect data used in the compilation of the Consumer Price Index (CPI). However, the advent of high-frequency electronic-point-of-sale "scanner data" has made increasingly detailed and comprehensive data on consumer purchases available to price statisticians. The use of more detailed data means that aggregation issues become even more complex when attempting to estimate price change. There are a number of dimensions over which data can potentially be aggregated before an index is calculated; i.e., transactions can be aggregated over different package sizes, over different stores in a region or over different time periods. These aggregated prices and quantities are then inserted into a bilateral index number formula of the type studied by Fisher (1922). In this paper we are primarily concerned with how different methods of *time* aggregation affect estimates of price change.

Only a handful of authors have used scanner data to examine this issue, including Reinsdorf (1999), Hawkes (1997), Bradley et al. (1997), de Haan and Opperdoes (1997), Dalen (1997) and Feenstra and Shapiro (2003). Reinsdorf (1999) found that the use of different aggregation methods over time resulted in estimates of price change which differed by as much as 7.9% while de Haan and Opperdoes (1997; 10) found that 'taking unit values [average prices] over one week every month instead of unit values over the entire month as the price concept leads to differences in the formula that exceed by far the differences due to alternative elementary aggregate index formula'. These results indicate that time aggregation decisions are likely to be important, particularly when high frequency data are used.

A limitation of existing studies is that they typically use data on a small number of product categories. For instance, Reinsdorf (1999), Hawkes (1997), and de Haan and Opperdoes (1997) all had information on only one product category (coffee), while Dalen (1997) had information on four product categories (fats, detergent, breakfast cereal and frozen fish). This makes it difficult to draw broad conclusions or make generalisations from these studies. A major benefit of the current study is that we have information on 19 major supermarket item categories and over 8000 individual products. This allows us to examine whether results found in other studies hold for a larger set of products and whether regularities, resulting from different aggregation methods and the use of different index number formulae, can be identified across different item categories.

In this paper we focus on how different methods of time aggregation (i.e., weekly, monthly or quarterly) impact on the measurement of price change when scanner data are used. We also examine the use of fixed base indexes versus chained indexes. Fixed base indexes have the advantage of being free of chain drift but they have a major disadvantage as well: over time, new products appear and old products disappear and it becomes increasingly difficult to match items that are available in the current period with items which were available in the base period. As a result, the relevance of a fixed base index diminishes over time. In sections 5 and 6, we propose two new techniques which combine the best features of fixed base and chained indexes; i.e., no chain drift and updating of the basket of goods in each period, in the scanner data context.

Understanding how best to use scanner data in the context of constructing consumer price indexes is particularly important at the present moment as statistical agencies worldwide are becoming increasingly interested in using scanner data in their official CPI figures. To our knowledge, scanner data are currently used directly in the CPI by only a handful of statistical agencies: the Central Bureau of Statistics in the Netherlands and Statistics Norway. New Zealand uses scanner data to help inform weighting decisions in the CPI. The establishment of robust methods for using these scanner data, which will allow maximum matching of products over time, while avoiding chain drift problems associated with the use of chained indexes, is an important priority for statistical agencies.

The basic problem we address in this paper is that of chain index drift. Chain index drift becomes increasingly problematic when high frequency (scanner) data are used to form the components of a monthly CPI. Usually, in a time series context, the use of chained superlative indexes is recommended to compute a monthly CPI using scanner data. This is because, in principle, more matches will be obtained using a chained index. In addition we would also expect price and quantity differences to be smaller when a chained index rather than a fixed base index is used. If this is in fact the case then all chained superlative indexes should approximate each other more closely than their fixed base counterparts. However, this explanation does not take into account the presence of price discounts or sales.

Many retailers, and in particular supermarkets, engage in price discounting or sales behaviour, during which volumes sold can spike up by 100 fold or more for short periods of time.[6] As a result it is not necessarily the case that prices and quantities in adjacent periods are more similar than those in periods which are not adjacent when subannual data are used. In particular, when an item goes off sale and prices return to their "regular" price, we expect that the use of a chained superlative index would simply (more or less exactly) reverse the previous downward movement in the index and take us back to the "regular" price level. However, in practice this may not happen. This is because consumers engage in "inventory shopping": when an item is on sale consumers will stock up on that item and then when the item comes off sale, consumers are likely to purchase less than the "average" quantity of that item for some period of time until their inventories of the item have been depleted. It is only over time that the quantities of the item sold will gradually recover to their pre-sale levels. If prices do not change in the post sale period (i.e., prices go back to their pre-sale, "regular" price level), we would expect all reasonable indexes to show no price change over these "regular" price periods. However, when sales occur, chained superlative indexes will tend to exhibit a *downward drift* when compared to their fixed base counterparts due to the lag in the quantities sold returning to their pre sale level. A solution to this problem is to simply use a fixed base index. However, there area a number of drawbacks with using a fixed base strategy:

- With thousands of new supermarket products introduced every year, over time, there would be a large fall in matches of products available in the current period as compared to the base period.[7]
- If there are strongly seasonal commodities, then limiting the sample to monthly comparisons with a fixed base month would not make use of all of the available item matches over a year.

[6] See Figure 1b in de Haan (2008).
[7] See Diewert (1996; 33) and Diewert and Fox(1999; 261) who cited William Hawkes that the number of Universal Product Codes in the U.S. grew from 950,000 in January 1990 to 1,650,000 in September 1995.

The above considerations suggest that we make use of fixed base comparisons but use each month in turn as the fixed base and then average the resulting comparisons. This would make maximum use of all possible matches across the time period under consideration (and each of the separate fixed base monthly indexes is free from chain drift). However, this method is precisely analogous to a multilateral method for making index number comparisons. The Gini (1931) Eltetö and Köves (1964) and Szulc (1964) (GEKS) multilateral method sets the overall price index equal to the geometric mean of all the "star" fixed base comparisons, treating each month as the fixed base. In this paper we show that the GEKS multilateral method works well with an Australian scanner data set, spanning 15 months of data. An issue that arises with using this multilateral methodology in the CPI context is that as each new month of data becomes available all of the previous parities would have to be recomputed! This is not acceptable for a CPI which has to remain unrevised. To overcome the problem of revisions we propose the use of a rolling year GEKS method. This method uses the last 13 months of data to compute price change going from month 12 to month 13. This price change estimate is then used as the escalator for the monthly CPI.

The paper is set out as follows. Section 2 provides a brief discussion of the time aggregation problem and the use of unit values as prices that can be used in a bilateral index number formula. Section 3 describes the various unit value concepts that are used in later sections along with a description of the bilateral Laspeyres, Paasche and Fisher (1922) price indexes that are calculated in section 4. Section 3 also discusses how chain drift can be defined in a formal manner. Section 4 provides a brief description of the data and provides estimates of price change for each of the 19 food groups over a 65 week period, using various unit value concepts and both fixed base and chained index numbers. The results indicate that monthly and weekly chained indexes have a considerable amount of chain drift. Sections 5 and 6 attempt to overcome the problem of drift in chained indexes by using multilateral index number methods which are free of chain drift and also allow for a maximal amount of product matching. Section 5 explains the GEKS multilateral index number method in more detail and section 6 draws on a weighted version of Summers' (1973) Country Product Dummy (CPD) multilateral method. These methods are adapted and applied to the time series context. Section 7 concludes.

2. Aggregation and the Construction of Unit Values

Aggregation in this context refers to the calculation of average prices and total quantities which are used as inputs into the compilation of a price index. Aggregation over quantities is relatively straightforward; once the unit to aggregate over has been chosen, the quantities relevant to that unit are simply added up.[8] Aggregation over prices proceeds indirectly, through the construction of a unit value. Typically, in index number theory, we want the product of the aggregate price and quantity to equal the value of transactions for the specified commodity. In this case the price that matches up with the total quantity is the *unit value price*, which is equal to the transacted value divided by the total quantity transacted. Even though the definition of a unit value price is fairly straightforward, in practice its implementation is not necessarily straightforward. When a statistical agency decides to calculate a unit value (transacted value divided by transacted quantity), it has to decide on the *scope* of the unit value; i.e., what items should appear in the unit value, should the aggregation be over stores in the same chain in a region and finally, what is the length of the period over which the unit value is calculated? A unit value is, in effect, an average price over transactions, over a certain time period, over a particular product group and over stores.

How should the scope of a unit value be determined? With respect to item groupings, it seems best to work with the finest classification of items that is available; i.e., use each Universal Product Code as a separate unit value category. With respect to the store dimension, we will aggregate over stores for one set of index number computations and not aggregate over stores for another set of computations and compare the results. With respect to the time dimension, at first sight, it might seem to be best practice if we chose a week as the unit of time rather than a month or a quarter, since if inflation in the country is very rapid, weekly indexes will be more relevant than monthly or quarterly indexes. However, as the time period becomes shorter, two problems emerge:

- Transactions become more sporadic and there can be a lack of matching of items between any two (short) periods.

[8] See Hawkes and Piotrowksi (2003) for a range of potential aggregation units.

- Sales lead to large fluctuations in quantities purchased and this leads to large fluctuations in overall measures of price change; fluctuations which are not entirely reversed when the item reverts to its regular price.[9] Thus sales with heavily discounted prices typically lead to a chain drift problem.

Thus it is not clear what the "optimal" aggregation period over time is.

From a theoretical perspective, the use of unit value indexes is somewhat contentious. The source of this controversy largely stems from the failure of unit values to satisfy two axiomatic properties which are used to evaluate index number formulae; see Balk (1998).[10] These are the "identity" and "dimensional invariance" axioms.

The *identity axiom* states that "if the price of every good is identical during the two periods, then the price index should equal unity, no matter what the quantity vectors are"; see the ILO (2004; 293). This test can be regarded as somewhat controversial as it does not take into consideration shifts in the quantities purchased between the two periods. *Dimensional invarianc*e refers to the idea that the price index should not change if the units of measurement for each item are changed. A broadly defined unit value index fails to be invariant to the units of measurement used. However, in our present context, this test will be satisfied, as we do not aggregate over different items.

Balk (1998; 8) showed that a unit value index is equal to a partial Cost-of-Living Index (COLI)[11] if "base and comparison period expenditures on the commodity group are optimal with respect to the prevailing prices…and only if the underlying preference ordering can be represented by the simple sum utility function". Balk's finding holds only when items in the commodity group are either perfect substitutes or the utility function defined over the subgroup is Leontief. Bradley (2005; 41) argued that these two cases (i.e., perfect substitutes or Leontief sub-utility) are "extreme and most often do not hold". He went on to say that the use of unit value indexes, where the goods are not pure complements or perfect substitutes, will lead to inconsistent

[9] See Feenstra and Shapiro (2003) for more discussion on this point.
[10] For a more detailed explanation of the axiomatic approach to index number theory, see Chapter 16 of the CPI Manual; ILO (2004).
[11] A 'partial' COLI refers to a COLI for a particular commodity sub-group.

estimates. However, from our point of view, this discussion of the axiomatic properties of a unit value index is not directly relevant, particularly at the first stage of aggregation. As Diewert (1995; 20) noted,[12] "at some level of disaggregation, bilateral index number theory breaks down and it becomes necessary to define the average price and total quantity…using what might be called a 'unilateral' index number formula". In other words, at the first stage of aggregation, when we are constructing vectors of prices and quantities for two periods in order to insert these vectors into a bilateral index number formula, we are *forced* to aggregate the individual transactions which occur within a period into some sort of period average prices and total quantities. This leads to unit value prices as being the natural prices at this first stage of aggregation. Based on this reasoning it does not seem appropriate to apply the axiomatic approach to index number theory to this first stage aggregation problem.

It may be argued that rather than using unit values, a handful of what are thought to be "representative" price quotes could be used. However, this course of action would involve a loss of much of the information on consumer purchases that scanner data has to offer. Furthermore, Diewert (1995; 23) argued that "it should be evident that a unit value for the commodity provides a more accurate summary of an average transaction price than an isolated price quotation". Balk (1998) showed that a unit value index may actually be more accurate than a single price quotation.[13]

3. Estimating Price Change using Scanner Data and the Chain Drift Problem

A number of different index number formulae were used to calculate overall price change. The commonly used base period weighted Laspeyres index and its current period weighted counterpart, the Paasche index, were calculated. The theoretically more attractive "superlative" indexes (Fisher, Törnqvist and Walsh indexes) were also calculated; see Diewert (1976). As

[12] Diewert followed Walsh (1901; 96) (1921; 88) on this point.
[13] Balk (1998;9) argued that "if the unit value index is appropriate for a certain commodity group then it is equal to each single price ratio, and all those price ratios are equal." "In practice, however, there may be small distortions". A unit value index is able to capture these price distortions whereas a single price quote cannot.

price change estimates were not noticeably affected by the use of these standard superlative indexes, the results presented in this paper are based on the Fisher index.[14]

The (fixed base) Laspeyres price index can be written as follows:

$$Laspeyres_t = \sum_i w_{i0}\left(\frac{p_{it}}{p_{i0}}\right), \tag{1}$$

where p_{i0} is the base period price of item i, p_{it} is the price of item i in period t, for t = 1,…, T, and w_{i0} is good i's share of total expenditure in period 0. In practice, the prices are unit values for commodity class i for each period t of some pre-specified length (e.g. a week, month or quarter). Note that equation (1) aggregates unit value indexes by using appropriately defined share weights.

A common counterpart to the Laspeyres price index is the Paasche price index, which can be written as follows:

$$Paasche_t = \left[\sum_i w_{it}\left(\frac{p_{i0}}{p_{it}}\right)\right]^{-1}, \tag{2}$$

where w_{it} is good i's share of total expenditure in period t, for t = 0,…,T.

The Fisher index formula is the geometric mean of the Laspeyres and Paasche indexes, i.e. $Fisher_t = [Paasche_t \times Laspeyres_t]^{1/2}$.

For each index number formula,

1. average prices and total quantities were aggregated in turn, over weekly, monthly and quarterly intervals; and
2. items were in turn treated as different items if they were not located in the same store (*no* item aggregation over stores) or treated as the same good no matter which store they were in (item aggregation over stores).

[14] Diewert (1978) noted that all superlative indexes approximate each other to the second order and thus it should not matter which superlative index is used. Hill (2006) noted that Diewert's result breaks down for quadratic mean of order r indexes as r becomes large in magnitude. However, for "standard" superlative indexes, Diewert's approximation result appears to hold.

The issue of whether or not to aggregate items over stores was considered in tandem with the time aggregation problem as it is of interest to know if such store aggregation mitigates the effects of the choice of time aggregation. Currently, most statistical agencies appear to aggregate items over stores to form a unit value. This type of aggregation implicitly assumes that stores within the aggregation unit are 'alike' or offer the same level of quality. Not aggregating items over stores to form unit values will implicitly compensate for unmeasured quality differences across stores. It is of practical interest to establish whether different method of store aggregation has an appreciable impact on estimates of price change.

Direct (or fixed base) and chained indexes were also estimated for all of these combinations. For direct indexes, the basket of goods over which the price index is constructed is held fixed over time,[15] while for chained indexes, the base period index value is incrementally updated. Two types of chained indexes were estimated in this study. First, an index we refer to as a "fixed basket" index was estimated using a basket of items which was matched with the direct index — no new items which appeared in the sample period were incorporated into this index over time. This type of index provides a 'pure' comparison with the direct index as it is not affected by new items which appeared in periods subsequent to the first period.[16] Second, a "flexible basket" index that incorporated new items as they became available over time was also estimated; i.e., each chain link index used the set of all items which were sold in the two adjacent periods. It is of interest to see how this second chained index behaves relative to the "fixed chain" as new items "may experience price changes that differ substantially from the price changes of existing items"; ILO (2004; 138).

One of the important features of chained indexes is that the basket of goods is able to be constantly updated as new and disappearing items are able to be incorporated into estimates of price change over time. However, chained indexes may suffer from what is known as chain

[15] For the direct comparison between the first and last period, the index was computed using only the products which were purchased in both periods.
[16] For the "fixed basket" chained index, we started with the set of items which were sold in both the first and last periods. When calculating the chain link between periods 1 to 2, we intersected this starting set of items with the set of items which were also sold in period 2; when calculating the chain link between periods 2 to 3, we intersected the starting set of items with the set of items which were also sold in periods 2 and 3 and so on.

drift.[17] Chain drift occurs when an index "does not return to unity when prices in the current period return to their levels in the base period"; ILO (2004; 445). An objective method to test for the existence of chain drift is the *mutiperiod identity test*,[18] which was proposed by Walsh (1901; 401) and Szulc (1983; 540). This test is defined as follows:

$$P(p_1,p_2,q_1,q_2)P(p_2,p_3,q_2,q_3)\ P(p_3,p_1,q_3,q_1) = 1, \tag{3}$$

where $P(p_1,p_2,q_1,q_2)$ and $P(p_2,p_3,q_2,q_3)$ are price indexes between periods 1 and 2, and then 2 and 3, respectively. Their product gives the chained price index between periods 1 and 3. Each index in equation (3) is referred to as a chain link. Note that there is an additional link in the chain in equation (3), $P(p_3,p_1,q_3,q_1)$, which is a price index between periods 3 and 4, where the period 4 price and quantity data are the same as the period 1 data. So $P(p_3,p_1,q_3,q_1)$ takes us from period 3 directly back to period 1. The price index formula P will not suffer from *chain drift or chain link bias* if the product of all of these factors equals 1. In the following section, we will compute various chain indexes over our entire sample period and compare each of them with the corresponding direct indexes from the first period to the last period. If the direct and chained indexes give us the same results (and the index number formula satisfies the time reversal test), then (3) will be satisfied. However, if the direct and chained indexes are not equal, then chain drift is present.

Chain drift is thought to result from what is known as price oscillation or bouncing which are often accompanied by quantity shifts; see Hill (1993; 388). Price bouncing is commonly observed in supermarket scanner data as supermarkets tend to have sales frequently for short periods and with prices often (though not always) returning to their pre-sale levels when a sale ends. Scanner data not only capture price bouncing due to sales but also capture any associated quantity shifts due to sales. Triplett (2003) argued that quantity shifts (due to sales) may be largely due to two types of shoppers: shoppers who only buy when items are on sale and shoppers who stock up when an item is on sale; see also Feenstra and Shapiro (2003). Empirical

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[17] This term dates back to Frisch (1936; 8): "The divergency which exists between a chain index and the corresponding direct index (when the latter does not satisfy the circular test) will often take the form of a systematic drifting."
[18] Diewert (1993; 40-53) gave the test this name.

work by de Haan (2008) using scanner data has shown that quantity shifts in response to sales are substantial. Therefore, it is of interest to see if our estimates of price change suffer from chain drift.

Direct and chained indexes were estimated over a 15 month period as follows:

1. quarterly estimates of direct price change compared prices in quarter 1 with quarter 5; chained estimates compared prices in all quarters, from quarter 1 to quarter 5;
2. monthly estimates of direct price change compared prices in month 1 with month 15; chained estimates compared prices in all months, from month 1 to month 15; and
3. weekly estimates of direct price change compared prices in week 1 with week 65; while chained estimates compared prices in all weeks, from week 1 to 65.

4. Direct and Chained Weekly, Monthly and Quarterly Results for Laspeyres, Paasche and Fisher Indexes

We use a scanner data set collected by A.C. Nielsen, which contains information on four supermarket chains located in one of the major capital cites in Australia. In total, over 100 stores are included in this data set with these stores accounting for approximately 80% of grocery sales in this city; see Jain and Abello (2001). The data set contains 65 weeks of data, collected between February 1997 and April 1998. Information on 19 different supermarket item categories, such as bread, biscuits and soft drinks are included. A large number of observations on transactions exist for all item categories, with a minimum of 225,789 observations for the item category “butter” and a maximum of 2,639,642 observations for the item category “juices”. An observation here refers to the average weekly price (weekly unit value) and total weekly quantity sold of each item transacted in each store in each week. For example, from Table 1, there were 2,452,797 sales observations on biscuits over the 65 week period.

For each item category the data set contains price and quantity information on all of the different items, brands and package sizes which are sold in that particular item category in all of the stores in each week; for example, Table 1 shows there were 1,327 different types of biscuits traded across all stores over the period. Additional information includes the item brand name, a unique

13 digit identifier (known as the European Article Number/Australian Product Number (EANAPN)) and, where relevant, the physical weight of the item.

Price change estimates are presented for Fisher, Paasche and Laspeyres indexes, and for direct and chained indexes using the methods described in section 3 for each of the 19 major supermarket item categories. In general, the results point to a high degree of variation in index number estimates across the different methods of time aggregation and different index number formulae; see Tables 2 to 7. The results are presented in index terms with a base of 100, so that, e.g., 100.21−100 = 0.21% price change over the period. In general, the results indicate that more time aggregation leads to increasingly stable estimates of price change, for all types of indexes. However, the degree of the instability varies considerably across the different indexes.

The impact of time aggregation is extremely pronounced when chained indexes are used. This is particularly true for the Laspeyres index, where a number of price change estimates appear to explode as the frequency of chaining increases. For example, table 5 shows that Laspeyres price change estimates for the item category toilet paper based on quarterly, monthly and weekly time aggregation (with no item aggregation over stores) range from a somewhat reasonable (106.71−100=) 6.71% (quarterly, fixed basket) to a massive (11,955−100=) 11,855% (weekly, fixed basket) over the 15 month period.[19] Overall, for the Laspeyres chained (fixed and flexible basket) indexes, the *difference* in price change estimates for the 19 item categories across different methods of time aggregation ranges from 14.88% to an incredible 46,463.71% .With item aggregation over stores and using flexible-basket chained Laspeyres indexes (Table 2), over the 19 item categories the average absolute difference between weekly and quarterly price change estimates is approximately 298%. When we look at indexes where items have been disaggregated over stores (Table 5) this becomes 3,176%!

The Fisher index appears to be relatively less affected by time aggregation than the Laspeyres and Paasche index. Despite this, even the Fisher index shows a degree of variation which seems to be a cause for concern. For example, from Table 7, the Fisher flexible-basket chained estimates of price change for the item category toilet paper (no item aggregation over stores)

[19] For Paasche indexes, the converse occurs, with chained estimates of price change falling rapidly.

were calculated at (100.43−100=) 0.43%, (98.61−100=) −1.39% and (79.86−100=) −20.14% for quarterly, monthly and weekly time aggregation respectively. Overall, for chained (fixed and flexible basket) Fisher indexes, the *difference* in price change estimates for the 19 item categories across different methods of time aggregation ranges from 0.28% to a surprisingly large 29.73%. With item aggregation over stores and using the flexible-basket chained Fisher index, we find that on average the absolute difference between weekly and quarterly price change estimates is approximately 8%. When we look at indexes where items have been disaggregated over stores (Table 7), the average absolute difference increases to approximately 14%.

The observed volatility and extreme nature of some of our index number estimates (which is particularly evident when low levels of aggregation are combined with chaining) are consistent with findings in the existing literature; see Feenstra and Shapiro (2003); Reinsdorf (1999) and Dalen (1997). It is known that non-superlative (Laspeyres) indexes are prone to drift when price bouncing is evident (see Frisch (1936), Forsyth and Fowler (1981) and Szulc (1983)). Importantly, our results indicate that even superlative indexes, when applied to weekly supermarket data, do not seem to be able to deal well with price bouncing behaviour; i.e., chained weekly superlative indexes, while not as unstable as the chained Paasche and Laspeyres results, also give us some implausible results.

Estimates of possible bias in CPI's due to the use of a fixed basket price index formula can also be obtained from Tables 2 to 7. The last row in each table contains the geometric mean of the Laspeyres, Paasche and Fisher indexes for the whole sample period across all of the 19 supermarket item categories. The geometric mean of the 19 item category estimates of price change for the *Laspeyres* direct quarterly, monthly and weekly index number estimates (with item aggregation over stores) were 102.15 (quarterly), 102.90 (monthly) and 103.75 (weekly); see table 2. The corresponding geometric mean of the 19 item category estimates of price change for the *Fisher* direct quarterly, monthly and weekly index number estimates were 101.77 (quarterly), 101.95 (monthly) and 102.00 (weekly); see Table 4. By subtracting the geometric mean of the Fisher index numbers from their Laspeyres counterparts we obtain an approximate estimate of the average *bias* which is introduced when the Laspeyres formula is used in place of the superlative Fisher formula.[20] Bias is estimated at 0.38, 0.95 and 1.75 index points for the quarterly, monthly and weekly indexes, respectively.

These estimates of bias are based on unit values which aggregate transactions of the same item over stores in the region. Theoretically, it would be more appropriate to treat items sold in different stores as separate commodities in the index number formula since the various stores may have differences in the quality of their service.[21] The geometric mean of the 19 item category estimates of price change for the *Laspeyres* direct quarterly, monthly and weekly index number estimates (with no item aggregation over stores) were 102.83 (quarterly), 104.12 (monthly) and 105.55 (weekly); see Table 5. The corresponding geometric mean of the 19 item category estimates of price change for the *Fisher* direct quarterly, monthly and weekly index number estimates were 101.98 (quarterly), 102.12 (monthly) and 102.35 (weekly); see Table 7. The approximate estimates of bias are 0.85, 2.00 and 3.20 index points for the quarterly, monthly and weekly indexes, respectively. These are very substantial bias estimates, which suggest that there are potentially large gains in index accuracy when moving from the use of a fixed base index to a superlative index.[22]

As we indicated above, the chained estimates of price change appear to be quite unreliable and so cannot be used to explore what difference it makes to use unit values that either do or do not aggregate over stores. However, we can look at the direct comparisons of the Fisher indexes in Tables 4 and 7 to cast some light on the differences that result from different methods of aggregating over stores. From Table 4, the geometric means of the Fisher formula direct quarterly, monthly and weekly estimates of the 19 estimates of group price change over the 5 quarters in the sample period were 101.77 (quarterly), 101.95 (monthly) and 102.00 (weekly).

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[20] Statistical agencies do not actually use the Laspeyres formula; they use what is now called the Lowe (1823) index. However, under certain conditions, it can be shown that the bias in the Lowe index as compared to a superlative index is likely to be of the same order of magnitude (or bigger) than the bias between the Laspeyres index and the superlative index; see the ILO (2004;272-274).

[21] However, the drawback to treating each item in each store as a separate item is that matching sales of items across time periods becomes more difficult. If the time period is a month or a quarter, this difficulty is not a substantial one.

[22] It is somewhat troublesome that the bias estimates are so much larger (for weekly and monthly data) when we use the most disaggregated unit values as our price data as opposed to when we use unit values that are aggregated over stores. This unanticipated divergence in results suggests that even superlative price indexes may just be inherently unreliable when the unit value concept is defined over short time periods and disaggregated over stores due to the irregularity of purchases and the lack of matching.

These estimates are based on unit values that were formed by aggregating sales of a particular item across stores. From Table 7, the geometric means of the Fisher formula direct quarterly, monthly and weekly estimates of the 19 estimates of group price change over the 5 quarters in the sample period were 101.98 (quarterly), 102.12 (monthly) and 102.35 (weekly). Estimates in Table 7 (since the unit values are not aggregated over stores) are uniformly *higher* than their counterparts in Table 7, the differences being 0.21 (quarterly), 0.17 (monthly) and 0.35 (weekly) index points. Our results show that making an inappropriate decision on store aggregation can result in an annual *bias* in the order of 0.1 to 0.3 percentage points a year. So this leads to the question of when to aggregate over stores.

In general, it is assumed that aggregation should occur across ‘alike’ or homogenous units (Balk, 1998; Dalen, 1992; Reinsdorf, 1994). Typically, in this literature, stores are considered to be homogenous if they offer the same level of service or quality. Therefore, statistical agencies will need to determine whether the stores (or any subset of the stores) which comprise their sample are considered to be homogenous as incorrect aggregation will lead to biased estimates of price change. As our data set does not include information on store characteristics it is difficult to determine which aggregation method is appropriate for this particular data set. However, our results do indicate that, in general, aggregating over stores to construct unit values will lead to lower estimates of price change.

However, an important caveat does exist to the above recommendations. We have seen that as the time period over which we construct unit values becomes smaller (i.e., from quarterly to monthly to weekly) our index number estimates become increasingly volatile and unreliable. This same pattern of increased volatility is also present when we move from constructing unit values for items over all stores to constructing unit values for an item over each store. In general our results indicate that, when using scanner data, indexes which are based on highly disaggregated unit values will lead to unstable estimates of price change. Therefore, our (tentative) recommendation to not aggregate over heterogeneous stores should only be implemented when doing so does not result in unwarranted price index volatility.

Tables 2 to 7 also indicate that index estimates of price change are generally higher for the fixed-basket chained indexes relative to their flexible-basket chained counterparts. Thus looking at Table 2 (where unit values are aggregates over stores), we see that the geometric means of the 19 quarterly, monthly and weekly measures of chained fixed basket end of period prices are 102.86, 112.52 and 269.10 respectively. The geometric mean of the 19 corresponding measures of chained flexible basket Laspeyres end of period prices are 102.41, 111.54 and 263.97, so that the flexible chained basket estimates are lower than their fixed basket counterparts by 0.45, 0.98 and 5.13 index points. There are similar differences between the fixed basket and flexible basket Paasche and Fisher indexes in Tables 3 and 4, with the fixed basket estimates being higher than their flexible basket counterparts. These differences are quite pronounced when Laspeyres and Paasche indexes are used. When the superlative Fisher index is used, this result is still apparent but considerably less pronounced.[23] Since the flexible basket methodology seems to be clearly "better" in the sense that the flexible basket comparisons make maximum use of the data pertaining to any two consecutive periods (whereas the fixed basket comparisons do not), our results suggest that it is important to introduce new items into the basket as soon as they show up in the marketplace. If our findings can be generalised to other item categories, then this implies that fixing a market basket, particularly for item categories where item turnover is high, could bias price change estimates upwards.

At first glance, we would expect the impact of time aggregation on direct index estimates of price change to be minimal. But if there are substantial trends in prices within the first and last quarters, then comparing price change from the first week to the last week in the 65 weeks in our data base is different from comparing price change from the first quarter to the last quarter. In any case, the differences between some of the estimates of price change due to time aggregation are considerable.

Our tentative conclusions are as follows:

- The use of weekly chained index numbers, even those based on superlative index number formulae, is not recommended due to the erratic nature of the resulting indexes.

[23] Our results may be due to severe discounting of discontinued items. The fixed basket method would not pick up this discounting.

- Fixed base or direct comparisons of a current period with a base period seem to give reasonably reliable results, at least using monthly or quarterly data. However, these fixed base comparisons suffer from the problems associated with new and disappearing goods; i.e., over time, it becomes increasingly difficult to match items. This lack of matching seems to result in an upward bias.
- Fixed base Laspeyres or Paasche indexes have large biases and should not be used in the scanner data context.
- It appears that forming unit values by aggregating the same product over stores in the same local market leads to superlative index numbers which are consistently lower than their counterpart indexes which do not aggregate over stores. Recommendations about whether or not to aggregate over stores will depend on whether quality differences exist across stores (and whether volatility increases with the disaggregation over stores). At this stage of our knowledge, we recommend that statistical agencies that have access to scanner data, form their unit values by *not* aggregating over stores if quality differences exist across the stores which comprise the sample. This type of aggregation (i.e., no item aggregation over stores) will implicitly compensate for unmeasured quality differences across stores. However, if stores offer the same (or similar) levels of quality (and this may be the case with stores which belong to the same supermarket chain), then we recommend that statistical agencies form their unit values by aggregating over similar stores.

Although we believe that the above recommendations are useful, they do not resolve the problem of how a statistical agency should use scanner data to aid in computing their CPI. A statistical agency could simply fix a base month or quarter and make a series of direct comparisons of the price and quantity data in the current month with the corresponding data in the base month using a superlative formula but due to the introduction of new items and the disappearance of old items, the amount of item matching would steadily decrease over time, resulting in increasingly unreliable indexes. The use of chained indexes would avoid this problem, but as we have seen, price and quantity bouncing makes chained indexes very unreliable. However, we believe that the problems associated with both direct and chained indexes outlined above can be solved by applying multilateral index number theory to our data. The use of various multilateral index methods are explored in sections 5 and 6.

5. The Use of a Multilateral Index Number Method to Eliminate Chain Drift

Multilateral index numbers are often used for price and output comparisons across economic entities, such as countries; e.g., see Kravis (1984), Caves, Christensen and Diewert (1982) and Diewert (1999a). These multilateral indexes satisfy a circularity requirement so that the same result is achieved if entities are compared with each other directly, or with each other through their relationships with other entities. Standard bilateral index-number formulae do not satisfy this circularity or "transitivity" requirement. The transitive GEKS multilateral index (Gini (1931), Eltetö and Köves (1964) and Szulc (1964)) is the geometric mean of the ratios of all bilateral Fisher indexes, where each entity is taken in turn as the base.[24] Consider the case where there are M entities that we wish to make transitive comparisons across. Let P_{jl} denote a (Fisher) price index between entities *j* and *l*, *l* = 1,…,M, and let P_{kl} denote a (Fisher) price index between *k* and *l*. Then the GEKS index between *j* and *k*, can be written as follows:

$$GEKS_{jk} = \prod_{l=1}^{M} \left[P_{jl}/P_{kl} \right]^{1/M} . \tag{4}$$

It can be easily shown that this index satisfies the transitivity property, so that $GEKS_{jk} = GEKS_{jl}/GEKS_{kl}$. If we treat each time period as an 'entity' we can make transitive comparisons across time periods using equation (4).[25] It can easily be verified that this index satisfies Fisher's (1922) circularity test and hence is free of chain drift.[26]

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[24] Sometimes the term 'GEKS', or just 'EKS', is used to refer to the method of making any bilateral index number formula transitive using the same geometric averaging technique. Here we employ the more common usage of the term so that it refers to the multilateral index based on the bilateral Fisher index formula.

[25] This approach is typically not used for constructing indexes across time due to the loss of characteristicity; see Drechsler (1973). Characteristicity refers to the "degree to which weights are specific to the comparison at hand"; Caves, Christensen and Diewert (1982). Drechsler (1973; 17) noted that "characteristicity and circularity are always…in conflict with each other." This conflict is usually resolved in the time series context by imposing chronological ordering as the unique ordering so that the issue of transitivity or circularity is not considered.

[26] Other researchers have noted that the use of transitive multilateral index number methods would eliminate the chain drift problem in a time series context; see Balk (1981) and Kokoski, Moulton and Zieschang (1999; 141). What is new in our proposed method is the suggestion that the last link in a rolling year multilateral index be used to update a month to month or quarter to quarter CPI.

The advantage of this approach over direct (fixed base) indexes is that we can use the flexible basket approach for each of the bilateral comparisons in the GEKS index. This is also the advantage of using chained indexes, allowing us to make comparisons using data on all items present in the two periods being compared.

In this paper we estimate two types of GEKS indexes – first, the 'standard' GEKS index and second, a Rolling Window (or Rolling Year) GEKS Index. 'Standard' GEKS indexes were estimated as follows. To begin, bilateral Fisher price indexes are calculated between all time periods i and j where i,j = 1…15. This leads to t×(t-1) bilateral Fisher comparisons denoted by P(i/j), which represent the price level in period i relative to period j. We then use each time period j as the base, and calculate the following series of numbers:

$$P(j) = [P(1/j), P(2/j),...,P(15/j)] , \qquad (5)$$

where j = 1,2,...,15.

These 15 price series are then combined into a single series by taking the geometric mean of the above parities. From this we obtain a preliminary series which we will refer to here as PS:

$$\begin{aligned} PS &= [PS(1), PS(2),....,PS(15)] \\ &= [\{P(1/1)P(1/2)...P(1/15)\}^{(1/15)}, [\{P(2/1)P(2/2)...P(2/15)\}^{(1/15)} \\ &\qquad ..., [\{P(15/1)P(15/2)...P(15/15)\}^{(1/15)}]. \end{aligned}$$

(6)

To obtain the final t month GEKS series all components of the vector in (6) are simply divided by the first component of the vector, PS(1). The final 15 months GEKS series is:

$$GEKS = PS/PS(1). \qquad (7)$$

GEKS indexes were calculated for the nineteen item categories. The following four aggregation methods were used:

1. monthly time aggregation, with item aggregation over stores;

2. monthly time aggregation, with no item aggregation over stores;
3. quarterly time aggregation, with item aggregation over stores; and
4. quarterly time aggregation, with no item aggregation over stores.

The above aggregation methods are consistent with those used to estimate the price indexes in Section 4.

As GEKS indexes provide us with a drift free measure of price change we can use these indexes to determine the extent to which the chained indexes (see tables 3-7) suffer from chain index drift. To do so we compare index number results from the standard GEKS indexes and their chained index counterparts.

GEKS chained indexes were calculated at both quarterly and monthly intervals (see tables 8 and 9). Quarterly and monthly GEKS and Fisher indexes were also plotted for two item categories: jam and oil, to illustrate the differences between the indexes over time (see figures 1- 8).When GEKS and Fisher indexes constructed with quarterly time aggregation were compared, the Fisher indexes tended to exhibit downward drift. The Fisher index was found to be lower than the GEKS index for 15 of the 19 item categories when there was no item aggregation over stores and 14 of the 19 item categories when there was no item aggregation over stores. In some cases the drift appeared to be quite small. However for a number of item categories (eg. biscuits, pasta, jams and juices) the extent of drift was not negligible. For the item categories that exhibited downward drift, the extent of drift ranged from -0.03% to -2.05% for item aggregation over stores and -0.11% to -0.97% with no item aggregation over stores.

For indexes where monthly time aggregation was used, the Fisher indexes again appeared to be consistently lower than the GEKS indexes. The Fisher index was found to be lower than the GEKS index for 16 of the 19 item categories when there was item aggregation over stores and 15 of the 19 item categories when there was no item aggregation over stores. With monthly time aggregation (as opposed to quarterly time aggregation), the extent of downward drift observed for many item categories over a relatively short period of time (i.e. 15 months) was quite substantial. The downward drift ranged from approximately -0.12% to -5.13% for item aggregation over stores and approximately -0.4% to -3.9% with no item aggregation over stores.

Our results show that the use of a monthly chained superlative index such as the Fisher may be problematic, particularly over longer time periods where drift may lead to increasingly (downwardly) biased estimates of price change.

Overall, the results indicate that for some item categories, quarterly aggregation over time appears to be able to sufficiently smooth out the price and corresponding quantity bouncing behaviour that is captured in scanner data and leads to chain drift. However, even with quarterly time aggregation, considerable drift is still found for a number of item categories. In practice, many statistical agencies produce monthly indexes. The results for monthly chained indexes indicate that the monthly chained Fisher indexes tend to exhibit considerable downward chain drift. Importantly, this downward drift can readily be controlled using the suggested GEKS methodology.

A potential drawback of using the GEKS method as described above is that when a new period of data becomes available all of the previous period parities must be recomputed. For a statistical agency, this continuous process of revision is likely to be unacceptable. To overcome this problem while still maintaining the attractive properties of GEKS indexes we propose the use of, what we have termed, a Rolling Window GEKS (RWGEKS) index. The RWGEKS approach uses a moving window to continuously update the price series as data for new periods become available without the need to revise parities for previous periods. The rolling window works as follows: suppose we initially have a window that covers data for the periods 1,…,t. When a new period of data becomes available our window moves forward one period in time, and will then be comprised of data for the periods 2,…, t+1. For each new time period that becomes available, the first time period is dropped from the rolling window and the new time period is added to our rolling window.

To calculate a RWGEKS index, a decision must be made about the number of periods included in the window, i.e. how many time periods should be included in the window? We suggest that a natural choice for the length of a window is 13 months as it allows strongly seasonal commodities to be compared. We now describe how the RWGEKS series would be calculated in practice. The following description is based on a 15 month time period, where the rolling window consists of a 13 months of data. As the window is based on a 13 month period we will refer to our index as a Rolling Year GEKS (RYGEKS) index.

The RYGEKS series starts off with a GEKS which uses only 13 months of data. For the 13 month GEKS series 13×12=156 bilateral Fisher comparisons are calculated. As with the 'standard' GEKS, each time period j is chosen as the base, and the following series of numbers is calculated:

$$p(j) = [P(1/j), P(2/j),...,P(13/j)] \; ; \; j = 1,2,...,13. \tag{8}$$

These 13 price series are now combined into a single series by taking the geometric average of the above parities to obtain the preliminary series ps say:

$$ps = [ps(1), ps(2),....,ps(13)] = [\{P(1/1)P(1/2)...P(1/13)\}\{P(2/1)P(2/2)...P(2/13)\}... \{P(13/1)P(13/2)...P(13/13)\}]^{(1/13)}. \tag{9}$$

For the first 13 entries in the rolling year GEKS series, all components of the above vector are divided by the first component, ps(1) so that the first 13 months RYGEKS series is given by:

$$RYGEKS = ps/ps(1). \tag{10}$$

To calculate the next step of the rolling year GEKS series month 1 is dropped from the first 13 months and data from month 14 is added. Again, we pick each time period j as the base, and calculate the following series of numbers:

$$p2(j) = [P(2/j), P(3/j),...,P(14/j)] \; ; \; j = 2,3,...,14. \tag{11}$$

These 13 series are then combined into a single series by taking the geometric average of the above parities to obtain the preliminary series ps2 (which covers months 2 through 14):

$$ps2 = [ps2(2), ps2(3),....,ps2(14)] = [\{P(2/2)P(2/3)...P(2/14)\}\{P(3/2)P(3/3)...P(3/14)\}....\{P(14/2)P(14/3)...P(14/14)\}]^{(1/13)}. \tag{12}$$

The rolling year GEKS parities for months 1 to 13 do not change; they are given by the series defined above by (10). Observation 13 in that series is equal to:

$$\text{RYGEKS}(13) = \text{ps}(13)/\text{ps}(1). \tag{13}$$

To obtain observation 14 for the rolling year GEKS, the ratio of the last two components in ps2 defined by (12), ps2(14)/ps2(13), is used as the chain link to update RYGEKS(13) defined by (13); i.e., RYGEKS(14) is defined as follows:

$$\text{RYGEKS}(14) = \text{RYGEKS}(13)\times[\text{ps2}(14)/\text{ps2}(13)] = [\text{ps}(13)/\text{ps}(1)][\text{ps2}(14)/\text{ps2}(13)]. \tag{14}$$

In general, additional links in the Rolling Year GEKS price series are defined as:

$$\text{RYGEKS}(t) = \text{RYGEKS}(t\text{-}1)\times[\text{ps}(t-12)(t)/\text{ps}(t-12)(t-1)]. \tag{15}$$

The RYGEKS method is the method we recommend for use by statistical agencies.[27] As most statistical agencies produce monthly price series we calculate a monthly RYGEKS series. RYGEKS indexes were calculated for all nineteen product categories and the following two aggregation methods:

1. monthly time aggregation, with item aggregation over stores;
2. monthly time aggregation, with no item aggregation over stores;

Again, the above aggregation methods are consistent with those used to estimate the price indexes in Section 4.

It is of interest to compare the GEKS and RYGEKS series as this will give us some indication of whether the RYGEKS index is sensitive to the length of window chosen. It will also indicate whether a 13 month window is long enough to provide us with a stable price series. We compare

[27] While a RWGEKS index, such as the RYGEKS, will not satisfy transitivity in practice and hence will be potentially subject to chain drift, comparisons within each window are transitive. Using this approach, chain drift is therefore unlikely to be a significant problem in any context likely to be faced by a statistical agency. Also, alternative approaches to linking the indexes could be investigated, such as using different overlapping periods for doing the linking, taking the geometric mean of overlapping comparisons in multiple windows, and so forth. The most obvious approach is pursued in this paper and works well in our empirical applications. An investigation into alternative approaches is left for future research.

the monthly GEKS price indexes with our RYGEKS indexes. The results show that there is very little difference between the standard GEKS and RYGEKS series, with plots of the GEKS and RYGEKS series sitting virtually on top of each other (see Table 9). The average absolute differences between the GEKS and RYGEKS price series at the end of the 15 month period ranged from 0.005% to 0.16% for item aggregation over stores and 0.01% to 0.13% for no item aggregation over stores. To illustrate how close the GEKS and RYGEKS indexes are over the whole time series, both GEKS and RYGEKS series were plotted for two item categories; toilet paper and butter (see figures 9 to 12). These results are very encouraging, particularly from the point of view of a statistical agency, as they indicate that the GEKS indexes provide us with a very stable method for estimating price change. Perhaps most importantly, the GEKS indexes (unlike some of their chained index counterparts) give us both reasonable and plausible estimates of price change. To obtain such stable results for item categories such as toilet paper and soft drinks where price bouncing is a common feature of the price series, and where price discounts are typically accompanied by large shifts in the quantities purchased, indicates that GEKS indexes can deal well with item categories which have quite volatile price and quantities series.

6. Comparison of ABS Quarterly CPI Estimates with Corresponding Quarterly GEKS Estimates

It is of interest to compare the GEKS indexes by product category with the corresponding official CPI figures in order to determine whether there might be any potential bias in the official figures. To do these comparisons, GEKS indexes were estimated for six item categories. Categories were chosen where official CPI figures were available for what were thought to be comparable item categories (see table 10 for the sub group headings in the Australian CPI which were matched to our scanner data item categories).

In Australia the CPI is estimated on a quarterly basis. To obtain a reasonable match with the official figures quarterly GEKS indexes were estimated. As our scanner data time series was quite short we were able to match only 4 quarters worth of data with the official CPI series (i.e. the first quarter ending in June 1997, the second quarter ending in September 1997, the third quarter ending in December 1997 and the 4th quarter ends in March 1998). With four quarters of data it was not possible to estimate any RYGEKS indexes. Therefore, GEKS indexes, as described in equations 5-7, were estimated between quarters 1 and 4. GEKS indexes were estimated for two types of aggregation: first, with item aggregation over stores and second, with no item aggregation over stores.

As mentioned in section 4, our scanner data set contains information from four supermarket chains located in one of the major capital cities in Australia. Official CPI figures for our item categories were not available at the capital city level. Therefore, the official CPI figures that we use to compare our GEKS indexes with will reflect price change for the relevant item category for the whole of Australia. Thus our comparisons are only indicative of possible bias in the official CPI since our geographic and outlet coverage is very different from the national coverage used by the ABS.

Our results show that our two GEKS price indexes are very similar, with the method of item aggregation seen to have only a minimal impact on the index number estimates (see Table 10). In general the GEKS indexes seem to be fairly similar to the official figures, with the exception of the product category cereal. There also does not seem to be any consistent pattern between the differences in the GEKS estimates and the official figures, i.e. the GEKS indexes are not consistently higher or lower than the official figures. Overall, the (absolute) differences between the GEKS indexes and the official figures range from 0.13% to 2.08% with item aggregation over stores and 0.04% to 2.11% with no item aggregation over stores. When the item category cereal is excluded the differences range from 0.14% to 0.75% with item aggregation over stores and 0.04% to 1.27% with no item aggregation over stores. Over this (relatively short) time period the official figures seem to compare quite well with the GEKS figures.

7. The Country Product Dummy Method: An Alternative to GEKS

A potential drawback of the GEKS methodology is that there are no standard errors on our index series. The use of an alternative approach, the "Country Product Dummy" method, again borrowed from the international comparisons literature with appropriate adaptation, could also be used to provide indexes free of chain drift but the resulting estimates have standard errors associated with them.

The Country Product Dummy (CPD) method is a stochastic approach which is typically used to make multilateral international price comparisons. This method, first proposed by Summers (1973), is based on an hedonic regression model where “the only characteristic of a commodity is the commodity itself”; Diewert (2004). Importantly, the CPD method is transitive; i.e., the resulting (relative) price indexes do not depend on the choice of a base country. Furthermore, this method provides standard errors on the coefficients of interest in the regression model, which are used in constructing the price index.

The standard CPD setup is as follows:

$$\ln P_{ic} = \sum_{i=1}^{I} \pi_i D_i + \sum_{c=1}^{C} \eta_c D_c + \varepsilon_{ic} \ , \qquad (16)$$

where $\ln P_{ic}$ is the natural logarithm of the price of item i in country c, D_i is a dummy variable for item i, for i = 1…I, D_c is a dummy variable for country c, for c = 1…C, and ε_{ic} is a random disturbance term.

As with the GEKS method, countries (c =1…C) are replaced with time periods (t =1…T). Doing so gives us a model from which we can obtain transitive estimates of price change across time. Taking the (exponent of the) coefficients on the time dummy variables gives us our price change estimates. However, Kennedy (1981) notes that for a semi-logarithmic model, simply multiplying the exponentiated dummy variable coefficient by 100 will give a biased estimate of price change. Drawing on the work of Goldberger (1968), he recommends the use of an adjustment factor of $0.5 \times \hat{V}_t(\hat{\eta}_t)$ to reduce this bias, where $\hat{\eta}_t$ is the estimated parameter on the time dummy variable, and $\hat{V}_t$ is the variance of the estimated parameter on the time dummy variable. This factor is subtracted from the dummy variable parameter estimate prior to exponentiation.

In equation (16) all observations are weighted equally. Diewert (2004) noted that “best practice index number theory typically involves weighting prices by their economic importance”. Thus, we weight each observation by the square root of an item i’s expenditure share in time period t,

$$w_{it} = \frac{p_{it} q_{it}}{\sum_{i=1}^{I} p_{it} q_{it}} ,$$

where w_{it} is the expenditure share of item i in period t, for t = 1…T, i = 1…I, p_{it} is the price of item i in period t, and q_{it} is the quantity of item i purchased in period t.[28]

The CPD model can be estimated with either fixed or varying samples across time. In our model the sample size is allowed to vary across time, so that new items are allowed to enter the sample and disappearing items can exit the sample. To estimate the model parameters, we must impose a restriction on the model. We impose the restriction that $\eta_1 = 0$, so that time period 1 is set as the base period in our model.[29]

CPD models were estimated for the two item categories: toilet paper and butter. The time and item aggregation methods for the CPD models were consistent with those used to calculate GEKS indexes. In this paper results are presented for the weighted CPD models.[30] Tables 11 and 12 present the time dummy coefficients and corresponding standard errors. The coefficients appear to have been estimated to a high degree of precision, at least for the models with low levels of aggregation (no item aggregation over stores) where the number of observations is very large.

Results for data aggregated at quarterly intervals are shown in figures 13-16 and results for data aggregated at monthly intervals are shown in figures 17-20. The plots show that there is very little difference between price change estimates for the GEKS and CPD methods. Both methods appear to track each other quite closely, with upward and downward movements in the GEKS price series matched by those in the CPD series. On average, the absolute value of the differences between the quarterly GEKS and CPD series is approximately 0.29%, with differences between the series ranging between 0.02% and 1.07%. The upper bound of 1.07% may be a little misleading as the next highest value is 0.58%. For monthly aggregation the average (absolute) difference between the GEKS and CPD series is larger than that observed for

[28] A number of authors, including Silver (2002), Diewert (2003) (2004) and Rao (2005) have discussed the use of alternative weighting systems in regression models used to estimate price change.
[29] However, the price of any period relative to any other period is unaffected by this normalization.
[30] Results for the unweighted CPD models are available from the authors on request.

the quarterly series, at 0.488% with a range of differences between 0.01% and 1.56%. The differences between the GEKS and CPD estimates for the item category butter (0.01% to 0.54%) are much smaller than those for the item category toilet paper (0.77% to 1.56). Basically, the quarterly and monthly GEKS and CPD estimates of price change for butter are identical while the CPD estimates for toilet paper are a bit below their GEKS counterparts.

The results indicate that statistical agencies that use scanner data may be able to use either the GEKS or CPD approach to obtain drift free estimates of price change with some confidence as both methods give very similar results. One issue to be considered is that of temporal fixity. With traditional multilateral index number methods, index numbers are generated not only for the current period but also for all past periods in the domain of definition of the multilateral index. Thus a drawback of traditional multilateral indexes applied in the time series context is that they violate temporal fixity, which means that when a time period is added to the multilateral index the index number results for previous periods may change. With our recommended "rolling year GEKS" approach we avoid this problem of having to make constant revisions to past values of the index as the data for a new period become available.

8. Conclusion

One of the key results of this work has been to show that, when using high frequency data, decisions about how to aggregate and whether or not chaining is used can have a huge impact on estimates of price change. It is known that when price bouncing is present, the use of chained indexes in combination with non-superlative indexes tend to exhibit large chain drift. However, the extent of drift seen for many item categories over what is a relatively short time period is, to say the least, surprising. In addition, it is also of concern to see that indexes which we would typically consider to be much more stable, such as chained superlative indexes, show a troubling degree of volatility when high frequency data are used. These results indicate that traditional index number theory appears to break down when high frequency data are used.

Our results suggest that using unit values defined over months or quarters is preferable to unit values defined over weeks. Whether or not items are aggregated over stores in constructing the unit values appears to be a relatively minor consideration compared to the choices of time aggregation and index number formula, but we did find that Fisher indexes that did not aggregate over stores were consistently higher than their counterparts formed using unit values based on aggregating over stores.

An additional contribution of the paper is the suggestion that multilateral index number methods can be used to provide drift free estimates of price change. Our results show that when monthly chained Fisher indexes were compared with their GEKS counterparts they were typically found to exhibit downward chain index drift, which in a number of cases was quite substantial. We also found that even quarterly time aggregation may not be sufficient to eliminate the downward chain index drift found in the Fisher index.

Table 1. Data: Descriptive statistics

Item Category	Observations	Number of items
Biscuits	2,452,797	1,327
Bread	752,884	430
Butter	225,789	79
Cereal	1,147,737	554
Coffee	514,945	205
Detergent	458,712	177
Frozen peas	544,050	231
Honey	235,649	113
Jams	615,948	389
Juices	2,639,642	1,125
Margarine	312,558	98
Oil	483,146	314
Pasta	1,065,204	715
Pet food	2,589,135	1,073
Soft drinks	2,140,587	966
Spreads	283,676	103
Sugar	254,453	118
Tin tomatoes	246,187	130
Toilet paper	438,525	164

Table 2. Laspyeres Index: price change estimates – item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	98.89	100.74	101.94	98.50	109.04	185.77	96.21	101.66	166.95
Bread	104.33	106.69	108.87	104.91	114.05	562.24	104.88	113.76	615.50
Butter	100.95	102.91	100.11	101.50	106.85	145.14	101.91	107.48	145.60
Cereal	100.27	102.00	104.02	100.94	107.45	215.57	100.65	107.01	210.04
Coffee	111.14	112.38	115.70	111.57	126.21	274.76	111.49	125.72	267.83
Detergent	102.71	105.71	105.25	103.09	112.31	165.05	102.64	111.54	164.11
Frozen peas	100.78	100.73	101.75	101.28	108.25	202.12	100.94	107.24	195.92
Honey	104.77	105.93	105.52	104.87	108.14	120.40	104.42	107.27	119.30
Jams	100.49	101.52	102.08	100.99	107.29	174.15	100.09	105.47	167.01
Juices	101.74	101.77	104.21	102.69	110.82	332.11	101.90	109.65	318.52
Margarine	104.29	102.80	104.10	106.86	124.53	1606.77	106.81	124.86	1562.35
Oil	92.93	90.87	87.37	93.48	100.48	141.16	92.82	100.05	142.56
Pasta	100.88	101.16	104.88	101.22	110.46	347.14	100.30	109.38	342.19
Pet food	100.46	101.64	103.52	101.11	106.17	165.54	100.82	105.64	161.59
Soft drinks	104.13	106.41	108.65	105.95	132.27	1074.89	105.83	132.21	1024.45
Spreads	104.86	107.88	107.14	104.98	111.163	122.84	104.70	110.64	121.94
Sugar	106.37	107.20	106.71	106.07	111.39	149.44	106.09	111.43	149.47
Tin tomatoes	101.33	98.93	101.68	101.95	110.51	165.82	101.14	109.42	164.62
Toilet paper	100.61	99.62	100.46	103.99	125.71	1656.92	103.67	124.69	1571.90
Geo Mean	**102.15**	**102.90**	**103.75**	**102.88**	**112.52**	**269.10**	**102.41**	**111.54**	**263.97**

Table 3. Paasche Index: price change estimates – item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	98.44	99.68	99.71	97.24	91.93	48.12	96.38	88.75	45.28
Bread	102.83	102.89	101.66	102.79	97.14	19.33	102.35	94.48	16.91
Butter	100.30	101.25	99.07	99.84	97.74	66.45	99.98	97.85	66.50
Cereal	100.23	100.73	102.64	99.33	94.98	43.82	99.12	94.47	43.87
Coffee	109.30	110.04	111.23	108.71	98.70	35.00	108.62	98.43	35.57
Detergent	102.39	104.67	103.82	101.89	97.83	61.16	101.52	96.68	59.82
Frozen peas	100.33	100.32	100.21	100.11	93.65	44.32	99.86	92.77	44.94
Honey	104.37	105.30	104.52	104.12	102.82	89.54	103.84	102.42	89.13
Jams	100.39	100.73	98.18	99.67	95.49	46.62	99.04	94.24	46.37
Juices	100.69	99.43	98.65	100.15	91.77	27.29	99.12	90.23	27.37
Margarine	103.14	97.96	102.39	101.37	80.57	5.52	100.72	80.31	5.59
Oil	91.05	87.72	83.21	90.07	75.76	42.41	88.93	74.02	39.83
Pasta	100.37	100.63	100.92	99.78	92.05	25.75	99.25	90.25	24.17
Pet food	100.56	99.88	101.84	99.92	95.35	59.10	99.65	94.73	59.74
Soft drinks	102.77	102.31	103.32	101.33	80.19	6.06	101.01	79.36	6.22
Spreads	103.91	105.87	105.57	103.81	103.123	88.23	103.73	102.85	87.85
Sugar	106.14	106.99	106.23	105.93	101.23	66.06	105.97	101.25	66.06
Tin tomatoes	101.32	98.16	98.73	100.46	89.45	53.31	99.5892	88.64	51.96
Toilet paper	99.32	96.58	87.06	96.61	76.65	3.68	96.70	76.67	3.82
Geo Mean	**101.40**	**101.01**	**100.27**	**100.62**	**92.06**	**33.03**	**100.20**	**91.10**	**32.58**

Table 4. Fisher Index: price change estimates – item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	98.66	100.21	100.82	97.87	100.12	94.55	96.29	94.99	86.95
Bread	103.58	104.77	105.20	103.85	105.25	104.25	103.61	103.67	102.03
Butter	100.62	102.08	99.59	100.67	102.19	98.20	100.94	102.56	98.40
Cereal	100.25	101.37	103.33	100.13	101.02	97.19	99.88	100.54	95.99
Coffee	110.22	111.20	113.44	110.13	111.61	98.07	110.05	111.24	97.61
Detergent	102.55	105.19	104.53	102.49	104.82	100.48	102.08	103.84	99.08
Frozen peas	100.55	100.52	100.98	100.70	100.68	94.64	100.40	99.74	93.83
Honey	104.57	105.61	105.02	104.49	105.45	103.83	104.13	104.81	103.12
Jams	100.44	101.12	100.11	100.33	101.22	90.10	99.56	99.69	88.00
Juices	101.21	100.59	101.39	101.41	100.84	95.21	100.50	99.47	93.37
Margarine	103.72	100.35	103.24	104.08	100.16	94.17	103.72	100.14	93.44
Oil	91.99	89.28	85.26	91.76	87.25	77.37	90.86	86.05	75.35
Pasta	100.62	100.90	102.88	100.50	100.84	94.55	99.77	99.36	90.95
Pet food	100.51	100.76	102.68	100.51	100.61	98.91	100.23	100.04	98.25
Soft drinks	103.45	104.34	105.95	103.62	102.99	80.70	103.39	102.43	79.80
Spreads	104.39	106.87	106.35	104.39	107.07	104.11	104.22	106.67	103.50
Sugar	106.26	107.10	106.47	106.00	106.19	99.36	106.03	106.22	99.36
Tin tomatoes	101.32	98.55	100.20	101.20	99.43	94.02	100.363	98.48	92.49
Toilet paper	99.96	98.09	93.52	100.23	98.16	78.13	100.13	97.77	77.51
Geo Mean	**101.77**	**101.95**	**102.00**	**101.74**	**101.78**	**94.28**	**101.30**	**100.80**	**92.73**

Table 5. Laspeyres Index: price change estimates – no item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	99.77	102.11	102.99	101.60	121.16	318.33	100.65	116.05	281.30
Bread	104.81	108.10	112.48	106.18	125.77	3146.25	106.16	126.05	2815.28
Butter	101.26	103.22	100.78	102.59	113.99	193.00	102.80	114.15	193.21
Cereal	100.77	103.56	104.53	102.54	123.24	361.49	102.36	122.85	354.71
Coffee	111.97	114.25	116.98	113.70	155.80	543.34	113.72	154.65	511.04
Detergent	103.27	106.61	105.69	104.15	125.14	227.96	103.50	123.70	228.01
Frozen peas	101.27	101.51	102.88	102.35	119.17	300.51	101.92	117.13	273.91
Honey	104.87	105.97	105.85	105.32	111.22	128.45	105.05	110.65	126.76
Jams	101.50	103.28	105.61	102.23	118.08	294.13	101.40	114.53	257.39
Juices	102.33	102.86	106.13	104.12	124.84	821.30	103.51	123.64	764.47
Margarine	105.54	106.09	107.85	111.53	182.67	13897.59	111.94	187.85	14578.97
Oil	93.00	91.10	88.33	94.18	103.21	132.41	94.10	104.66	155.57
Pasta	101.28	102.61	108.07	102.44	122.15	790.75	101.97	123.78	788.53
Pet food	101.32	102.01	104.82	102.93	114.15	263.49	102.53	113.264	241.45
Soft drinks	106.37	108.51	113.28	111.39	175.13	46575.10	111.82	175.88	28420.37
Spreads	104.77	107.67	107.49	105.72	115.39	140.14	105.51	115.43	140.69
Sugar	106.97	108.44	108.51	107.43	119.64	176.18	107.20	119.17	173.62
Tin tomatoes	102.48	101.12	103.57	103.44	119.06	212.26	103.15	117.36	208.30
Toilet paper	101.49	101.24	102.66	106.71	158.29	11955.97	107.31	162.65	11815.05
Geo Mean	**102.83**	**104.12**	**105.55**	**104.68**	**127.27**	**612.55**	**104.46**	**126.85**	**579.88**

Table 6. Paasche Index: price change estimates – no item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	98.25	98.99	99.07	96.37	84.02	23.68	95.25	80.41	22.67
Bread	102.63	101.11	98.53	102.113	88.35	3.20	101.87	86.54	3.50
Butter	100.00	100.47	98.52	98.95	91.88	48.46	98.91	91.93	48.23
Cereal	100.04	99.96	101.92	98.39	83.71	19.75	98.04	82.69	20.11
Coffee	108.87	108.79	110.46	107.07	79.44	13.65	106.97	79.83	15.08
Detergent	102.09	104.06	102.61	101.43	87.81	37.90	100.64	86.46	37.11
Frozen peas	100.37	99.97	99.97	99.65	86.20	26.71	99.20	85.79	29.23
Honey	104.18	104.89	104.27	103.66	99.90	81.14	103.38	99.54	80.94
Jams	100.86	101.19	97.60	100.21	89.29	23.92	98.49	86.80	25.79
Juices	100.57	98.89	97.17	99.21	82.54	10.51	98.09	80.96	10.82
Margarine	102.17	97.28	100.06	96.92	55.60	0.45	96.73	54.99	0.43
Oil	90.92	87.89	84.03	89.68	77.50	54.02	88.65	73.65	42.06
Pasta	100.48	99.98	97.74	99.03	83.65	8.33	98.28	79.39	7.65
Pet food	100.44	99.25	100.90	98.85	88.78	35.64	98.48	88.18	37.41
Soft drinks	101.76	100.50	101.23	97.46	59.76	0.12	96.74	59.49	0.19
Spreads	103.82	105.47	105.11	103.49	98.77	73.13	103.27	97.86	70.60
Sugar	106.15	106.34	105.46	105.31	95.36	46.09	105.08	94.49	46.55
Tin tomatoes	100.93	97.31	97.46	100.18	83.08	35.65	99.53	83.09	37.28
Toilet paper	98.26	92.66	86.90	93.89	59.74	0.48	93.98	59.78	0.54
Geo Mean	**101.14**	**100.15**	**99.24**	**99.50**	**81.92**	**12.77**	**98.95**	**80.69**	**13.18**

Table 7. Fisher Index: price change estimates – no item aggregation over stores

	Direct			Chained (Fixed basket)			Chained (Flexible basket)		
	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly	Quarterly	Monthly	Weekly
Biscuits	99.01	100.54	101.01	98.95	100.90	86.82	97.91	96.60	79.86
Bread	103.72	104.54	105.27	104.13	105.41	100.26	104.00	104.44	99.32
Butter	100.63	101.84	99.64	100.75	102.34	96.71	100.83	102.44	96.53
Cereal	100.41	101.74	103.22	100.45	101.57	84.50	100.18	100.79	84.47
Coffee	110.41	111.49	113.67	110.34	111.25	86.13	110.30	111.11	87.79
Detergent	102.68	105.33	104.14	102.78	104.83	92.95	102.06	103.42	91.99
Frozen peas	100.82	100.73	101.42	100.99	101.35	89.60	100.55	100.24	89.48
Honey	104.52	105.43	105.06	104.49	105.41	102.09	104.21	104.95	101.29
Jams	101.18	102.23	101.53	101.22	102.68	83.88	99.93	99.71	81.48
Juices	101.45	100.86	101.55	101.63	101.51	92.90	100.76	100.05	90.94
Margarine	103.85	101.59	103.88	103.97	100.77	79.26	104.06	101.63	79.35
Oil	91.95	89.48	86.16	91.90	89.43	84.58	91.33	87.80	80.89
Pasta	100.88	101.28	102.78	100.72	101.08	81.18	100.11	99.13	77.68
Pet food	100.88	100.62	102.84	100.87	100.67	96.90	100.49	99.94	95.04
Soft drinks	104.04	104.43	107.09	104.19	102.30	75.53	104.01	102.29	74.28
Spreads	104.29	106.56	106.29	104.60	106.76	101.23	104.39	106.28	99.66
Sugar	106.56	107.38	106.97	106.36	106.81	90.11	106.14	106.12	89.90
Tin tomatoes	101.70	99.20	100.47	101.80	99.46	86.99	101.32	98.75	88.12
Toilet paper	99.86	96.86	94.45	100.10	97.24	75.79	100.43	98.61	79.86
Geo Mean	**101.98**	**102.12**	**102.35**	**102.05**	**102.10**	**88.45**	**101.67**	**101.17**	**87.43**

Table 8. Quarterly GEKS and Chained (Flexible) Fisher Indexes

	Item aggregation over stores		No item aggregation over stores	
	GEKS	**Fisher**	**GEKS**	**Fisher**
Biscuits	98.34	96.29	98.88	97.91
Bread	103.48	103.61	103.67	104.00
Butter	100.72	100.94	100.70	100.83
Cereal	100.10	99.88	100.29	100.18
Coffee	110.16	110.05	110.44	110.30
Detergent	102.40	102.08	102.56	102.06
Frozen peas	100.43	100.40	100.76	100.55
Honey	104.42	104.13	104.44	104.21
Jams	100.16	99.56	100.74	99.93
Juices	101.01	100.50	101.28	100.76
Margarine	103.65	103.72	103.78	104.06
Oil	91.61	90.86	91.80	91.33
Pasta	100.34	99.77	100.65	100.11
Pet food	100.46	100.23	100.84	100.49
Soft drinks	103.42	103.39	104.12	104.01
Spreads	104.34	104.22	104.35	104.39
Sugar	106.25	106.03	106.51	106.14
Tin tomatoes	101.05	100.36	101.58	101.32
Toilet paper	100.03	100.13	100.03	100.43

Table 9. Monthly GEKS, RYGEKS and Chained (Flexible) Fisher indexes

	Item aggregation over stores			No item aggregation over stores		
	GEKS	RYGEKS	Fisher	GEKS	RYGEKS	Fisher
Biscuits	100.12	100.11	94.99	100.53	100.51	96.60
Bread	104.11	103.95	103.67	104.10	103.97	104.44
Butter	102.30	102.34	102.56	101.91	101.93	102.44
Cereal	101.24	101.16	100.54	101.49	101.38	100.79
Coffee	111.22	111.25	111.24	111.63	111.61	111.11
Detergent	104.83	104.75	103.84	105.04	104.95	103.42
Frozen peas	100.42	100.37	99.74	100.72	100.71	100.24
Honey	105.39	105.35	104.81	105.35	105.34	104.95
Jams	100.88	100.82	99.69	101.86	101.75	99.71
Juices	100.52	100.48	99.47	100.88	100.86	100.05
Margarine	99.82	99.77	100.14	101.36	101.31	101.63
Oil	88.46	88.33	86.05	89.21	89.14	87.80
Pasta	100.40	100.32	99.36	100.97	100.90	99.13
Pet food	100.72	100.70	100.04	100.76	100.79	99.94
Soft drinks	104.47	104.43	102.43	104.41	104.31	102.29
Spreads	106.79	106.82	106.67	106.72	106.80	106.28
Sugar	107.11	107.12	106.22	107.36	107.35	106.12
Tin tomatoes	98.71	98.81	98.48	99.45	99.58	98.75
Toilet paper	97.98	97.93	97.77	97.00	97.02	98.61

Table 10. Index number comparison: ABS CPI and GEKS indexes

		GEKS indexes		Official CPI figures Australia
Item category		Item aggregation over stores	No item aggregation over stores	
Scanner data	ABS	April 97-March 98 (4 Quarters) Base=100	April 97-March 98 (4 Quarters) Base=100	April 97-March 98 (4 Quarters) Base=100
Cereal	Breakfast cereals	99.59	99.62	97.51
Bread	Bread	101.85	102.20	102.41
Butter	Butter	99.75	99.93	99.89
Juices	Fruit juice	101.63	101.69	100.99
Sugar	Sugar	104.60	104.72	105.35
Soft drinks	Soft drinks & cordial	103.90	104.70	103.43
Geo mean	Geo mean	101.87	102.13	101.56

Table 11. Parameter estimates and standard errors for monthly time dummy variables in models with monthly time aggregation

	Butter		Toilet paper	
	No item aggregation over stores	**Item aggregation over stores**	**No item aggregation over stores**	**Item aggregation over stores**
Month DV2	0.0120	0.0108	-0.0226	-0.0050
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0092)
Month DV3	0.0188	0.0214	-0.0226	-0.0133
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV4	0.0114	0.0141	-0.0174	0.0006
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV5	0.0147	0.0161	-0.0297	-0.0130
(S.E)	(0.0017)	(0.0067)	(0.0014)	(0.0092)
Month DV6	0.0199	0.0196	-0.0203	-0.0042
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV7	0.0116	0.0135	-0.0086	0.0064
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV8	0.0096	0.0115	-0.0248	-0.0095
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV9	0.0131	0.0091	-0.0076	0.0020
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV10	-0.0015	-0.0030	-0.0802	-0.0648
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV11	0.0055	0.0090	-0.0185	-0.0041
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV12	0.0176	0.0179	-0.0174	-0.0126
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV13	0.0186	0.0181	-0.00563	-0.0048
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV14	0.0170	0.0146	-0.0225	-0.0130
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Month DV15	0.0229	0.0232	-0.0362	-0.0300
(S.E)	(0.0017)	(0.0066)	(0.0014)	(0.0093)
Observations	**54096**	**964**	**107130**	**1691**

Table 12. Parameter estimates and standard errors for quarterly time dummy variables in models with quarterly time aggregation

	Butter		Toilet paper	
	No item aggregation over stores	**Item aggregation over stores**	**No item aggregation over stores**	**Item aggregation over stores**
Quarter DV2	0.0025	0.0062	-0.0042	0.0031
(S.E)	(0.00095)	(0.0054)	(0.0011)	(0.0079)
Quarter DV3	-0.0006	0.0021	0.0058	0.0089
(S.E)	(0.00095)	(0.0054)	(0.0011)	(0.0079)
Quarter DV4	-0.0081	-0.0037	-0.0304	-0.0283
(S.E)	(0.00095)	(0.0055)	(0.0011)	(0.0080)
Quarter DV5	0.0071	0.0089	-0.0049	-0.0105
(S.E)	(0.00096)	(0.0055)	(0.0011)	(0.0080)
Observations	**18932**	**338**	**37842**	**680**

Figures 1 - 8 : GEKS and chained index results

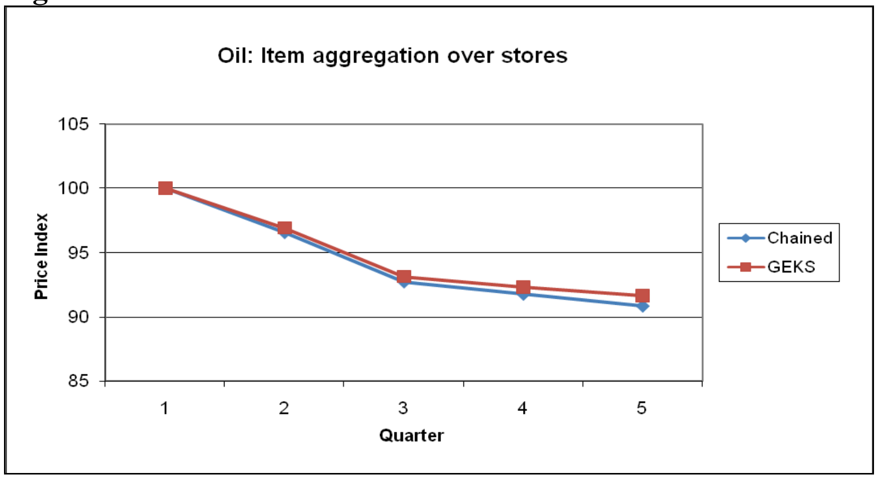

Figure 1

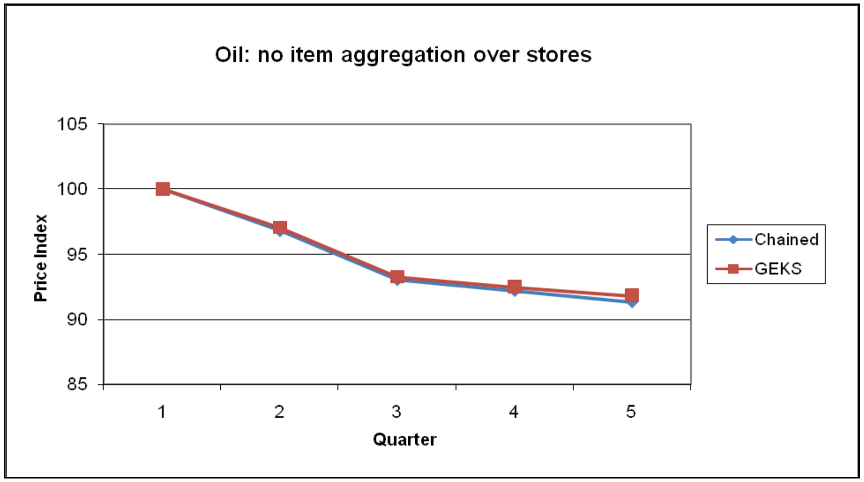

Figure 2

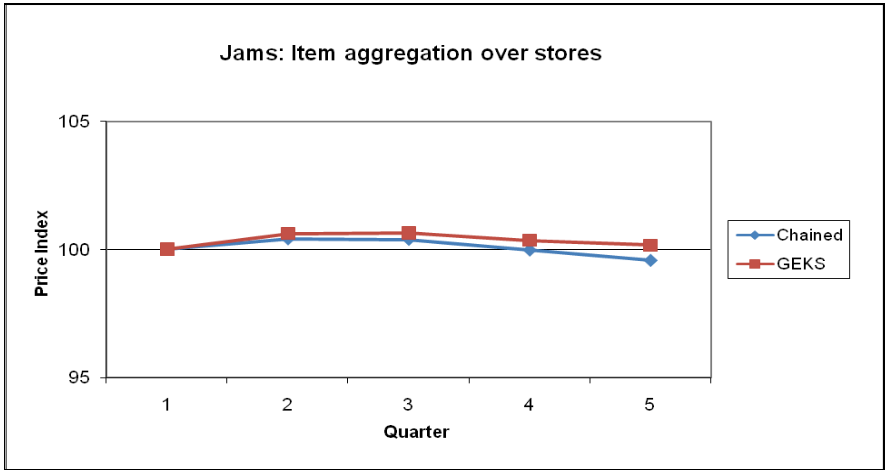

Figure 3

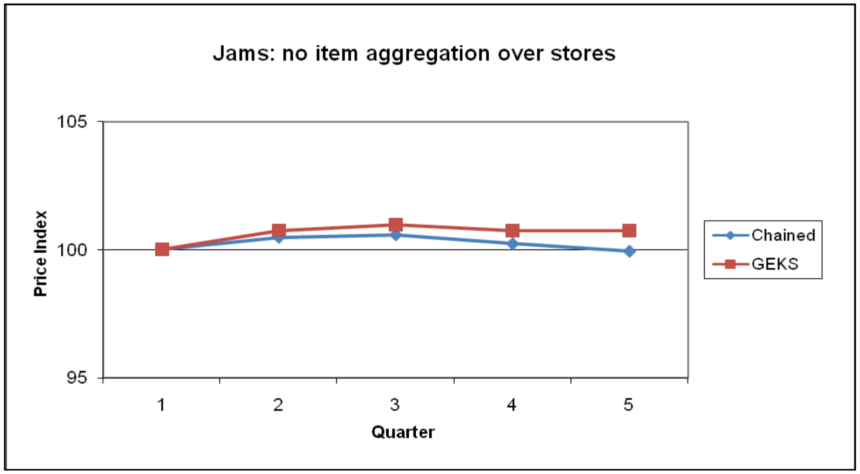

Figure 4

Figures (cont.)

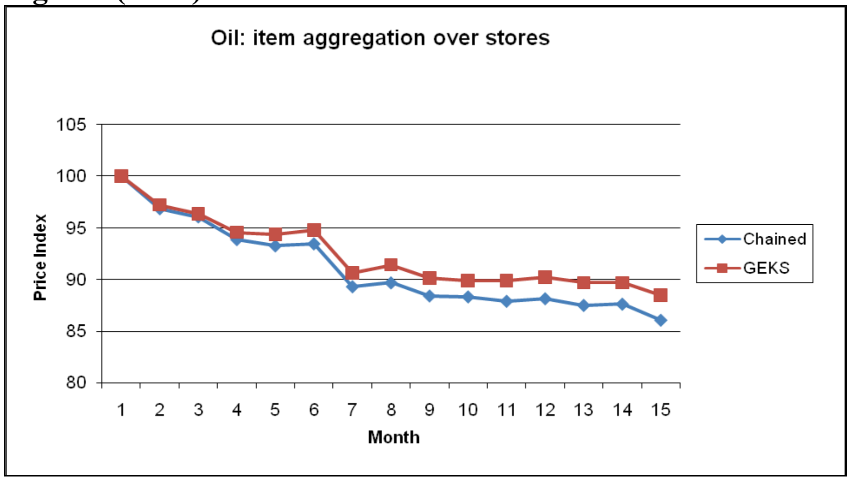

Figure 5

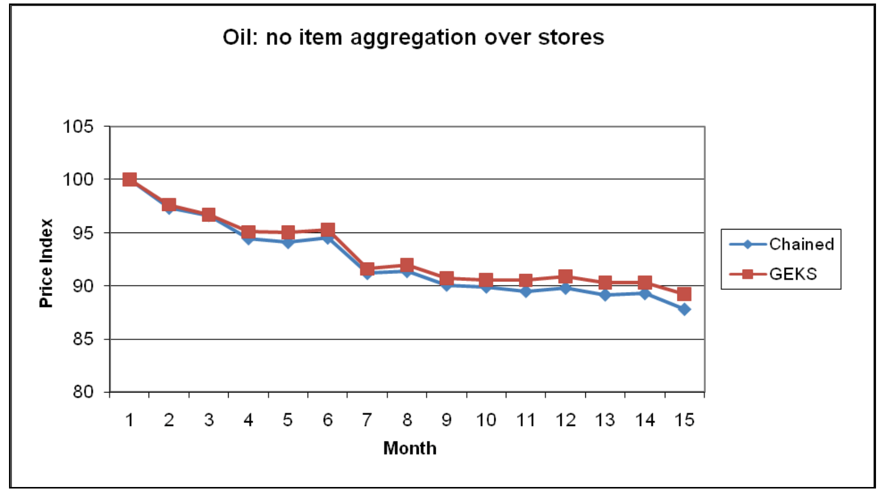

Figure 6

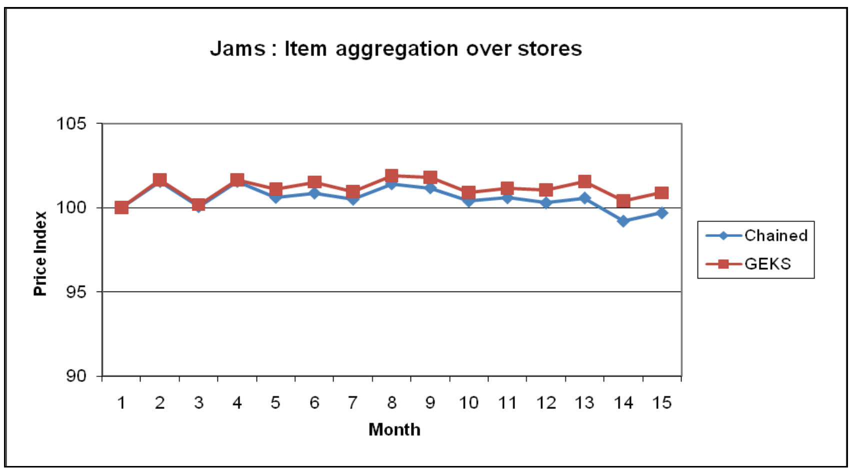

Figure 7

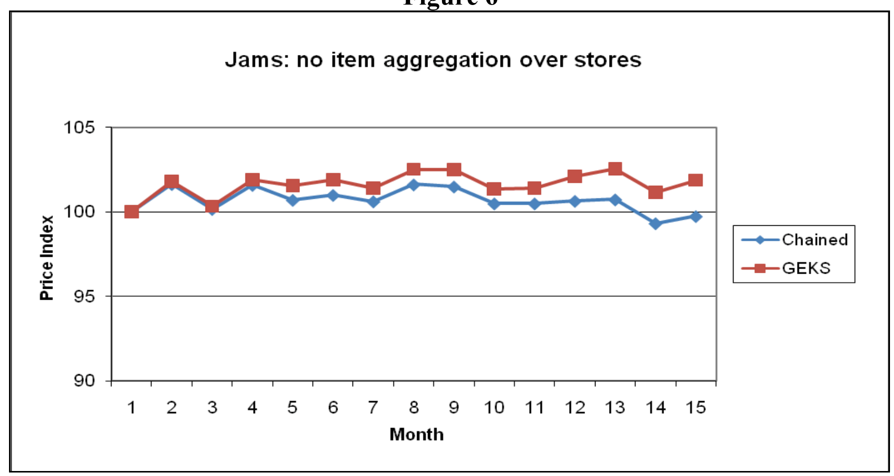

Figure 8

Figures 9 - 12: GEKS and RYGEKS indexes

Figure 9

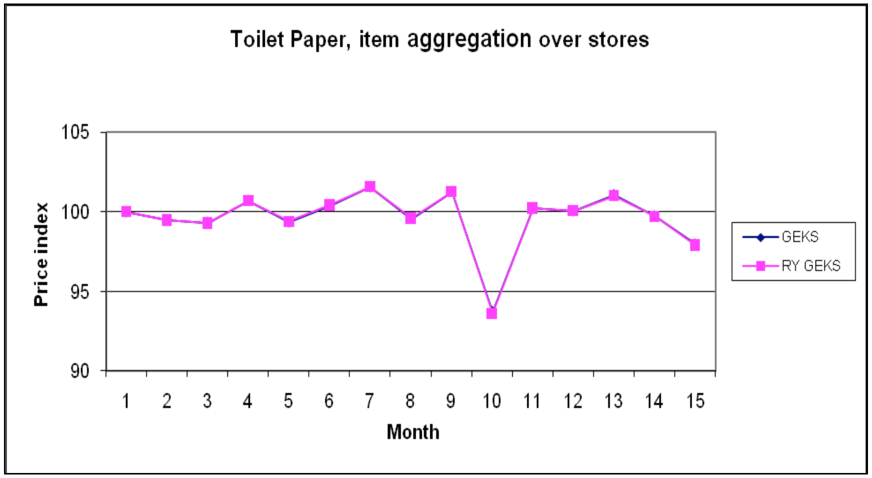

Figure 10

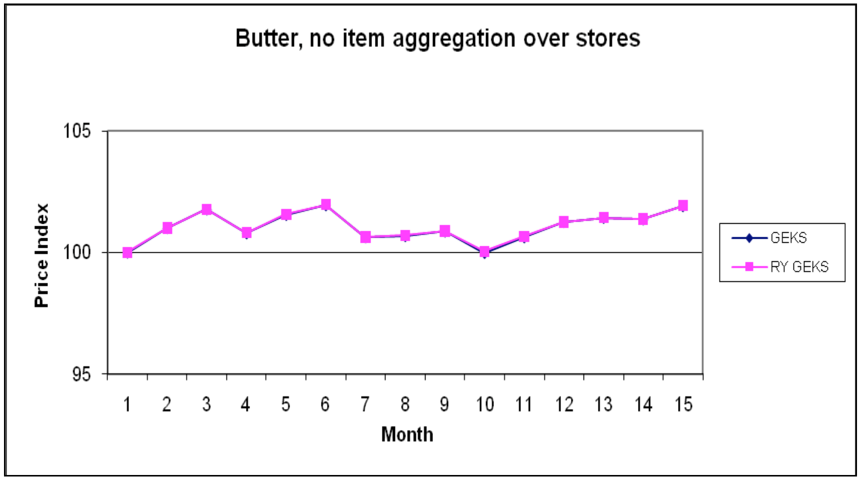

Figure 11

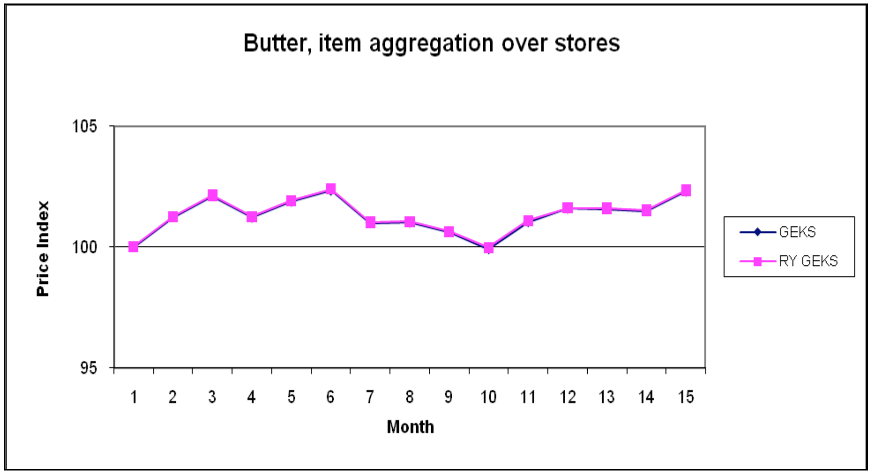

Figure 12

Figures 13 – 20: GEKS and CPD index results

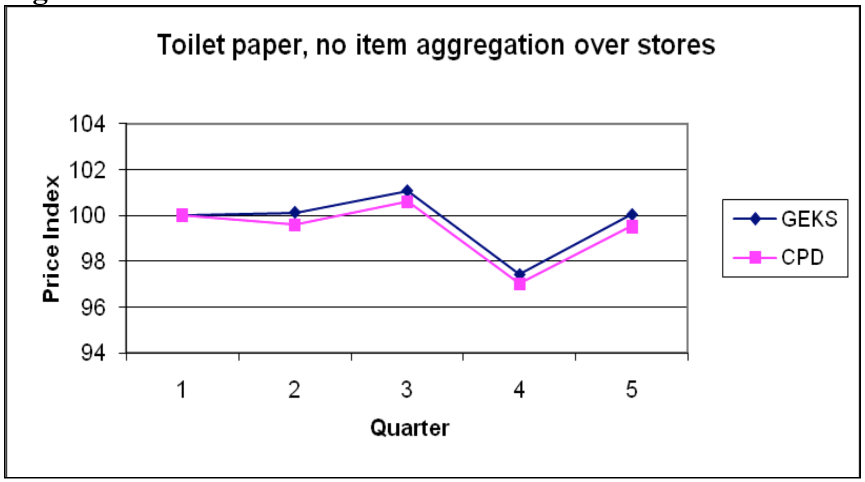

Figure 13

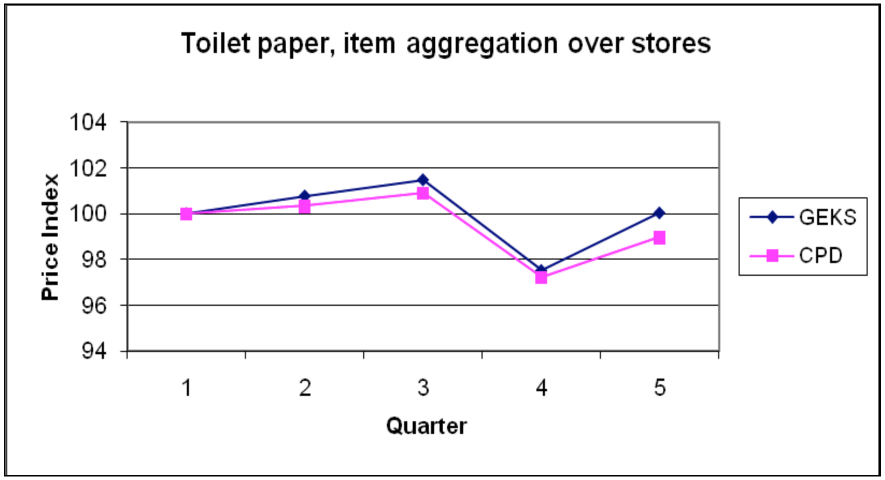

Figure 14

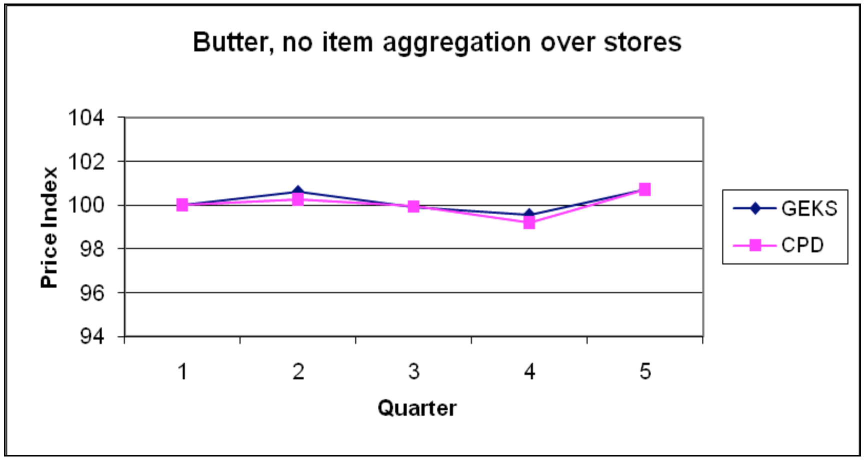

Figure 15

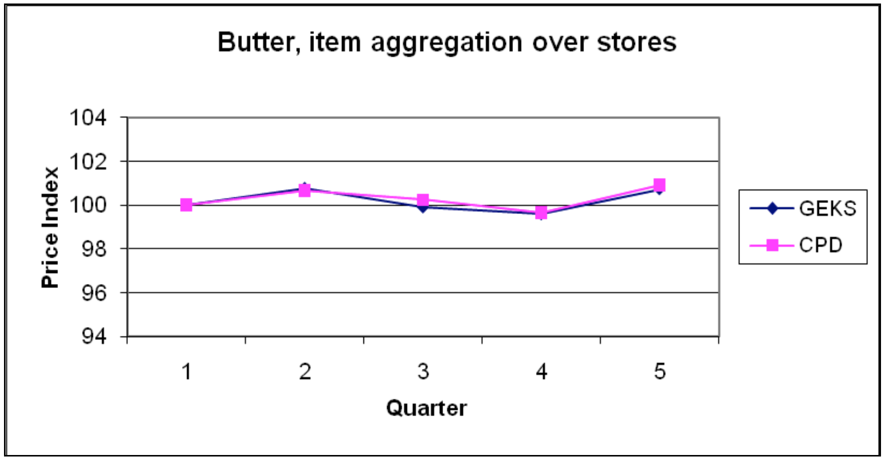

Figure 16

Figures (cont.)

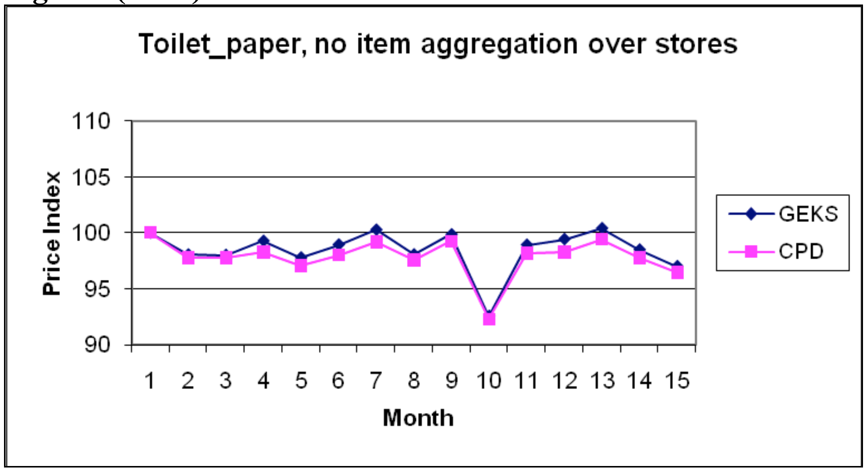

Figure 17

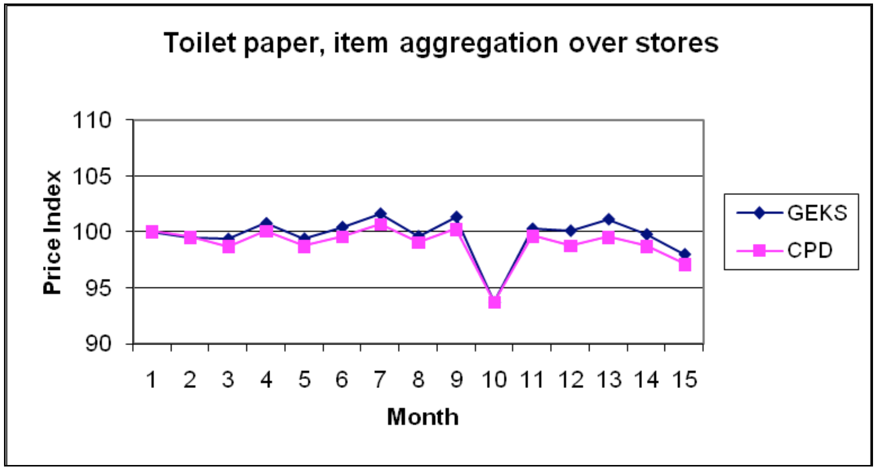

Figure 18

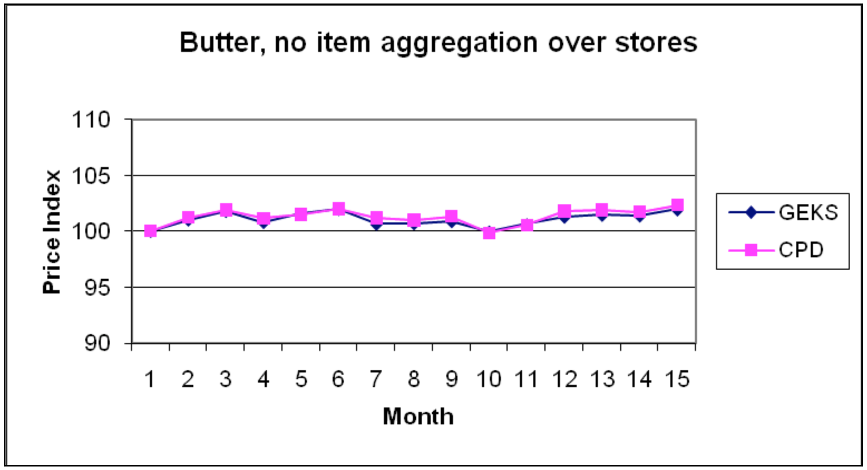

Figure 19

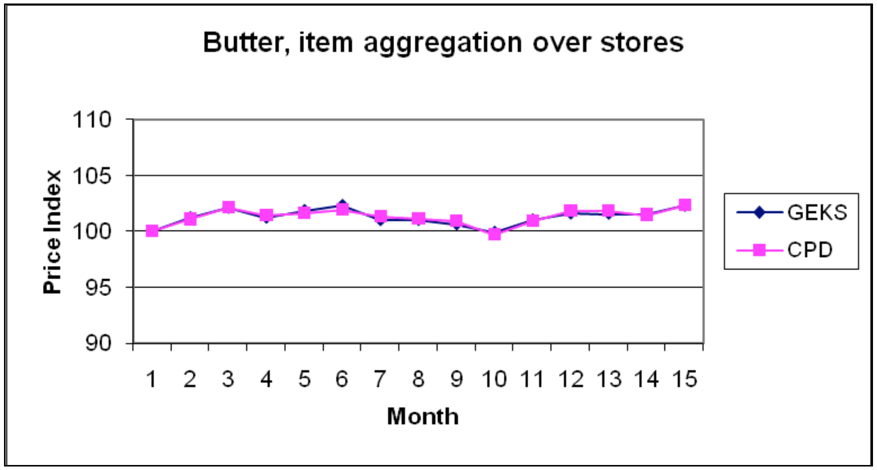

Figure 20

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