The Treatment of Unmatched Items in Rolling Year GEKS Price Indexes: Evidence from New Zealand Scanner Data

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Abstract: The recently developed rolling year GEKS procedure makes maximum use of all matches in the data in order to construct price indexes that are (approximately) free from chain drift. A potential weakness is that unmatched items are ignored. In this paper we use imputation Törnqvist price indexes as inputs into the rolling year GEKS procedure. These indexes account for quality changes by imputing the "missing prices" associated with new and disappearing items. Three imputation methods are discussed. The first method makes explicit imputations using a hedonic regression model which is estimated for each time period. The other two methods make implicit imputations; they are based on time dummy hedonic and time-product dummy regression models and are estimated on pooled data. We present empirical evidence for New Zealand from scanner data on eight products and find that imputations can make a substantial difference. The choice of imputation method also matters.

Key words: hedonic regression, imputation, multilateral index number methods, quality adjustment, scanner data, transitivity.

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1. Introduction

Barcode scanning data, or scanner data for short, contain information on the prices and quantities sold of all individual items. One obvious advantage of using scanner data in the compilation of the Consumer Price Index (CPI) is that price indexes at the level of product categories have complete coverage rather than being based on a small sample of items as is usual practice. Another advantage is that – since real time expenditure data is available – the construction of *superlative indexes*, such as Fisher or Törnqvist indexes, is now feasible.[1] Superlative indexes treat both time periods in a symmetric fashion and have attractive properties, like taking into account the consumers' substitution behavior. Most statistical agencies still rely today on fixed-weight, "Laspeyres-type" indexes to compile the CPI.

Scanner data typically show substantial item attrition; many new items appear and many "old" items disappear. This makes it difficult if not impossible to construct price indexes using the standard approach where the prices of a more or less fixed set of items are tracked over time. Chain linking period-on-period price movements seems an obvious solution, but that can lead to a drifting time series under certain circumstances. Ivancic, Diewert and Fox (2011) resolved the problem of *chain drift* by adapting a well-known method from price comparisons across countries to comparisons across time. Their rolling year (RY) GEKS approach makes optimal use of the matches in the data and yields price indexes that are approximately free from chain drift.

A potential weakness of matched-item approaches, including RYGEKS, is that the price effects of new and disappearing items are neglected. High-tech products, such as consumer electronics, usually experience rapid quality changes; new items are often of higher quality than existing ones. It is well established in the literature that *adjusting for quality change* is an essential part of price measurement; see e.g. ILO *et al*. (2004). The purpose of this paper is to show how quality-adjusted RYGEKS price indexes can be estimated. This provides us with a benchmark measure that can be used to assess the performance of easier to construct quality-adjusted price indexes.

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[1] Statistics Netherlands has been using scanner data for supermarkets in the CPI since 2004. In 2010, a new computation method was introduced and the coverage in terms of supermarket chains was expanded. The new Dutch method does not make use of weighting information at the individual item level, however. Van der Grient and de Haan (2011) describe the method and explain the choice for using an unweighted index number formula at the elementary aggregation level.

The RYGEKS procedure is based on combining "bilateral" superlative indexes, which compare two time periods, with different base periods. In the original setup, the bilateral indexes only take account of the matched items, i.e., those that are available in both periods compared. Quality mix changes can occur within the set of matched items. For example, an overall quality improvement will result when consumers increasingly purchase higher-quality items. Changes in the quality mix of a matched set do not need special attention here, however; they will be handled appropriately using matched-item superlative indexes. The issue at stake is how to account for quality changes associated with new and disappearing items. We do this by estimating bilateral *imputation* price indexes, which serve as inputs into the RYGEKS procedure. Imputation indexes adjust for quality changes by imputing the unobservable or "missing" prices to construct price relatives for the new and disappearing items.

The paper is structured as follows. Section 2 outlines the RYGEKS procedure. Sections 3-5 discuss three regression-based bilateral imputation Törnqvist indexes. The method described in section 3 makes explicit imputations using a *hedonic regression model* which is estimated on cross section data for each period. The two other methods are based on making implicit imputations. In section 4 we discuss a result derived by de Haan (2004), which is that estimating a *time dummy hedonic model* on the pooled data of two time periods by a particular type of weighted least squares regression implicitly defines an imputation Törnqvist price index. A non-hedonic variant of the bilateral time dummy model is presented in section 5. In this *time-product dummy model*, the only "characteristic" included is an item identifier. It turns out, however, that a matched-item price index results, so that this method does not lead to meaningful imputations for new and disappearing items.

In section 6 we summarize the foregoing by listing the steps to be followed for estimating Imputation Törnqvist (IT) RYGEKS indexes and point to a few additional issues. Section 7 then presents empirical evidence for New Zealand using scanner data on eight products from the category of consumer electronics. We find that imputations can make a substantial difference and that the choice of imputation method matters. We also compare our ITRYGEKS indexes with simpler quality-adjusted price indexes that do not employ the GEKS procedure, in particular rolling year versions of the standard multi-period time dummy hedonic approach and the multi-period time-product dummy approach. Section 8 concludes.

2. The Rolling Window GEKS Method

Suppose that we know the prices p_i^t and expenditure shares s_i^t for all items *i* belonging to a product category *U* in all time periods $t = 0,...,T$. For the moment, we assume that there are no new or disappearing items so that *U* is fixed over time. The Törnqvist price index going from the starting period 0 to period *t* (>0) is defined as

$$P_T^{0t} = \prod_{i \in U} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{s_i^0 + s_i^t}{2}} ; \qquad t = 1,...,T . \tag{1}$$

This index compares the prices in each period *t* (>0) directly with those in the starting or base period 0. The Törnqvist index is *superlative* and has useful properties, both from the economic approach and the axiomatic approach to index number theory.[2] However, the index series defined by (1) is *not transitive*, i.e., the results of the price comparisons between two periods depend on the choice of base period.[3] In (1), the starting period 0 was chosen as the base or price reference period, but this choice is rather arbitrary if we want to make comparisons between any pair of time periods.

To illustrate the non-transitivity property, let us take period 1 as the base instead of period 0 and make a comparison with period *T*. The Törnqvist index P_T^{1t} going from period 1 to period *T* is

$$P_T^{1T} = \prod_{i \in U} \left(\frac{p_i^T}{p_i^1} \right)^{\frac{s_i^1 + s_i^T}{2}} . \tag{2}$$

Using period 0 as the base (as in (1)), the price change between periods 1 and *T* will be calculated as the ratio of the index numbers in periods *T* and 1:

$$\frac{P_T^{0T}}{P_T^{01}} = \frac{\prod_{i \in U} \left(\frac{p_i^T}{p_i^0} \right)^{\frac{s_i^0 + s_i^T}{2}}}{\prod_{i \in U} \left(\frac{p_i^1}{p_i^0} \right)^{\frac{s_i^0 + s_i^1}{2}}} = P_T^{1T} \left[\prod_{i \in U} (p_i^0)^{s_i^1 - s_i^T} \prod_{i \in U} (p_i^1)^{s_i^T - s_i^0} \prod_{i \in U} (p_i^T)^{s_i^0 - s_i^1} \right]^{\frac{1}{2}} . \tag{3}$$

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2 For more information on superlative indexes and on the different approaches, see ILO *et al*. (2004).

3 Transitivity is also referred to as *circularity*, especially in the case of spatial price comparisons such as price comparisons between countries. This is an important requirement: the choice of base country should not affect measured price level differences across countries.

In general, the bracketed factor in (3) will differ from 1 and we have $P_T^{0T} / P_T^{01} \neq P_T^{1T}$, indicating non-transitivity.

In a time series context, transitivity implies that the period-on-period chained, or shifting base, index equals the corresponding direct (fixed base) index since the choice of base period does not matter. Put differently, transitive price indexes will be free from *chain drift*. Chain drift can be defined as a situation where the chain price index, unlike its direct counterpart, differs from 1 when the prices of all items return to their initial (period 0) values.[4] Empirical research on scanner data has shown that, in spite of their symmetric structure, superlative indexes can exhibit substantial chain drift under high-frequency chaining (see Feenstra and Shapiro, 2003; Ivancic, Diewert and Fox, 2011; de Haan and van der Grient, 2011).

But there may be circumstances when chaining is called for. This is the case, for example, if there are a large number of new and disappearing items. Chaining enables us to maximize the set of matched products, i.e., those products that are available in the periods compared. But what should be done, given that high-frequency chaining might lead to a drifting time series? To resolve this problem, Ivancic, Diewert and Fox (2011) adapted the GEKS (Gini, 1931; Eltetö and Köves; 1964; Szulc, 1964) method, which is well known from price comparisons across countries, to price comparisons across time. Below, we outline their methodology for constructing transitive price indexes.[5]

The proposed GEKS index is equal to the geometric mean of the ratios of all possible "bilateral" price indexes, based on the same index number formula, where each period is taken as the base. Taking 0 as the index reference period (the period in which the index equals 1) and denoting the link periods by l $(0 \leq l \leq T)$, the GEKS price index going from 0 to t is

$$P_{GEKS}^{0t} = \prod_{l=0}^{T} \left[P^{0l} / P^{tl} \right]^{1/(T+1)} = \prod_{l=0}^{T} \left[P^{0l} \times P^{lt} \right]^{1/(T+1)} ; \qquad t = 0,...,T . \tag{4}$$

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[4] This definition seems a little restrictive. In a less formal way, chain drift can alternatively be described as a situation in which the chain index drifts further and further away from the underlying "true" trend. If there are no new or disappearing items, the "true" trend can be measured by the direct index according to some preferred formula. More or less random deviations from the trend do not reflect drift and should not bother us too much.

[5] In the context of price indexes for seasonal goods, Balk (1981) describes a method that is equivalent to the GEKS method. Kokoski, Moulton and Zieschang (1999) also pointed to the possibility of adapting the GEKS approach to intertemporal price comparisons.

Equation (4) presupposes that the bilateral indexes satisfy the time reversal test, i.e., that $P^{0t} = 1/P^{t0}$. The GEKS index will then also satisfy this test. It can easily be shown that the GEKS index is transitive and can therefore be written as a period-on-period chained index.

Using the second expression of (4), the GEKS index going from period 0 to the last (most recent) period T can be expressed as

$$P_{GEKS}^{0T} = \prod_{t=0}^{T} \left[P^{0t} \times P^{tT} \right]^{1/(T+1)} . \tag{5}$$

So far, the number of time periods (including the index reference period 0) was fixed at $T+1$. In practice, we want to extend the series as time passes. If we add data pertaining to the next period $(T+1)$, then the GEKS index for this period is

$$P_{GEKS}^{0,T+1} = \prod_{t=0}^{T+1} \left[P^{0t} \times P^{t,T+1} \right]^{1/(T+2)} . \tag{6}$$

Extending the time series in this way has two drawbacks. The GEKS index for the most recent period $T+1$ does not only depend on the data of periods 0 and $T+1$ but also on the data of all intermediate periods. Hence, when the time series is extended, there will be an increasing *loss of characteristicity*.[6] Furthermore, the GEKS method suffers from *revision*: the price index numbers for periods $1,...,T$ computed using the extended data set will differ from the previously computed index numbers.

To reduce the loss of characteristicity and circumvent the revision of previously computed price index numbers, Ivancic, Diewert and Fox (2011) propose a *rolling year approach*. This approach makes repeated use of the price and quantity data for the last 13 months (or 5 quarters) to construct GEKS indexes. A window of 13 months has been chosen as it is the shortest period that can deal with seasonal products. The most recent month-on-month index movement is then chain linked to the existing time series. Using $P_{GEKS}^{0,12}$ as the starting point for compiling a monthly time series, the Rolling Year GEKS (RYGEKS) index for the next month becomes

$$P_{RYGEKS}^{0,13} = P_{GEKS}^{0,12} \prod_{t=1}^{13} \left[P^{12,t} \times P^{t,13} \right]^{1/13} = \prod_{t=0}^{12} \left[P^{0t} \times P^{t,12} \right]^{1/13} \prod_{t=1}^{13} \left[P^{12,t} \times P^{t,13} \right]^{1/13} . \tag{7}$$

[6] Caves, Christensen and Diewert (1982) define characteristicity as the "degree to which weights are specific to the comparison at hand". The GEKS procedure can be interpreted as a means of preserving characteristicity as much as possible.

One month later, the RYGEKS index is

$$P_{RYGEKS}^{0,14} = P_{RYGEKS}^{0,13} \prod_{t=2}^{14} \left[P^{13,t} \times P^{t,14} \right]^{1/13} . \qquad (8)$$

This chain linking procedure is repeated each next month.

Ivancic, Diewert and Fox (2011) used bilateral matched-item Fisher indexes in the above formulas. Following de Haan and van der Grient (2011), we will use bilateral Törnqvist indexes since their geometric structure facilitates a decomposition analysis, as will be shown later on. Both the Fisher index and the Törnqvist index satisfy the time reversal test and usually generate very similar results.

Unlike GEKS indexes, RYGEKS indexes are not by definition free from chain drift. Nevertheless, it is most likely that any chain drift will be very small; since each 13 month GEKS series is free from chain drift, we would expect chain linking the GEKS index changes not to lead to a drifting series. Empirical evidence from scanner data on goods sold at supermarkets lends support to our expectation that RYGEKS indexes are approximately drift free; see e.g., Ivancic, Diewert and Fox (2011), de Haan and van der Grient (2011), Johansen and Nygaard (2011), and Krsinich (2011).

Although matched-item GEKS indexes are free from *chain drift*, this does not necessarily mean they are completely drift free; there may be other causes for a drifting or biased time series. Greenlees and McClelland (2010) show that matched-item GEKS price indexes for apparel suffer from significant downward bias. The prices of apparel items typically exibit a downward trend so that any matched-item index will measure a price decline. The problem here is a lack of explicit quality adjustment.[7] Of course this quality change problem carries over to RYGEKS indexes.

The problem can in principle be dealt with by using bilateral *imputation price indexes* as inputs into the RYGEKS procedure rather than their matched counterparts, provided that the imputations "make sense". Imputation indexes use all the matches in the data and, in addition, impute the "missing prices" that are associated with new and disappearing items. In section 3 below, we discuss the (hedonic) imputation Törnqvist index and decompose this index into three factors: the contributions of matched items, new items and disappearing items.

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[7] As mentioned by van der Grient and de Haan (2010), this problem may be partly due to the use of a too detailed item identifier, in which case items that are comparable from the consumer's perspective would be treated as different items.

3. Hedonic Imputation Törnqvist Price Indexes

The issue considered in this section (and in sections 4 and 5) is how the *unmatched* new and disappearing items should be treated in a bilateral Törnqvist price index, where we compare two time periods. For the sake of simplicity, we compare period 0 with period *t* $(t = 1,...,T)$. In section 6 we will show how to handle all the bilateral price comparisons that show up in the RYGEKS framework and also give an overview of the steps to be followed for estimating imputation Törnqvist-RYGEKS indexes.

We will denote the set of items that are available in both period 0 and period *t* by U^{0t}. For these matched items, we have base period prices p_i^0 and period *t* prices p_i^t, so that we can compute price relatives p_i^t / p_i^0. The set of disappearing items, which were observed in period 0 but are no longer available in period *t*, is denoted by $U^0_{D(t)}$. Here, the base period price is known but the period *t* price is unobservable. To compute price relatives for the disappearing items, values $\hat{p}_i^t$ have to be predicted (imputed) for the "missing" period *t* observations. The set of new items, which are observed in period *t* but were not available in period 0, is denoted by $U^t_{N(0)}$. In this case the period *t* prices are known but the base period prices are "missing" and must be imputed by $\hat{p}_i^0$ to be able to compute the price relatives. Note that $U^{0t} \cup U^0_{D(t)} = U^0$, the total set of items in period 0, and $U^{0t} \cup U^t_{N(0)} = U^t$, the total set of items in period *t*. Using the observed and imputed prices, the imputation Törnqvist price index – which equals the square root of the product of the imputation geometric Laspeyres and Paasche indexes – is given by

$$P_{SIT}^{0t} = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_i^0} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_i^0} \right]^{\frac{1}{2}} \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_i^t} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_i^t} \right]^{\frac{1}{2}}$$

$$= \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{s_i^0 + s_i^t}{2}} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{\frac{s_i^0}{2}} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{\frac{s_i^t}{2}} . \qquad (9)$$

P_{SIT}^{0t} is a so-called *single* imputation Törnqvist index. Statistical agencies use the term imputation for estimating missing observations, and so "single" imputation would be the usual approach. In the index number literature, "double" imputation has also been used. In a double imputation price index, the observed prices of the unmatched new and disappearing items are replaced by the predicted values. Hill and Melser (2008) discuss all kinds of different imputation indexes based on hedonic regression. They argue that the double imputation method may be less prone to omitted variables bias because the biases in the numerator and denominator of the estimated price relatives for unmatched items are likely to cancel out, at least partially.[8] Although we will also estimate double imputation Törnqvist indexes in the empirical section 7, the single imputation variant is our point of reference because, as will be shown in section 4, this links up with the use of a weighted time dummy variable approach to hedonic regression.

In Appendix 1 it is shown that P_{SIT}^{0t} can be decomposed as[9]

$$P_{SIT}^{0t} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{s_{i(0t)}^0 + s_{i(0t)}^t}{2}} \left[\frac{\prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_{iD(t)}^0}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0}} \right]^{\frac{s_{D(t)}^0}{2}} \left[\frac{\prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_{iN(0)}^t}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t}} \right]^{\frac{s_{N(0)}^t}{2}}, \tag{10}$$

where $s_{i(0t)}^0$ and $s_{i(0t)}^t$ denote the expenditure share of item *i* with respect to the set U^{0t} of matched items in period 0 and period *t*, respectively; $s_{iD(t)}^0$ is the period 0 expenditure share of *i* with respect to the set $U_{D(t)}^0$ of disappearing items, and $s_{iN(0)}^t$ is the period *t* expenditure share of *i* with respect to the set $U_{N(0)}^t$ of new items; $s_{D(t)}^0 = \sum_{i \in U_{D(t)}^0} s_i^0$ is the aggregate period 0 expenditure share of disappearing items, and $s_{N(0)}^t = \sum_{i \in U_{N(0)}^t} s_i^t$ is the aggregate period *t* expenditure share of new items. The first factor in (10) is the matched-item Törnqvist index. The second factor equals the ratio, raised to the power of $s_{D(t)}^0 / 2$, of the imputation geometric Laspeyres index for the disappearing items and the geometric Laspeyres index for the matched items. The third factor is the ratio, raised to the power of $s_{N(0)}^t / 2$, of the imputation geometric Paasche index for the new items and the geometric Paasche index for the matched items.

The product of the second and third factor can be viewed as an *adjustment factor* by which the matched-item Törnqvist price index should be multiplied in order to obtain a quality-adjusted price index. If someone prefers the matched-item index as a measure of aggregate price change, then from an imputations perspective she is either assuming that the second and third factors cancel each other out (which would be a coincidence) or that the "missing prices" are imputed such that both factors are equal to 1. The latter occurs if $\hat{p}_i^t$ for the disappearing items is calculated through multiplying the period 0

[8] See also Syed (2010), who focuses on consistency rather than bias and makes a similar case.

[9] A similar decomposition holds for the double imputation Törnqvist index.

price by the matched-item geometric Laspeyres price index $\prod_{i \in U^{0t}} (p_i^t / p_i^0)^{s_{i(0t)}^0}$ and if $\hat{p}_i^0$ for the new items is calculated through dividing the period *t* price by the matched-item geometric Paasche price index $\prod_{i \in U^{0t}} (p_i^t / p_i^0)^{s_{i(0t)}^t}$. There is no a priori reason to think this would be appropriate.

The imputations should measure the Hicksian *reservation prices*, i.e., the prices that would have been observed if the items had been available on the market. Of course these fictitious prices can only be estimated by using some kind of modelling. Hedonic regression is an obvious choice in this respect.[10] The hedonic hypothesis postulates that a good is a bundle of, say, *K* price determining characteristics. We will denote the fixed "quantity" of the *k*-th characteristic for item *i* by z_{ik} $(k = 1,...,K)$. Triplett (2006) and others have argued that the functional form should be determined empirically, but we will only consider the logarithmic-linear model specification:

$$\ln p_i^t = \alpha^t + \sum_{k=1}^{K} \beta_k^t z_{ik} + \varepsilon_i^t ; \qquad t = 0,...,T, \qquad (11)$$

where β_k^t is the parameter for characteristic *k* in period *t* and ε_i^t is an error term with an expected value of zero. The log-linear model specification has been frequently applied and usually performs quite well. It has three advantages: it accounts for the fact that the (absolute) errors are likely to be bigger for higher priced items, it is convenient for use in a geometric index such as the Törnqvist, and it can be compared with the models we will be using in sections 4 and 5.

We assume that model (11) is estimated separately for each time period by least squares regression. Using the estimated parameters $\hat{\alpha}^t$ and $\hat{\beta}_k^t$, the predicted prices are denoted by $\hat{p}_i^t = \exp(\hat{\alpha}^t + \sum_{k=1}^{K} \hat{\beta}_k^t z_{ik})$. The predicted values for $i \in U_{D(t)}^0$ and $i \in U_{N(0)}^t$ serve as imputations in the single imputation Törnqvist price index P_{SIT}^{0t} given by (9). It is easily verified that P_{SIT}^{0t} satisfies the time reversal test. An issue is whether we should use either Ordinary Least Squares (OLS) or Weighted Least Squares (WLS) regression. From an econometric point of view, some form of WLS could help increase efficiency (i.e., reduce the standard errors of the regression coefficients) when heteroskedasticity is present. With homoskedastic errors, OLS would seem to be appropriate. Silver (2003)

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[10] This is true for product varieties which are comparable in the sense that they can be described by the same set of characteristics so that their prices can be modeled by the same hedonic function. We do not address the problem of entirely new goods, which have different characteristics than existing goods due to, for example, new production techniques.

pointed out, however, that we have *multiple observations* for item *i*, equal to the number of sales q_i^t, rather than a single observation. Running an OLS regression on a data set where each item counts q_i^t times is equivalent to running a WLS regression where the q_i^t serve as weights. This type of WLS would reflect the economic importance of the items in terms of quantities sold.

Instead of quantities or quantity shares[11] we could alternatively use expenditure shares as weights in the regressions. In section 4 we will explain that a particular type of expenditure-share weighting is "optimal" when estimating a (two-period) pooled time dummy variable hedonic model. But in the current situation, where we estimate separate models for each time period, the weighting issue is not completely settled. It may be worthwhile following a two-stage approach by first using expenditure share weights and next adjusting these weights for any observed heteroskedasticity.

4. The Weighted Time Dummy Hedonic Method

The hedonic imputation method discussed in section 3 has the virtue of being flexible in the sense that the characteristics parameters are allowed to change over time. In spite of this, it may be useful to constrain the parameters to be the same in the periods compared to increase efficiency. Again, we will be looking at bilateral comparisons (to be used in an RYGEKS framework) where the starting period 0 is compared with period *t*, and where *t* runs from 1 to *T*. Replacing the β_k^t in the log-linear hedonic model (11) by time-independent parameters β_k yields

$$\ln p_i^t = \alpha^t + \sum_{k=1}^{K} \beta_k z_{ik} + \varepsilon_i^t \; ; \qquad t = 0,...,T \,. \tag{12}$$

Model (13) should be estimated on the pooled data of the two periods compared. Using a dummy variable D_i^t that has the value 1 if the observation relates to period t $(t \neq 0)$ and the value 0 if the observation relates to period 0, the estimating equation for the *time dummy variable method* becomes[12]

[11] When using the item's quantity share, i.e., the quantity sold divided by the aggregate quantity sold, as its weight, the weights of the different items add up to 1 while leaving the estimates unaffected. Note that aggregating quantities across different items has no particular economic interpretation.

[12] Diewert, Heravi and Silver (2009) and de Haan (2010) compare the (weighted) hedonic imputation and time dummy approaches.

$$\ln p_i^t = \alpha + \delta^t D_i^t + \sum_{k=1}^{K} \beta_k z_{ik} + \varepsilon_i^t \; ; \qquad t = 0,...,T , \qquad (13)$$

where ε_i^t is an error term with an expected value of zero, as before. Note that the time dummy parameter δ^t shifts the hedonic surface upwards or downwards. The estimated time dummy and characteristics parameters are $\hat{\delta}^t$ and $\hat{\beta}_k$. Since model (13) controls for changes in the characteristics, $\exp \hat{\delta}^t$ is a measure of quality-adjusted price change between periods 0 and *t*. The predicted prices in the base period 0 and the comparison periods *t* are $\hat{p}_i^0 = \exp(\hat{\alpha} + \sum_{k=1}^{K} \hat{\beta}_k z_{ik})$ and $\hat{p}_i^t = \exp(\hat{\alpha} + \hat{\delta}^t + \sum_{k=1}^{K} \hat{\beta}_k z_{ik})$, so we have $\exp \hat{\delta}^t = \hat{p}_i^t / \hat{p}_i^0$ for all i $(t = 1,...,T)$.

The question arises what regression weights are optimal, in the sense that they would properly reflect the items' economic importance when estimating equation (13) by WLS. In Appendix 2 it is shown that if the weights for the matched items are the same in periods 0 and *t*, i.e., if $w_i^0 = w_i^t = w_i^{0t}$ for $i \in U^{0t}$, then the time dummy index can be expressed as

$$P_{TD}^{0t} = \exp \hat{\delta}^t = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{w_i^{0t}} \prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{w_i^0} \prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{w_i^t} \right]^{\frac{1}{w^{0t} + w_{D(t)}^0 + w_{N(0)}^t}} , \qquad (14)$$

where, as before, U^{0t} is the set of matched items (with respect to periods 0 and *t*), $U_{D(t)}^0$ is the set of disappearing items, and $U_{N(0)}^t$ is the set of new items; $w^{0t} = \sum_{i \in U^{0t}} w_i^{0t}$, $w_{D(t)}^0 = \sum_{i \in U_{D(t)}^0} w_i^0$ and $w_{N(0)}^t = \sum_{i \in U_{N(0)}^1} w_i^t$

Following up on the work of Diewert (2003), de Haan (2004) suggested taking the average expenditure shares as weights for the matched items, i.e., $w_i^{0t} = (s_i^0 + s_i^t)/2$ for $i \in U^{0t}$, and taking half of the expenditures shares for the unmatched items (in the periods they are available), i.e, $w_i^0 = s_i^0 / 2$ for $i \in U_{D(t)}^0$ and $w_i^t = s_i^t / 2$ for $i \in U_{N(0)}^t$.[13] Since now $w^{0t} + w_{D(t)}^0 + w_{N(0)}^t = 1$, substitution of the proposed weights into (14) gives

$$P_{TD}^{0t} = \exp \hat{\delta}^t = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{s_i^0 + s_i^t}{2}} \prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{\frac{s_i^0}{2}} \prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{\frac{s_i^t}{2}} . \qquad (15)$$

The weighted time dummy hedonic index (15) is a special case of the *single imputation* Törnqvist price index given by (9), where the "missing prices" for the unmatched items are imputed according to the estimated time dummy model. Note that the regression

[13] Diewert (2003) used the full expenditure shares for the unmatched items instead of half their values.

weights are identical to the weights used to aggregate the price relatives in the Törnqvist formula. So the notion of economic importance is the same in the weighted regression and in the index number formula, which is reassuring. Note further that the time dummy index satisfies the time reversal test.

If there are no new or disappearing items, then (15) reduces to the matched-item Törnqvist index. Thus, the result is independent of the set of characteristics included in the model. This is a desirable property: in this case we want the resulting price index to be based on the standard matched-model methodology and not be affected by the model specification. If we had used OLS regression to estimate model (13) on the pooled data of periods 0 and *t*, then in the matched-items case the time dummy index would equal the (unweighted) Jevons index. This is obviously undesirable, so the weighting issue is particularly important for the time dummy method.

5. The Weighted Time-Product Dummy Method

As mentioned previously, the hedonic hypothesis states that a product can be seen as a bundle of characteristics that determines the quality, hence the price, of the product. The number of relevant characteristics differs across product groups. In practice the set of characteristics is typically rather limited, often because sufficient information is lacking or because the inclusion of additional characteristics causes statistical problems such as multicollinearity. But what if detailed information on characteristics is missing? This is not an unrealistic situation. Statistical agencies are increasingly getting access to highly disaggregated (scanner) data on prices and quantities purchased, but the data sets often include only loose item descriptions. Obtaining sufficiently detailed information on item characteristics can be difficult or costly.

Let us look at the extreme case when no price determining characteristics at all are known and see what happens if the only "characteristic" of an item that is included in the time dummy model is a dummy variable that identifies the item. Suppose that we have N different items, both matched and unmatched ones. The estimating equation for the bilateral time dummy model then becomes

$$\ln p_i^t = \alpha + \delta^t D_i^t + \sum_{i=1}^{N-1} \gamma_i D_i + \varepsilon_i^t \ , \tag{16}$$

where the item or product dummy variable D_i has the value 1 if the observation relates to item *i* and 0 otherwise; γ_i is the corresponding parameter. We assume that the item for which a product dummy is excluded from model (16), i.e., $i = N$, belongs to the set of matched items.[14]

Model (16) is a so-called "fixed-effects" model and has been applied by several researchers to estimate price indexes, e.g., by Aizcorbe, Corrado and Doms (2003) and Krsinich (2011). In the international price comparisons literature, where countries are compared instead of time periods, the method is known as the Country-Product Dummy (CPD) method.[15] In the present intertemporal context we will refer to it as the *Time-Product Dummy* (TPD) method. The period 0 and period *t* predicted prices for item *i* are given by $\hat{p}_i^0 = \exp(\hat{\alpha} + \hat{\gamma}_i)$ and $\hat{p}_i^t = \exp(\hat{\alpha} + \hat{\delta}^t + \hat{\gamma}_i)$. The estimated fixed effect for item *i* equals (the exponential of) $\hat{\gamma}_i$, and the estimated two-period time dummy index is $\exp \hat{\delta}^t = \hat{p}_i^t / \hat{p}_i^0$, as before.

In the general exposition of section 4 we did not specify the set of characteristics included in the time dummy model, so the main results also apply in the present context. We list the most important properties:

- The TPD method automatically imputes the "missing prices" for the unmatched items.[16]
- The TPD index satisfies the time reversal test.
- If all items are matched during the two time periods compared, and if the model is estimated by OLS regression, then the bilateral TPD index equals the Jevons price index.

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[14] Alternatively, we could exclude the intercept term and include a dummy variable for this item (plus a time dummy for the base period). This would not affect the results. The only reason for us to include an intercept was to underline the similarity with the standard time dummy hedonic model.

[15] There is a large literature on international price comparisons and the associated measurement problems. An elementary introduction can be found in Eurostat and OECD (2006). For more advanced overviews, see Diewert (1999) and Balk (2001) (2008).

[16] This property of "filling holes" in an incomplete data set was the reason for Summers (1973) to propose the (multilateral) CPD method as an alternative to the (G)EKS method. It has been argued that another advantage of the CPD method is the possibility to calculate standard errors. But the interpretation of these standard errors is not straightforward if, as with scanner data, we observe the entire finite population of items. For example, if all items are observed and matched, then the bilateral weighted TPD index equals the Törnqvist price index, which has no sampling error but does have a standard error attached to it. This standard error is in fact a measure of model error rather than sampling error (unless one would be willing to assume that the finite population is a sample from a "super population").

- If a WLS regression is run on the pooled data of (the two) periods 0 and t with appropriate expenditure share weights, then the resulting TPD index is a single imputation Törnqvist index.

One interpretation of the TPD model goes as follows. Hedonic regressions are susceptible to omitted variables bias because many of the important price-determining characteristics may be unobservable. If the number of potential characteristics is very large, then each item would be a unique bundle of characteristics so that the total effect on the price will also be unique. This item-specific effect is "fixed" if all characteristics parameters are assumed constant over time, in agreement with the time dummy variable method.[17] Thus, the TPD method can be viewed as a variant of the time dummy method where item-specific effects are measured through dummy variables. Since the weighted TPD method accounts for new and disappearing items by making implicit imputations, the resulting index may seem preferable to the matched-item Törnqvist index.

There are a number of issues involved, however. First, the above interpretation of the TPD approach ignores the usefulness of multivariate analysis. Even if the bundle of characteristics would be unique for each item, there will typically still be overlapping characteristics across items, albeit in different quantities. This enables the estimation of the characteristics' shadow prices and the computation of quality-adjusted price indexes based upon them. Second, the item-specific effects will be inaccurately estimated in the bilateral case because we have only one price observation for an unmatched item. Third, because these effects are measured through dummy variables, the observed prices of the unmatched items in the periods they are available are equal to the predicted prices.

The third point has an interesting implication. Substituting $p_i^0 = \hat{p}_i^0$ for $i \in U_{D(t)}^0$ and $p_i^t = \hat{p}_i^t$ for $i \in U_{N(0)}^t$ into decomposition (10), and recalling that $\hat{p}_i^t / \hat{p}_i^0 = \exp \hat{\delta}^t$, the weighted bilateral TPD index turns out to be a weighted mean of the matched-item geometric Laspeyres and Paasche price indexes:

$$P_{TPD}^{0t} = \exp \hat{\delta}^t = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0} \right]^{\frac{s_M^0}{s_M^0 + s_M^t}} \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t} \right]^{\frac{s_M^t}{s_M^0 + s_M^t}}, \qquad (17)$$

where s_M^0 and s_M^t denote the aggregate expenditures shares of the matched items in the two periods. If $s_M^0 > s_M^t$ $(s_M^0 < s_M^t)$, the weight attached to the matched-item geometric

[17] For a similar argumentation, see Aizcorbe, Corrado and Doms (2003).

Laspeyres index will be greater (smaller) than the weight attached to the matched-item geometric Paasche index. If $s_M^t = s_M^0$, then (17) reduces to the matched-item Törnqvist index. In the unweighted case, the bilateral TPD index would be equal to the matched-item Jevons index. This result was derived earlier by Silver and Heravi (2005), so our result is a generalization of theirs.

It can be seen that, conditional on the weights for the matched items, expression (17) is insensitive to the choice of weights for the unmatched items. That is, due to the least squares (orthogonality) property with respect to the residuals, the bilateral TPD method implicitly imputes the "missing prices" in such a way that the weights for the new and disappearing items become redundant and a matched-item index results. Thus, this method does not resolve the quality-change problem.

6. Estimating Imputation Törnqvist-RYGEKS Indexes

In sections 3, 4 and 5 we discussed the estimation of (single) imputation Törnqvist price indexes. Three different imputation variants were presented: explicit imputation, based on a log-linear hedonic model and estimated separately for each time period (section 3); implicit imputation, based on a weighted version of the time dummy method (section 4); and implicit imputation based on the weighted time-product dummy method (section 5). In all three cases, the bilateral indexes compared each time period *t* directly with the base period 0. In order to estimate imputation Törnqvist RYGEKS indexes, we need all kinds of bilateral comparisons. However, the general idea stays the same, and the three methods can be easily extended to other comparisons.

Recall expression (5) for the GEKS index, which we repeat here:

$$P_{GEKS}^{0T} = \prod_{t=0}^{T} \left[P^{0t} \times P^{tT} \right]^{1/(T+1)}, \tag{18}$$

where *T* denotes the most recent period; when using monthly data, *T* will be equal to 12. This expression holds for the three bilateral imputation Törnqvist price indexes as they all satisfy the time reversal test. In addition to bilateral indexes P^{0t} going from 0 to *t*, we require bilateral indexes P^{tT} going from *t* to *T*. The construction of P^{tT} is similar to that of P^{0t}; we only need to change the two time periods compared. Extending this to the RYGEKS framework is also straightforward. We move the 13-month window one month forward, estimate GEKS price indexes again, compute the latest monthly index change and chain link this change to the existing series. This procedure is repeated each month.

For convenience, we will list the steps to be followed for estimating Imputation Törnqvist Rolling Year GEKS (ITRYGEKS) price indexes using bilateral time dummy hedonic indexes. A similar procedure (excluding step 1) can be applied to ITRYGEKS indexes using bilateral TPD indexes, but in this case modeling is unnecessary because, as shown by equation (17), the weighted bilateral TPD indexes are equal to a weighted average of the matched-item geometric Laspeyres and Paasche indexes.

We distinguish eight steps:

1. Select an appropriate set of price-determining characteristics for the product category in question that will be used in the log-linear time dummy hedonic model.[18]
2. Estimate bilateral time dummy models by weighted least squares regression using data pertaining to the first 13 months $(0,...,12)$, where the weights are expenditure shares as defined in section 4.
3. Compute the corresponding bilateral time dummy price index numbers.
4. Calculate the GEKS index numbers for months $1,...,12$ according to equation (17) using these bilateral time index numbers; the index for period 0 is equal to 1.
5. Repeat steps 2, 3, and 4 for the period covering months $1,...,13$.
6. Compute the most recent GEKS index change by dividing the index number for month 13 by the index number for month 12.
7. Chain link the index change through multiplication to the existing series.
8. Repeat steps 5, 6, and 7 for subsequent 13-month windows.

There are two issues that may need further clarification. First, the time dummy method assumes that the characteristics parameters are constant over time. In a rolling-year framework, this assumption is relaxed since the parameters are constrained to be the same for no more than 13 months. There is an inconsistency in assuming fixity of the parameters during, say, the first 13-month period (months 0,…,12) and then during the second 13-month period (months 1,…,13) because the parameters relating to months

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[18] For practical advice on the estimation of hedonic regression models, see ILO *et al*. (2004), Triplett (2006), and Destatis (2009).

1,…,12 are allowed to take on different values in the two 13-month windows, which is at variance with the underlying assumption. However, the flexibility of the rolling year approach is a very useful property, and it seems to us that this type of inconsistency is not a major problem.[19] Note that the rolling year approach is also flexible in the sense that it facilitates changing the set of characteristics included in the hedonic model when deemed necessary.

Second, one may wonder why we are not using a more straightforward approach to estimating transitive, quality-adjusted price indexes. In particular, pooling the data of many periods and running a time dummy (or TPD) regression would generate transitive indexes because the results of a pooled regression is insensitive to the choice of base period.[20] To mitigate the problem that the indexes will increasingly be based on model predictions as the number of matched items decreases over time, we could restrict the regression to 13 months and apply a rolling year procedure; this would also circumvent the problem of revisions.

The point is that our choice for the regression weights that implicitly produces a single imputation Törnqvist price index in the two-period case cannot be extended to the multi-period case because we would have multiple weights for the observations of the matched items in the starting period 0. In the empirical section 7 we will nevertheless estimate rolling year multilateral time dummy and TPD indexes, using monthly varying expenditure shares as regression weights,[21] to investigate how these simpler methods perform.

Other important questions addressed in section 7 are the following. What is the effect of imputing the "missing prices" in Törnqvist-RYGEKS indexes as compared to their matched-item counterparts? Does the choice of imputation method matter much? Are different product categories equally affected by the imputations?

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[19] Even if the *population* parameter values within each 13-month window were constant, the *estimated* parameters for the bilateral comparisons will generally differ because they are estimated on different data sets.

[20] Silver and Heravi (2005) mention that the equivalence of the TPD method in the two-period case to a matched-item index does not carry over to the case where there are more than two periods, but "it can be seen that in the many-period case, the .... [TPD] measures of price change will have a tendency to follow the chained matched-model results."

[21] In a preliminary version of their 2011 paper, Ivancic, Diewert and Fox (2009) compared matched-item Fisher-GEKS and expenditure-share weighted TPD indexes (but not weighted time dummy indexes) and found that these were very similar.

7. Evidence from New Zealand Scanner Data

7.1 Consumer electronics scanner data from GfK

Statistics New Zealand has been using scanner data for consumer electronics products from market research company GfK for a number of years, to inform expenditure weighting. This data contains sales values and quantities aggregated to quarterly levels for combinations of brand, model and up to 6 characteristics. Recently a much more detailed dataset was purchased for the three years from mid 2008 to mid 2011 for eight products: camcorders, desktop computers, digital cameras, DVD players and recorders, laptop computers, microwave ovens, televisions, and portable media players. Monthly sales values and quantities are disaggregated by brand, model and around 40 characteristics. Table 1 is an artificial example that shows the structure of the data received with a subset of characteristics. Note that, for confidentiality reasons, sales and quantities have had random noise added and brand and model names are omitted completely.

Table 1. Consumer electronics scanner data structure

OBS #	PERIOD	QUANTITY SOLD	TOTAL SALES	MODEL	BRAND	CF CARD	CHIPTYPE	DIGITAL INDEX
1	Mar-11	7	2277.59	*	*	NO CF CARD	CCD	DIGITAL INDEX
2	Mar-11	388	146213.38	*	*	N.A.	CCD	DIGITAL INDEX
3	Mar-11	152	67078.15	*	*	N.A.	CCD	N.A.
4	Mar-11	143	88634.93	*	*	NO CF CARD	CCD	DIGITAL INDEX
5	Mar-11	132	80531.68	*	*	NO CF CARD	CCD	DIGITAL INDEX
6	Mar-11	103	109032.06	*	*	NO CF CARD	CMOS	DIGITAL INDEX
7	Mar-11	83	27314.77	*	*	NO CF CARD	CCD	DIGITAL INDEX
8	Mar-11	58	53096.64	*	*	NO CF CARD	CMOS	DIGITAL INDEX
9	Mar-11	43	40971.79	*	*	N.A.	CMOS	N.A.
10	Apr-11	43	29163.53	*	*	NO CF CARD	CCD	N.A.
11	Apr-11	37	43785.84	*	*	NO CF CARD	CMOS	DIGITAL INDEX
12	Apr-11	29	24746.86	*	*	NO CF CARD	CMOS	N.A.
13	Apr-11	27	11563.74	*	*	NO CF CARD	CCD	DIGITAL INDEX
14	Apr-11	25	10852.06	*	*	NO CF CARD	CCD	DIGITAL INDEX
15	Apr-11	23	17257.10	*	*	NO CF CARD	CMOS	DIGITAL INDEX
16	Apr-11	17	25483.29	*	*	NO CF CARD	CMOS	DIGITAL INDEX
17	Apr-11	14	13488.18	*	*	NO CF CARD	CMOS	N.A.
18	Apr-11	13	25640.43	*	*	NO CF CARD	CMOS	N.A.
19	Apr-11	17	18819.06	*	*	NO CF CARD	CMOS	DIGITAL INDEX
20	Apr-11	16	6821.91	*	*	NO CF CARD	CMOS	N.A.
OBS #	**DIGITAL INPUT**	**HD Formats**	**IMAGE STABIL.**	**LCD SCREEN SIZE**	**MEMORY CAPACITY**	**OPTICAL ZOOM**	**OUTDOOR FUNCTIO**	**PIXEL TOTAL**
1	NO DIG. INPUT	SD	ELEC.STAB	2.7	60	32	N.A.	1.07
2	NO DIG. INPUT	SD	OPTICAL STAB.	2.7	N.A.	70	NO WATER_SHOCK	0.8
3	DIGITAL INPUT	SD	ELEC.STAB	2.7	4	60	NO WATER_SHOCK	1.07
4	NO DIG. INPUT	SD	OPTICAL STAB.	2.7	80	78	N.A.	0.8
5	DIGITAL INPUT	SD	ELEC.STAB	2.7	80	60	NO WATER_SHOCK	0.68
6	NO DIG. INPUT	HD HDD	OPTICAL STAB.	2.7	120	25	NO WATER_SHOCK	3.32
7	DIGITAL INPUT	SD	ELEC.STAB	2.7	N.A.	39	NO WATER_SHOCK	0.8
8	DIGITAL INPUT	HD MEMORY	OPTICAL STAB.	2.7	N.A.	25	N.A.	3.32
9	DIGITAL INPUT	HD MEMORY	ELEC.STAB	2.7	8	25	N.A.	2.36
10	NO DIG. INPUT	SD	ELEC.STAB	2.7	16	37	N.A.	0.8
11	DIGITAL INPUT	HD HDD	ELEC.STAB	2.7	120	25	NO WATER_SHOCK	2.36
12	NO DIG. INPUT	HD MEMORY	ELEC.STAB	3	4	10	N.A.	10
13	NO DIG. INPUT	SD	ELEC.STAB	2.7	N.A.	52	NO WATER_SHOCK	0.8
14	NO DIG. INPUT	SD	ELEC.STAB	2.7	N.A.	37	NO WATER_SHOCK	0.8
15	NO DIG. INPUT	HD MEMORY	OPTICAL STAB.	2.7	N.A.	20	NO WATER_SHOCK	3.32
16	NO DIG. INPUT	HD MEMORY	OPTICAL STAB.	3	N.A.	12	N.A.	9.15
17	NO DIG. INPUT	HD MEMORY	ELEC.STAB	2.7	32	20	N.A.	2.39
18	NO DIG. INPUT	HD MEMORY	OPTICAL STAB.	3.5	64	10	NO WATER_SHOCK	6.63
19	DIGITAL INPUT	HD HDD	OPTICAL STAB.	2.7	160	12	NO WATER_SHOCK	7.1
20	NO DIG. INPUT	HD MEMORY	ELEC.STAB	2.7	8	30	NO WATER_SHOCK	3.32

Also for confidentiality reasons, any brand with a share of more than 95%[22] of total sales for the month within a single retailer is renamed to 'tradebrand' in GfK's output system; similarly at the model level if more than 80% of the sales of that model are within a single retailer. The GfK output system currently has a maximum number of around 40 characteristics that can be produced for any product. Of the 8 products we were looking at, 6 of them had more than 40 characteristics available – most of these had around 60 characteristics. The aggregation to tradebrand at the brand and model level happens independently for each set of characteristics which means the resulting files were unable to be perfectly merged back together. We determined subsets of the full set of characteristics that would give virtually the same results for a time product dummy index (based on the imperfectly merged data) and requested these.

The resulting sets of around 40 characteristics used for each of the eight products are shown in Appendix 3. Ideally we would hope to find a way to bypass the need for this confidentialising to 'tradebrand' if we were to adopt scanner data in production for price indexes.

7.2 New and disappearing items

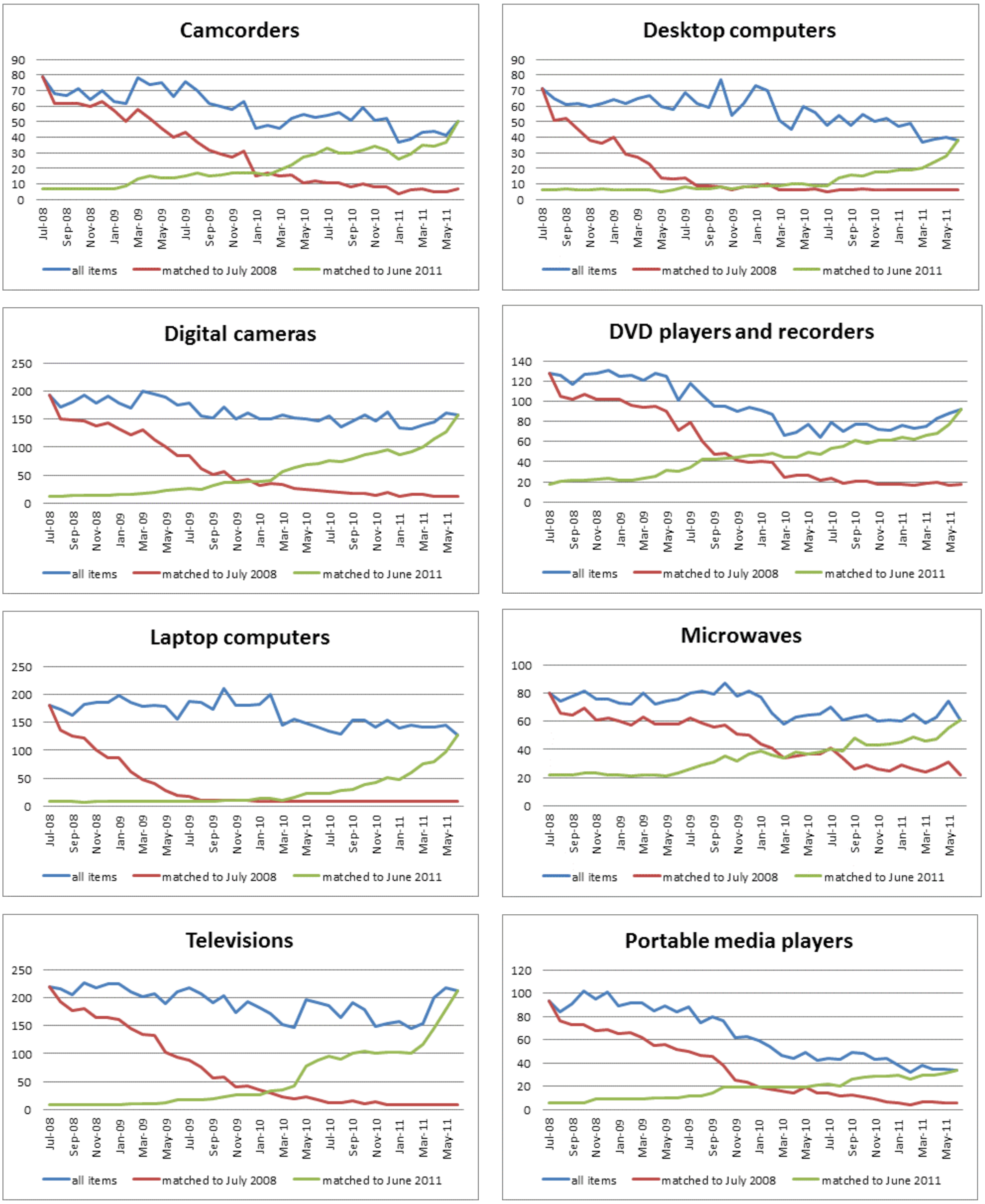
For ease of the following discussion, we will use the term 'item' to refer to a unique combination of brand, model and the full set of characteristics available in the scanner data. Note that for a given model of a product, there can be different combinations of characteristics available, so 'model' in itself is not sufficiently identifying.

A key feature of scanner data is that it reflects the high level of 'churn' in the specific items available and being sold from month to month. That is, there are many new models (and versions of models) of the product becoming available in the market and, conversely, old models dropping out of the market as they become obselete. Figure 1 shows, for each of the eight products, the number of items available over the three year period, alongside those items that existed at the start and end of the three year period. The y-axis shows the number of items being sold in each month. For each product, the blue line 'all items' shows the number of distinct items being sold in each

[22] For all the products looked at in this paper except microwaves, which has a threshold of 99%.

month. For example, in July 2008, there are over 200 different kinds of television being sold, while there are only around 70 different kinds of desktop computers being sold.

Figure 1. Total and matched items mid-2008 to mid-2011



For most of the products, the number of models being sold is gradually decreasing over the three year period. It is not clear whether this is a real-world effect or whether it may be a consequence of the aggregation to ‘tradebrand’ mentioned earlier. Perhaps concentration of particular brands or models being sold by a particular retailer might be increasing over time. This requires further investigation, but for the main purpose of this paper – comparing different methodologies on the same set of scanner data – this appears unlikely to be an issue.

The red line ‘matched to July 2008’ shows, for each product, the number of distinct items sold in each month that were also being sold at the start of the three year period, and similarly the green line ‘matched to June 2011’ shows the number of distinct items sold in each month that are also being sold in the final month of the three year period. We can see that for some products, such as desktop and laptop computers, the rates of new and disappearing items are very high whereas for other products, in particular microwaves, the churn is less extreme. This matches our expectations that there is more rapid technological change (embodied in new items) for high-technology products such as computers.

Figure 2 allows us to more easily compare the attrition rates of different products by showing the percentage of July 2008 items still being sold (i.e., the red line graphs from figure 1) for all products on one graph. This highlights that computers – both desktops and laptops – have the highest churn.

Figure 2. Percentage of July 2008 models available July 2008 to June 2011

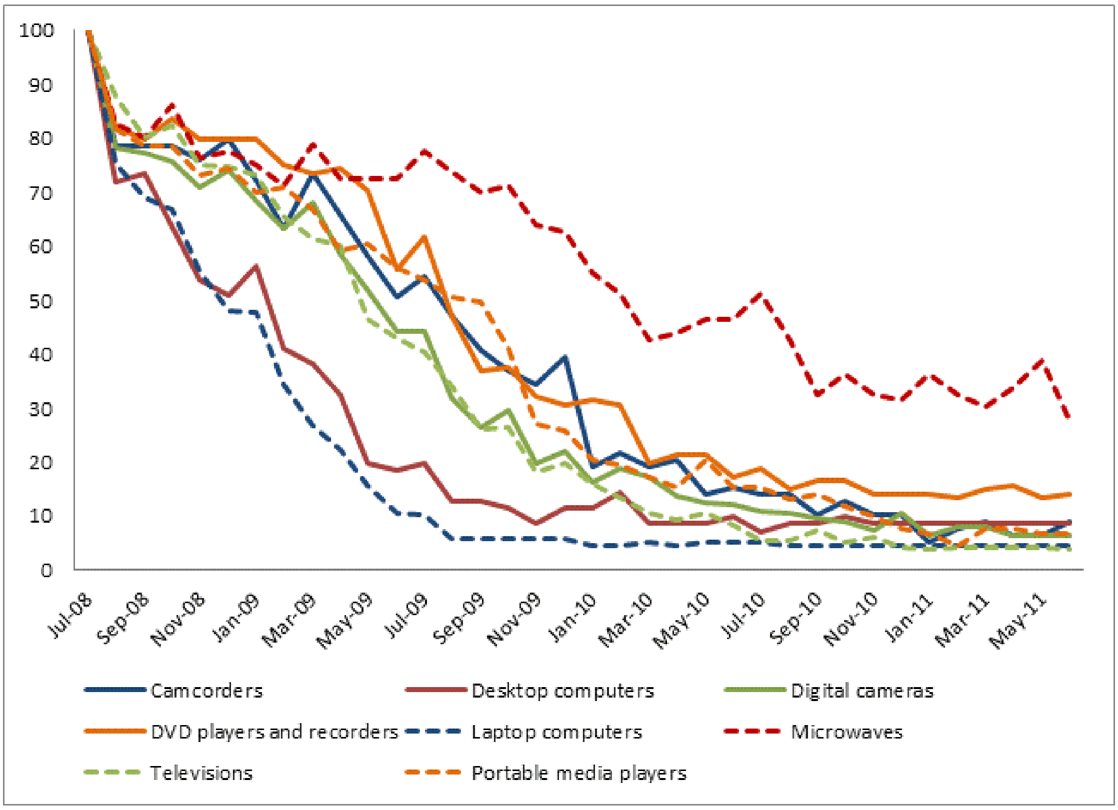
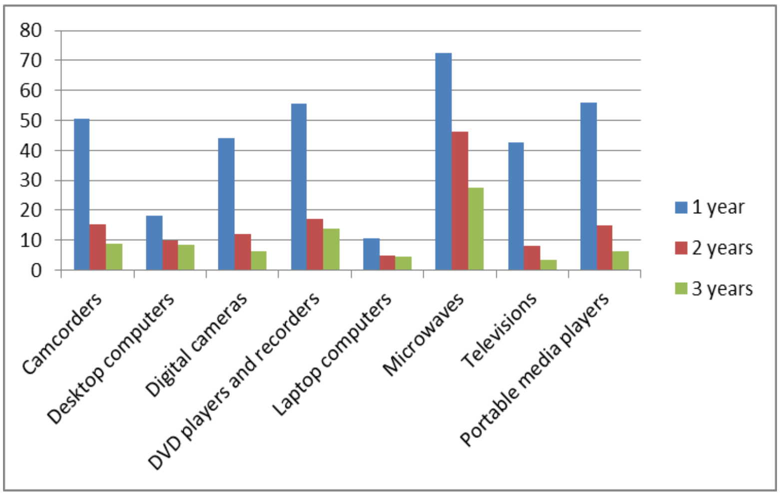


Figure 3 shows a more summarised version of the same information, with the percentage of models sold in July 2008 that are still available after 1, 2 and 3 years (as at June of 2009, 2010 and 2011). For most of the products, there are less than 10% of the items still matched after a three year period.

Figure 3. Percentage of July 2008 models available after 1, 2 and 3 years



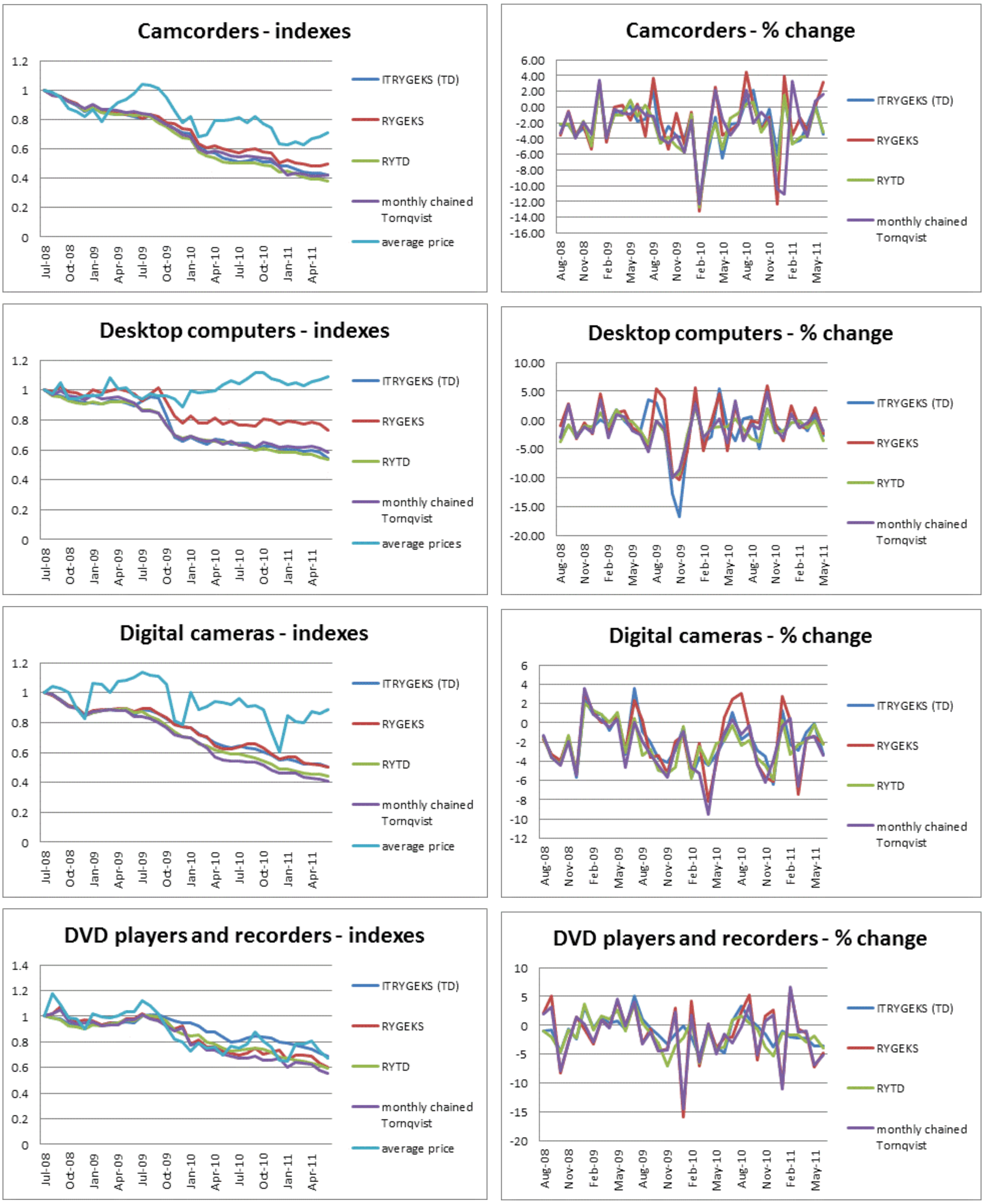
7.3 ITRYGEKS with time dummy implicit imputation

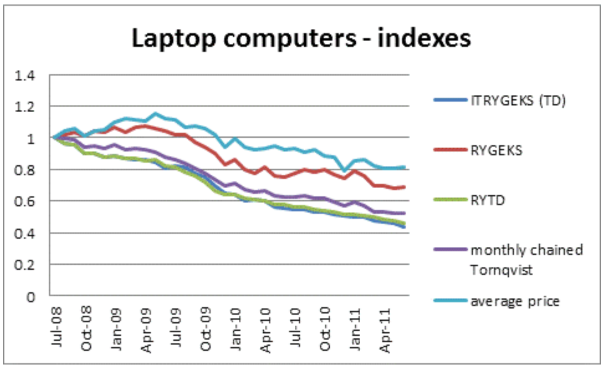
Section 4 provides the theoretical basis for the Imputation Törnqvist RYGEKS index based on the weighted time dummy hedonic method which we will refer to now as the ITRYGEKS(TD). We produced the ITRYGEKS(TD) for each of the eight consumer electronics products, using a 13-month rolling window. These are compared below in figure 4 to indexes based on three other methods:

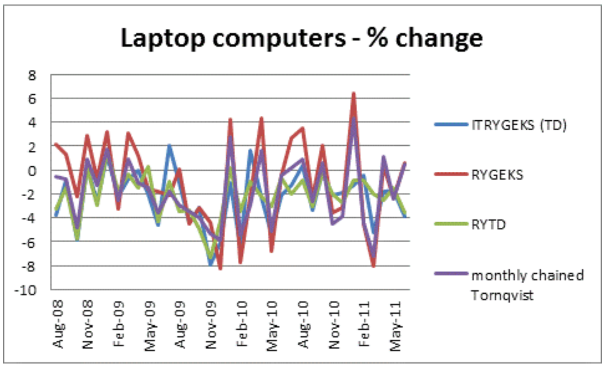
- a rolling year GEKS index based on bilateral matched-item Törnqvist indexes, with a 13-month rolling window (RYGEKS);
- a rolling year pooled time dummy hedonic index (using monthly expenditure share weights), with a 13-month rolling window (RYTD);
- a monthly chained Törnqvist index.

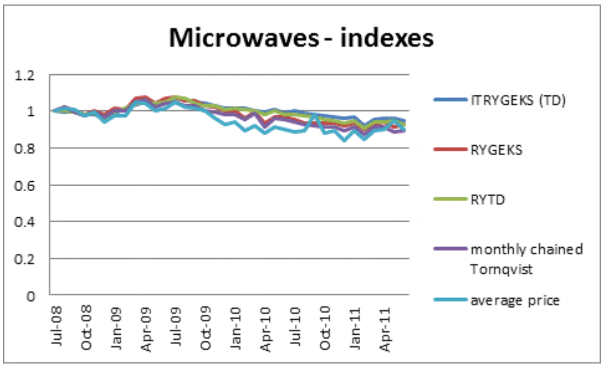
We also include a unit value index for each product each month, calculated as the total expenditure divided by the total quantity sold. This gives us an index of the prices unadjusted for quality change, which is useful in seeing how quality is changing over time, and for examining seasonal patterns. In particular note the strong seasonal dips for the average prices of digital cameras corresponding to cheaper cameras being sold over the Christmas period. Also shown in figure 4 are the corresponding monthly percentage price changes for each product.

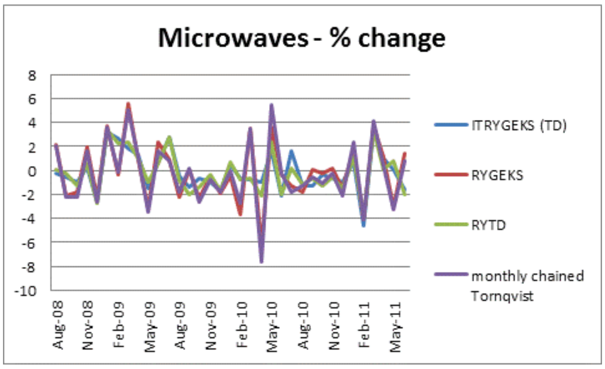
Figure 4. ITRYGEKS(TD) compared with other methods

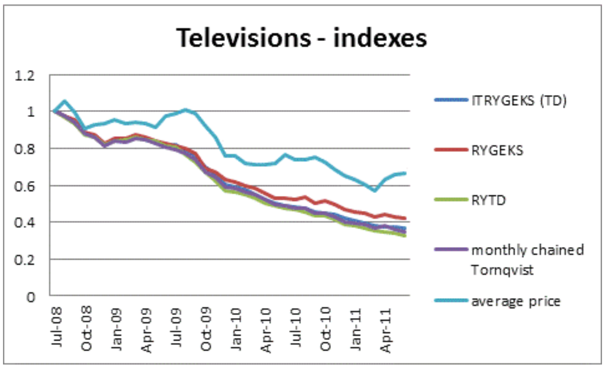


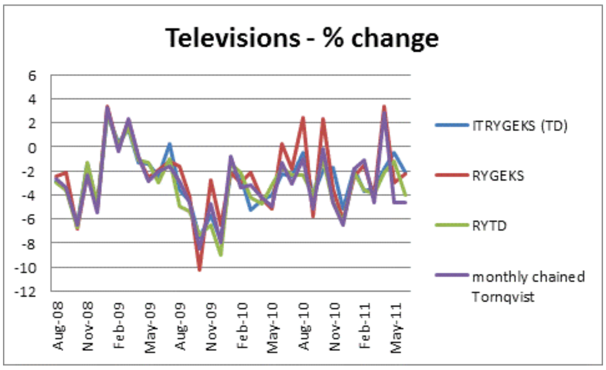

Laptop computers - indexes
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Jul-08
Oct-08
Jan-09
Apr-09
Jul-09
Oct-09
Jan-10
Apr-10
Jul-10
Oct-10
Jan-11
Apr-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist
average price

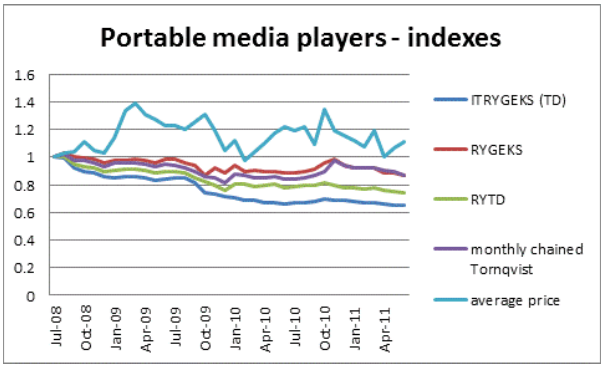

Laptop computers - % change
8
6
4
2
0
-2
-4
-6
-8
-10
Aug-08
Nov-08
Feb-09
May-09
Aug-09
Nov-09
Feb-10
May-10
Aug-10
Nov-10
Feb-11
May-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist

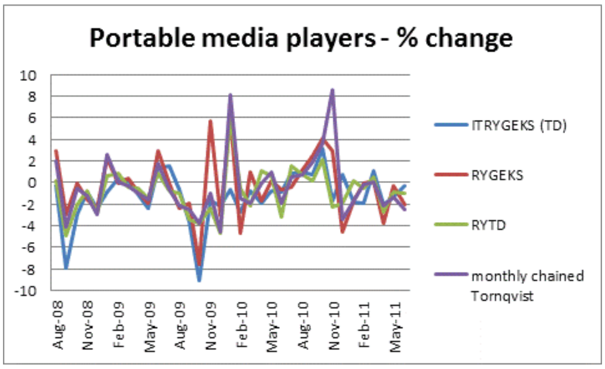

Microwaves - indexes
1.2
1
0.8
0.6
0.4
0.2
0
Jul-08
Oct-08
Jan-09
Apr-09
Jul-09
Oct-09
Jan-10
Apr-10
Jul-10
Oct-10
Jan-11
Apr-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist
average price


Microwaves - % change
8
6
4
2
0
-2
-4
-6
-8
-10
Aug-08
Nov-08
Feb-09
May-09
Aug-09
Nov-09
Feb-10
May-10
Aug-10
Nov-10
Feb-11
May-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist


Televisions - indexes
1.2
1
0.8
0.6
0.4
0.2
0
Jul-08
Oct-08
Jan-09
Apr-09
Jul-09
Oct-09
Jan-10
Apr-10
Jul-10
Oct-10
Jan-11
Apr-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist
average price


Televisions - % change
6
4
2
0
-2
-4
-6
-8
-10
-12
Aug-08
Nov-08
Feb-09
May-09
Aug-09
Nov-09
Feb-10
May-10
Aug-10
Nov-10
Feb-11
May-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist


Portable media players - indexes
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
Jul-08
Oct-08
Jan-09
Apr-09
Jul-09
Oct-09
Jan-10
Apr-10
Jul-10
Oct-10
Jan-11
Apr-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist
average price

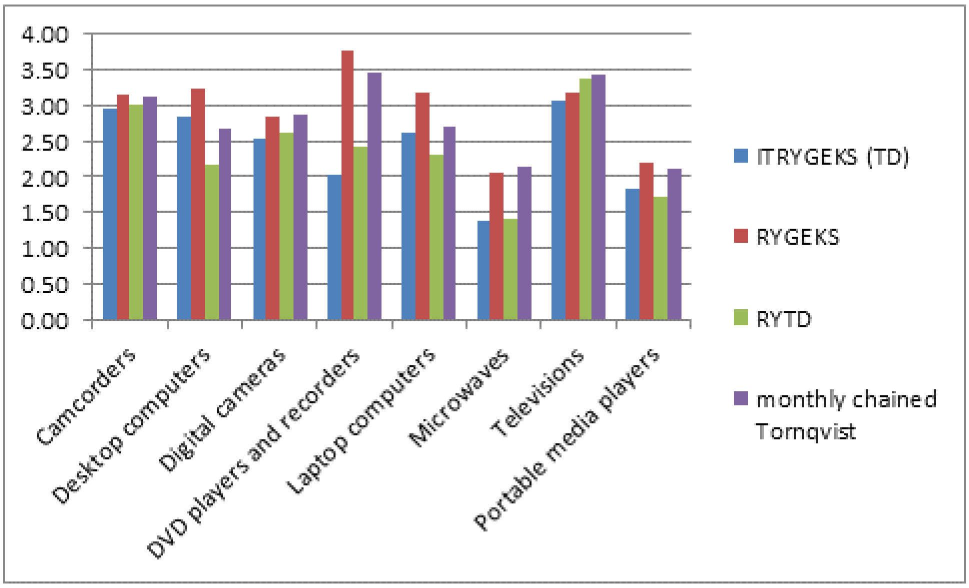

Portable media players - % change
10
8
6
4
2
0
-2
-4
-6
-8
-10
Aug-08
Nov-08
Feb-09
May-09
Aug-09
Nov-09
Feb-10
May-10
Aug-10
Nov-10
Feb-11
May-11
ITRYGEKS (TD)
RYGEKS
RYTD
monthly chained Tornqvist

The results vary across products; there is no consistent pattern in the relative behaviour of the different index methods. For both desktop and laptop computers, the ITRYGEKS(TD) is lower than the RYGEKS and similar to both the RYTD and (less so for laptops) the chained Törnqvist.

For many of the products the ITRYGEKS(TD) is lower than the RYGEKS and relatively close to both the RYTD and the chained Törnqvist. The exceptions to this are DVD players and recorders and microwaves, where the ITRYGEKS(TD) is higher than the other methods, and digital cameras where the ITRYGEKS(TD) is approximately the same as the RYGEKS. Portable media players is another exception where the ITRYGEKS(TD) is significantly below all the other methods.

Looking at the percentage changes we can see that both the ITRYGEKS(TD) and RYTD are less volatile than the other methods. This is confirmed in figure 5, which shows the volatility of each method, defined as the average of the absolute monthly percentage changes for each of the eight products.

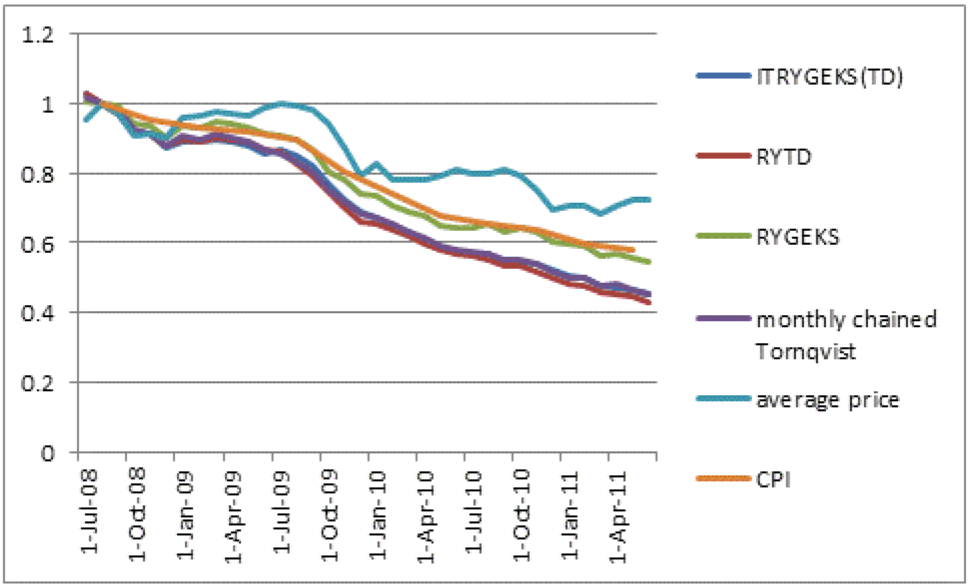
Figure 5. Volatility of each method



The different methods for calculating price indexes from the scanner data can give quite different results at the product level. To see how these aggregate up the CPI hierarchy we created a 'consumer electronics' aggregate of the eight products, using the expenditures from the GfK data to weight the individual products' price indexes for each of the methods compared. We also included in this comparison the price changes for the products that were incorporated into the New Zealand Consumers Prices Index for the corresponding period.

Figure 6 shows that, at this higher level, the existing New Zealand CPI gives a result that is very similar to the RYGEKS, while the other methods – monthly chained Tornqvist, rolling year time dummy and ITRYGEKS(TD) all sit lower and similar to each other. This suggests that the matched model approach of both the RYGEKS and the existing practice are tending to miss net price decreases associated with new and disappearing items.

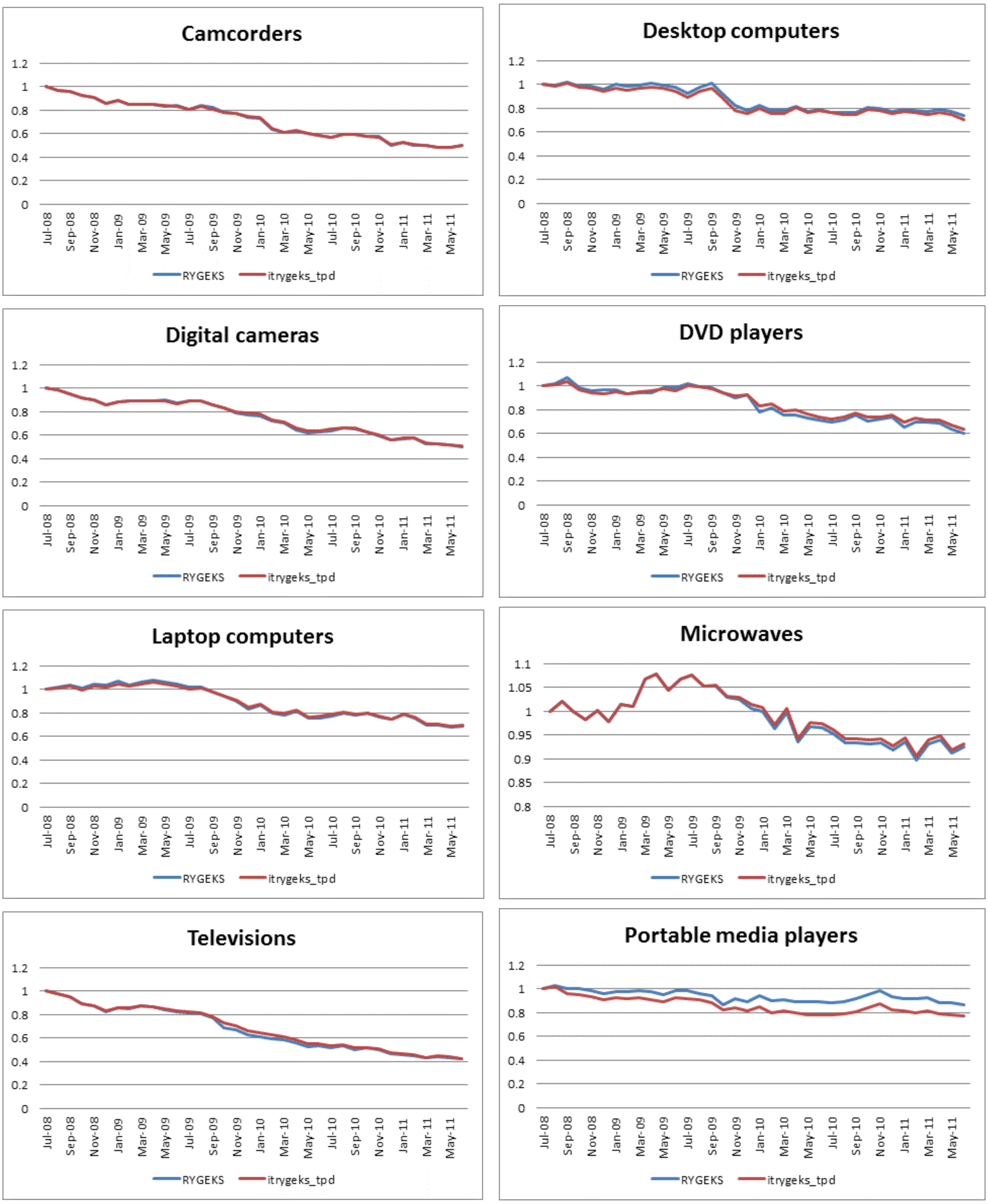
Figure 6. Products aggregated to 'consumer electronics' for each method



7.4 ITRYGEKS with time product dummy implicit imputation

As described in section 4 above, the ITRYGEKS using the time product dummy (TPD) implicit imputation method results in no imputation for the new and disappearing items, so the results from applying this method are are virtually the same as the RYGEKS. Any difference between the two is due to the change over time in the expenditure share of the matched items, as reflected in the weights used in the time product dummy modelling for the ITRYGEKS(TPD).

Figure 7. ITRYGEKS(TPD) compared with RYGEKS



7.5 ITRYGEKS with explicit hedonic imputation

Section 3 explained the ITRYGEKS based on explicit hedonic imputation. However, the explicit imputation version of the ITRYGEKS does not work for characteristics data which is mainly categorical, as is the case for our consumer electronics scanner data. The main reason why the method breaks down in this case is that new or disappearing items generally correspond to new or disappearing categories of one or more of the characteristics. They can also correspond to new combinations of existing categories of characteristics but this is less frequent. For example, generally there is a new model name associated with a new item, so the characteristic 'model' will have a new value. Because the regression modelling recognises categories of a categorical variable in the same way as dummy variables, this is equivalent to new binary characteristics appearing and disappearing in the data. That means that, for the periods in which we are trying to impute a value for the new or disappearing item there is likely to be at least one category of a characteristic corresponding to that item which does not exist in that period and therefore we cannot produce a predicted value for the new (or disappearing) item based on its characteristics.

Note that the explicit hedonic imputation version of the ITRYGEKS will work in the situation where the characteristics are numeric and/or where the characteristics are categoric but there are no new or disappearing categories of these categorical characteristics over the time period for which the index is produced.

8. Conclusions

The Imputation Törnqvist (IT) RYGEKS method explicitly or implicitly imputes price movements for new and disappearing items based on hedonic models and is equivalent to the RYGEKS (Törnqvist) for the subset of the population which is matched from period to period. The paper outlines three variants of the ITRYGEKS: explicit hedonic imputation, and implicit imputation via either a time-product dummy or time-dummy hedonic model.

Explicit hedonic imputation is not valid in the case of categorical variables which can have new categories appearing or disappearing.

Implicit imputation via a time-product dummy method results in no imputation for new and disappearing items and is therefore very close to the RYGEKS index. Any difference between the two reflects the change in the expenditure share of matched items which is reflected in the weights used for the time product dummy regression modelling.

Implicit imputation via the time dummy hedonic method gives results which can differ from any of the other methods examined (Rolling-Year Time Dummy, Rolling Year GEKS, monthly chained Törnqvist). The results are less volatile than the RYTD and RYGEKS and similar in their volatility to the monthly chained Törnqvist.

Although research on supermarket scanner data (Ivancic et al. (2009), Krsinich (2011)) has found evidence of substantial chain drift for monthly chained superlative price indexes, for the consumer electronics products examined here, there appears to be minimal, if any, chain drift. This is likely to reflect that, unlike supermarket products, consumer electronics products are not 'stockpiled' to anywhere near the same extent, and therefore the spiking in both prices (down) quantities (up) is not nearly so prevalent in the data.

While there can be significant differences between the methods at the product level, at the 'consumer electronics' level (as approximated by the aggregation of the eight products using expenditure shares from the GfK data) the differences cancel out to a certain extent. In particular, the aggregation of the price indexes from the current New Zealand CPI is very close to the aggregated ITRYGEKS (TD).

Appendix 1: Derivation of Decomposition (10)

In this appendix we derive decomposition (10) of the single imputation Törnqvist index (9). For convenience we write the index as

$$P_{SIT}^{0t} = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_i^0} \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_i^t} \prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_i^0} \prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_i^t} \right]^{\frac{1}{2}}, \tag{A.1}$$

where $\hat{p}_i^0$ and $\hat{p}_i^t$ are the imputed prices in periods 0 and *t*, and s_i^0 and s_i^t are the expenditure shares (with respect to the total set of items in periods 0 and *t*). As in the main text, we will denote the expenditure shares with respect to the set U^{0t} of matched items in periods 0 and *t* by $s_{i(0t)}^0$ and $s_{i(0t)}^t$; $s_{iD(t)}^0$ and $s_{iN(0)}^t$ are the expenditure shares of *i* with respect to the sets $U_{D(t)}^0$ and $U_{N(0)}^t$ of disappearing and new items; $s_{D(t)}^0$ and $s_{N(0)}^t$

are the period 0 and t aggregate expenditure shares of the disappearing and new items; s_M^0 and s_M^t are the period 0 and period t aggregate expenditure shares of the matched items.

Since $s_i^0 = s_{i(0t)}^0 s_M^0$ and $s_i^t = s_{i(0t)}^t s_M^t$ for $i \in U^{0t}$, $s_i^0 = s_{iD(t)}^0 s_{D(t)}^0$ for $i \in U_{D(t)}^0$ and $s_i^t = s_{iN(0)}^t s_{N(0)}^t$ for $i \in U_{N(0)}^t$, equation (A.1) can be written as

$$P_{SIT}^{0t} = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0 s_M^0} \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t s_M^t} \prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_{iD(t)}^0 s_{D(t)}^0} \prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_{iN(0)}^t s_{N(0)}^t} \right]^{\frac{1}{2}}$$

$$= \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0 (1 - s_{D(t)}^0)} \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t (1 - s_{N(0)}^t)} \prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_{iD(t)}^0 s_{D(t)}^0} \prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_{iN(0)}^t s_{N(0)}^t} \right]^{\frac{1}{2}}, \quad \text{(A.2)}$$

using $s_M^0 = 1 - s_D^0$ and $s_M^t = 1 - s_N^t$. Rearranging terms gives

$$P_{SIT}^{0t} = \left[\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0} \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t} \right]^{\frac{1}{2}} \left[\frac{\prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_{iD(t)}^0 s_{D(t)}^0}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0 s_{D(t)}^0}} \right]^{\frac{1}{2}} \left[\frac{\prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_{iN(0)}^t s_{N(0)}^t}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t s_{N(0)}^t}} \right]^{\frac{1}{2}}$$

$$= \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{s_{i(0t)}^0 + s_{i(0t)}^t}{2}} \left[\frac{\prod_{i \in U_{D(t)}^0} \left(\frac{\hat{p}_i^t}{p_i^0} \right)^{s_{iD(t)}^0}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^0}} \right]^{\frac{s_{D(t)}^0}{2}} \left[\frac{\prod_{i \in U_{N(0)}^t} \left(\frac{p_i^t}{\hat{p}_i^0} \right)^{s_{iN(0)}^t}}{\prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{s_{i(0t)}^t}} \right]^{\frac{s_{N(0)}^t}{2}}, \quad \text{(A.3)}$$

which is equation (18) in the main text.

Appendix 2: Derivation of Equation (14)

Following de Haan (2004), in this appendix we derive expression (14) for the bilateral time dummy hedonic index. Because an intercept term is included in model (13), the weighted sum of the regression residuals $e_i^t = \ln(p_i^t) - \ln(\hat{p}_i^t) = \ln(p_i^t / \hat{p}_i^t)$ is equal to 0 in each period, hence

$$\sum\nolimits_{i \in U^t} w_i^t \ln(p_i^t / \hat{p}_i^t) = \ln\left[\prod_{i \in U^t} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t}\right] = 0\,; \qquad t = 0,...,T\,, \qquad \text{(A.4)}$$

where w_i^t denotes the weight for item i in period t in a WLS regression. If we separate the base period 0 from the comparison periods t, the second expression of (A.4) can be written as

$$\ln\left[\prod_{i \in U^0} \left(\frac{p_i^0}{\hat{p}_i^0}\right)^{w_i^0}\right] = \ln\left[\prod_{i \in U^t} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t}\right] = 0\,; \qquad t = 1,...,T\,. \qquad \text{(A.5)}$$

Exponentiating (A.5) yields the following relation:

$$\prod_{i \in U^0} \left(\frac{p_i^0}{\hat{p}_i^0}\right)^{w_i^0} = \prod_{i \in U^t} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t} = 1\,; \qquad t = 1,...,T\,. \qquad \text{(A.6)}$$

Next, we rewrite (A.6) as

$$\prod_{i \in U^{0t}} \left(\frac{p_i^0}{\hat{p}_i^0}\right)^{w_i^0} \prod_{i \in U^0_{D(t)}} \left(\frac{p_i^0}{\hat{p}_i^0}\right)^{w_i^0} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t} (=1)\,, \qquad \text{(A.7)}$$

where, as before, U^{0t} denotes the set of matched items (with respect to periods 0 and t), $U^0_{D(t)}$ is the set of disappearing items, and $U^t_{N(0)}$ is the set of new items.

We now assume that the regression weights for the matched items are the same in periods 0 and t, i.e., $w_i^0 = w_i^t = w_i^{0t}$ for $i \in U^{0t}$. In that case, multiplying the right and left hand side of equation (A.7) by $\prod_{i \in U^{0t}} (\hat{p}_i^t / p_i^0)^{w_i^{0t}}$ gives

$$\prod_{i \in U^{0t}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^{0t}} \prod_{i \in U^0_{D(t)}} \left(\frac{p_i^0}{\hat{p}_i^0}\right)^{w_i^0} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0}\right)^{w_i^{0t}} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t}\,. \qquad \text{(A.8)}$$

Multiplying both sides of (A.8) by $\prod_{i \in U^0_{D9t)}} (\hat{p}_i^t / p_i^0)^{w_i^0}$ yields

$$\prod_{i \in U^{0t}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^{0t}} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^0} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0}\right)^{w_i^{0t}} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{p_i^0}\right)^{w_i^0} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^t}\right)^{w_i^t}\,. \qquad \text{(A.9)}$$

Next, multiplying both sides of (A.9) by $\prod_{i \in U^t_{N(0)}} (\hat{p}_i^t / \hat{p}_i^0)^{w_i^t}$ gives

$$\prod_{i \in U^{0t}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^{0t}} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^0} \prod_{i \in U^t_{N(0)}} \left(\frac{\hat{p}_i^t}{\hat{p}_i^0}\right)^{w_i^t} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0}\right)^{w_i^{0t}} \prod_{i \in U^0_{D(t)}} \left(\frac{\hat{p}_i^t}{p_i^0}\right)^{w_i^0} \prod_{i \in U^t_{N(0)}} \left(\frac{p_i^t}{\hat{p}_i^0}\right)^{w_i^t}\,. \qquad \text{(A.10)}$$

Using $\hat{p}_i^t / \hat{p}_i^0 = \exp \hat{\delta}^t$ for all i, equation (A.10) can be written as

$$\left[\exp \hat{\delta}^t\right]^{w^{0t}+w^0_{D(t)}+w^t_{N(0)}} = \prod_{i\in U^{0t}}\left(\frac{p_i^t}{p_i^0}\right)^{w_i^{0t}} \prod_{i\in U^0_{D(t)}}\left(\frac{\hat{p}_i^t}{p_i^0}\right)^{w_i^0} \prod_{i\in U^t_{N(0)}}\left(\frac{p_i^t}{\hat{p}_i^0}\right)^{w_i^t}, \tag{A.11}$$

where $w^{0t} = \sum_{i\in U^{0t}} w_i^{0t}$, $w^0_{D(t)} = \sum_{i\in U^0_{D(t)}} w_i^0$ and $w^t_{N(0)} = \sum_{i\in U^t_{N(0)}} w_i^t$. It follows that

$$\exp \hat{\delta}^t = P_{TD}^{0t} = \left[\prod_{i\in U^{0t}}\left(\frac{p_i^t}{p_i^0}\right)^{w_i^{0t}} \prod_{i\in U^0_{D(t)}}\left(\frac{\hat{p}_i^t}{p_i^0}\right)^{w_i^0} \prod_{i\in U^t_{N(0)}}\left(\frac{p_i^t}{\hat{p}_i^0}\right)^{w_i^t}\right]^{\frac{1}{w^{0t}+w^0_{D(t)}+w^t_{N(0)}}}, \tag{A.12}$$

which is equation (14) in the main text.

Appendix 3: Characteristics available for each product

Camcorders		**Desktop computers**		**Digital Cameras**		**DVD players and recorders**	
Characteristic	Levels	Characteristic	Levels	Characteristic	Levels	Characteristic	Levels
16:9 REC#FORMAT	2	3D	3	ANZ CAMERA TYPE	3	1080P UPSCALING	3
3 CHIP	2	APPLE OS	3	AUTOFOCUS	2	3D CONVERSION	2
BRAND	6	ASPECT RATIO	3	AVCHD / LITE	4	APP STORE(IPTV)	3
CF CARD	3	BLUETOOTH	2	BATTERY TYPE	3	BD LIVE	2
CHIPTYPE	2	BRAND	9	BAYONET MOUNT	7	BRAND	13
DIGITAL INDEX	2	BRIGHTNESS	2	BLUETOOTH	3	CF CARD	3
DIGITAL INPUT	2	CHIPSET BRAND	5	BRAND	15	COMMON INTER CI	3
DSC CAMC RES#	3	CHIPSET TYPE	43	BRIDGE CAMERA	2	CONSUMP STANDBY	29
HANDHELD POSIT#	2	CSP-MHZ	27	CHIPTYPE	5	CONSUMPTION W	43
HD Formats	5	DEPTH IN CM	6	COMPACT FLASH	2	DIVX	2
HDD CAPACITY	8	DESIGN	4	DEPTH IN MM	182	DLNA	2
HDMI	3	DVD WRITER	4	DIGITAL ZOOM	12	DTS DECODER	4
IEEE-1394	2	GPU BRAND	5	DISPL#RES# PIX#	30	DVB-T	3
IMAGE STABIL#	3	GPU MODEL	66	DSC CAMC RES#	4	DVD AUDIO	3
IMAGE STABILIZ#	4	HEIGHT IN CM	6	DUAL CAM	4	DVD Categories	10
LCD SCREEN SIZE	8	LED	3	EFFECTIVE PIXEL	50	DVD REC# FORMAT	9
MEMORY CAPACITY	15	MC-EDITION	2	FACE DETECTION	4	EPG	3
MEMORY CARD	2	MEMORY TECHNO	3	FOLDABLE LCD	3	GOOGLE TV	2
MEMORY STICK	3	MICROSOFT OS	10	FRAMES PER SEC	12	HDD CAPACITY	10
MODEL	78	MODEL	82	GPS	2	HDMI	2
MPEG STANDARD	3	NUMBER OF CORES	5	HDMI PORT	2	HDTV	3
MULTIMEDIA CARD	3	OFFICE SUITE	2	HEIGHT IN MM	144	LAYER	3
OPTICAL ZOOM	21	ONBOARD GRAPHIC	3	IMAGE STABIL#	3	LCD SCREEN SIZE	10
OUTDOOR FUNCTIO	3	PLATFORM	2	INNER ZOOM	4	MEDIAPLAYER	4
P2	2	PROCESSOR	23	KID CAMERA	3	MEMORY CARD	2
PIXEL TOTAL	38	PROCESSOR NUMBE	91	LCD MONITOR SIZ	15	MEMORY STICK	3
RESOLUTION	3	RAM-MB	9	LIVE VIEW	2	MODEL	105
SD CARD	3	REMOTE-CONTROL	2	MAX VIDEO HT RE	10	MP3 ENCODING	2
SD Format	7	SCREEN SIZE	2	MAX VIDEO WI RE	12	MP3 PLAYBACK	3
SD/HD Format	10	SECURITY SW	2	MAX# ISO SENSIT	15	MPEG-4 RECORD#	2
SMART MEDIA	2	SIZE/INCH	9	MEMORY TYPE	4	NO# OF DISC	3
TOUCHSCREEN	3	STORAGE CAPAC#	13	MICRO DRIVE	2	PC STREAMING	3
TYPE	2	TV OUT	2	MODEL	211	REAL DOLBY DEC#	6
Type Memory Cards	7	VIDEOCARD	2	Multiple Slots	3	SD CARD	3
USB CONNECTION	2	Vision	3	OPTICAL ZOOM	16	SUPER AUDIO CD	3
VIDEO FORMAT	8	V-RAM	12	OUTDOOR FUNCTIO	5	USB RECORDING	3
VIDEOTO MC	3	WEIGHT IN KG	5	PHOTOS PER SEC#	55	WEB CONTENT ACC	3
VIEWFINDER	3			PICTBRIDGE	2	WIRELESS INTERF	3
WEIGHT IN GRAM	62						
WIRELESS INTERF	2						
XD-PICTURE CARD	3						

Laptop computers		Microwaves		Televisions		Portable media players	
Characteristic	Levels	Characteristic	Levels	Characteristic	Levels	Characteristic	Levels
3G/BB BUNDLE	2	ARTICLE FLAG	3	3D	2	AIRPLAY	2
APPLE OS	4	BRAND	14	3D CONVERSION	2	BLUETOOTH	3
ASPECT RATIO	4	CAVITY MATERIAL	6	BRAND	14	BRAND	13
BLUETOOTH	3	CONSTR#2	2	BRIGHTNESS	20	BUILT IN CAMERA	3
BRAND	13	CONSTRUCTION	3	CONSUMP STANDBY	28	CE FUSION REPORTIN(	5
BRIGHTNESS	3	COOKING PLATE	4	CONSUMPTION W	128	CF CARD	3
CE FUSION REPORTII	2	COOKINGFUNCTION	4	CONTRAST RATIO	50	COLOUR DISPLAY	2
CENTRINO	2	DEPTH IN CM	34	DISPLAY HD DC	3	DAB	2
CHIPSET BRAND	5	DETAILED MAIN TYPES	7	DIVX	3	Dictation Machine total	2
CHIPSET TYPE	52	DIGITAL CLOCK	4	DLNA	3	DIGITAL SPEECH	2
DVD WRITER	4	DOOR OPENING S#	4	DVB-C	3	DIGITAL SYSTEM	2
FINGERPRINT-ID	2	DOOR TYPE	3	DVB-S	2	DISPLAY-TECHNO	6
FORM FACTOR	7	FRONT DECORAT#	8	DVB-T	3	DIVX	3
GPU BRAND	3	GROUPS AFFILIATION	7	DVD PLAYER/REC#	2	DRM	5
GPU MODEL	88	HEIGHT	40	ENERGY STAR AU#	11	GAMING	3
HARD DRIVE TYPE	2	HUMIDITY SENSOR	3	FRAME REFRESH	9	H264 PLAYBACK	3
HEIGHT IN CM	116	INFRARED SENSOR	3	FREQUENCY	4	MEMORY CARD	3
HYPER THREADING	2	INVERTER	3	HD READY	3	MEMORY STICK	2
LED	2	KEYFEATURES	3	HD Types	3	MODEL	75
LED TECHNOLOGY	2	LIMIT_HOURS	3	HDD CAPACITY	3	MODELTEXT	209
MC-EDITION	2	LIMIT_MINUTES	5	ISDB-T	3	MP3 ENCODING	3
MEMORY TECHNO	3	MAIN TYPES - IL-	4	LED TECHNOLOGY	4	MPEG 2	3
MICROSOFT OS	15	MODEL	88	MEDIAPLAYER	4	MPEG 4	3
MODEL	278	MODELTEXT	187	MODEL	245	MULTIMEDIA CARD	3
Next Gen Core	25	NUMBER OF TRAYS	3	NO OF HDMI	6	OPERATING SYST#	4
OFFICE SUITE	5	POWERSTEPS	10	PC STREAMING	4	PC CONNECTION	3
ONBOARD GRAPHIC	3	PROGRAMMER	4	REFLECTION ANGL	12	PHOTO VIEWER	2
PROCESSOR NUMBE	124	QUARTZ GRILL	4	RESOLUTION HIG#	9	RADIO BUILT-IN	2
REMOTE-CONTROL	2	SKEWER	3	RESOLUTION WID#	11	SD CARD	3
SCREEN SIZE	5	STEAM FUNCT#INT	4	RESPONSE TIME	18	SIZE/INCH	21
TRUE RESOLUTION	11	THERMO SENSOR	4	SCREEN FORMAT	3	STOR# CAPACITY	20
TV CARD	3	TIME CONTROL	3	SD CARD	3	TOUCHSCREEN	3
TV OUT	2	TOUCH CONTROL	3	SIZE/CM	38	TV OUT	3
USB PORTS	5	TURNTABLE	3	SIZE/INCH	26	VIDEORECORD	3
V-RAM	7	TYPE OF MICROW#	6	TELE-TEXT	3	WEIGHT IN GRAM	70
WIMAX	2	VOLUME LTRS	20	USB	3	XHTML BROWSER	3
WIRELESS LAN	2	WATTAGE	11	USB RECORDING	3		
		WEIGHT SENSOR	3	WIFI	4		
		WIDTH IN CM	42				
		WITH FAN/CONVEC	2				
		WITH GRILL	2				
		WITH TOP/BOTTOM	2				
		YEAR OF INTRO	6				

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