Price indexes from online data using the fixed-effects window-splice (FEWS) index

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Citation

Abstract

Automated web-scraping of online data gives the potential for timely and high-frequency price measurement. Two key limitations of online data, however, are that it lacks both quantities and characteristics.

Krsinich (2014) showed that the fixed-effects (or time-product dummy) index is equivalent to a fully-interacted time-dummy hedonic index based on all product characteristics, and that the 'window-splice' implicitly revises the index so that the price movements associated with the introduction of new products are reflected in the index with one period's lag.

This paper presents results from applying the fixed-effects window-splice (FEWS) index to online data collected by MIT's Billion Prices Project for a major New Zealand retailer. We also simulate the effect of not including quantities in the indexes for consumer electronics and supermarket products, using scanner data.

1. Introduction

Many retailers now post their prices online. Rather than price collectors physically visiting stores periodically[1] to collect prices for a sample of products, there is now potential to use automated web-scraping to collect prices at any frequency.

If robust automated procedures can be developed to estimate quality-adjusted price indexes appropriately from this online price data, then there is potential for a move from price measurement based on a sample of product-specifications at a sample of times, to full-coverage (or close to full-coverage) in both these dimensions.

However, online data has some key limitations which appear to limit its potential for price measurement.

First, there is no information on quantities sold from the online data. While quantities sold are also not available at the product level for the traditional approach, sampled products are those deemed to be popular and/or representative, which ensures a certain degree of implicit weighting towards higher-expenditure products. With a census of all products being equally incorporated into the price indexes there is a risk that unusual or unrepresentative price movements of small-expenditure products are over-represented in the index.

Second, there is generally little or no information in the online data on the characteristics of products with which to use explicit quality adjustment techniques such as hedonic models. While there is potential for characteristics to be manually collected in-house by analysts visiting the websites and populating the data with information on characteristics, this would be a resource intensive exercise which would seem to counter the opportunities of this type of 'big data' and risk the omission of key price-determining characteristics.

Matched model approaches to quality adjustment, such as the chained Jevons currently used by the Billion Prices Project and PriceStats[2] or the (unweighted) rolling year GEKS (RYGEKS) of Ivancic et al (2011) can adjust for changes in the quality mix, including that which results from product turnover. What they can't reflect, however, is the implicit price movements of new products entering, and old products disppearing, from the market. If these implicit price movements are differ from those of matched products, a bias will result.

In this paper we will discuss the application of the fixed-effects window-splice (FEWS) index of Krsinich (2014) to online data.

Section two gives the background to the development of the FEWS method.

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[1] The New Zealand Consumers Price Index is a quarterly index. The New Zealand Food Price Index is monthly.

[2] PriceStats is the commercial counterpart of the Billion Prices Project. See www.pricestats.com

Section three explains how the FEWS index is able to produce non-revisable quality-adjusted price indexes without product characteristic information. And, unlike the GEKS or chained-Jevons indexes, the FEWS index is able to reflect the implicit price movements of new and disappearing products.

Section four gives empirical results from applying the FEWS to 15 months of daily online data for four New Zealand consumer electronics products, based on data shared with us by MIT's Billion Prices Project. The effect of not having quantities is then simulated using scanner data for New Zealand consumer electronics products from market research company GfK, and for US supermarket products from IRI marketing.

Section five concludes with some suggestions for the potential of online data for the compilation of official CPIs.

2. Background

Price measurement from scanner data has been an active area of research for Statistics NZ over the last five years. Recently, consumer electronics scanner data was incorporated into the production of the New Zealand CPI (Statistics New Zealand, 2014; Krsinich, 2015) using the Imputation Tornqvist rolling year GEKS (ITRYGEKS) method of de Haan and Krsinich (2014a).

Since the research on the ITRYGEKS method, the time-dummy (TD) hedonic index has been shown to be a geometric version of a 'quality-adjusted unit-value' index by de Haan and Krsinich (2014b) which suggests it would be another viable option in production when a full set of characteristics exist in the data.

However, supermarket scanner data and online data do not contain sufficient information on characteristics to apply either the ITRYGEKS or TD indexes.

This has led to a revisiting of the fixed-effects index, also known as the 'time-product dummy' index that was used to benchmark the New Zealand housing rentals index (Krsinich, 2011).

'Fixed-effects' is a term used in a variety of ways. We follow Allison (2005) in using it to refer to the fitting of product-specific intercepts into the regression model.

Allison explains fixed-effects methods as follows:

> (p2) … by using [fixed-effects] it is possible to control for all possible characteristics of the individuals [products] in the study – even without measuring them – so long as those characteristics do not change over time.

> (p3) The essence of a fixed-effects method is captured by saying that each individual [product] serves as his or her [its] own control. That is accomplished by making comparison within individuals (hence the need for at least two measurements), and then averaging those differences across all the individuals in the sample.

The use of fixed-effects rather than characteristics in a hedonic-type model has been a controversial one. It has been argued that it is essentially the same as a matched-model approach, and is therefore not reflecting the implicit price movements of new and disappearing products.

While this is certainly the case for bilateral indexes, Krsinich (2014) shows that a multilateral fixed-effects index leverages off the longitudinal information in the data, to produce an index which is equivalent to a fully-interacted time-dummy hedonic index.

Consumer price indexes are generally non-revisable. This, in combination with the fact that the fixed-effects index requires at least two price observations before a new product is non-trivially incorporated into the estimation, was the motivation for a new approach to the splicing required in production - the 'window splice'. The window-splice uses the movement across the entire estimation window, rather than just the movement of the most recent period. This effectively revises for the implicit price movements associated with the introduction of new products, in the period after their introduction.

We refer to this combination of a fixed-effects index with window-splicing as the 'fixed-effects window-splice' (FEWS) index.

In the December 2013 quarter, Statistics NZ first introduced fixed-effects indexes into production for the New Zealand import price index, for mobile phones and televisions. For the major brands of these two products, comprehensive data on import prices and quantities is available at a detailed product level. Because the previous quarter of the New Zealand import price index is revisable, the window-splicing aspect of the method has not been as necessary as it would be for an unrevisable index such as the CPI. However, window-splicing is likely to be incorporated in the future.

Statistics New Zealand will consider using FEWS indexes for supermarket products in the New Zealand consumers price index if and when full-coverage scanner data can be obtained from the major supermarket chains.

After some initial research on New Zealand consumer electronics daily online data, shared with us by the Billion Prices Project at MIT and presented in section 4, we have entered into a research agreement with PriceStats, who are collecting and processing daily online data for us to investigate, for a wide range of major New Zealand retailers with strong online presences. This will help to inform future decisions about the viability of incorporating online data into the New Zealand CPI.

3. The FEWS index

3.1 The fixed-effects index

De Haan and Hendriks(2013) show that the unweighted[3] fixed-effects index can be expressed as

$$P_{FE}^{0t} = \exp(\hat{\delta}^t) = \frac{\prod_{i \in S^t} (p_i^t)^{\frac{1}{N^t}}}{\prod_{i \in S^0} (p_i^0)^{\frac{1}{N^0}}} \exp\left[\bar{\hat{\gamma}}^0 - \bar{\hat{\gamma}}^t\right] \tag{1}$$

Where p_i^t is the price of product i in time t; S^t is the set of products in time t; N^t is the number of products in time t; and $\bar{\hat{\gamma}}^t = \sum_{i \in S^t} \hat{\gamma}_i / N^t$ is the sample mean of the estimated fixed effects in time t.

Krsinich (2014) shows that this fixed-effects index is equivalent to the unweighted[4] fully-interacted time-dummy hedonic index on all characteristics of the products, if characteristics are expressed as categorical variables.

For simplicity, and without loss of generality, this is shown for the case of products with just two characteristics. Equation (1) is shown to be equivalent to

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[3] They extend this formulation to the weighted case.

[4] The equivalence is empirically demonstrated for the weighted case in Krsinich (2014).

$$P_{TD_{full}}^{0t} = \exp(\hat{\delta}^t) = \frac{\prod_{i \in S^t} (p_i^t)^{\frac{1}{N^t}}}{\prod_{i \in S^0} (p_i^0)^{\frac{1}{N^0}}} \exp\left[\sum_{l=1}^{L} \hat{\beta}_l (\overline{D}_l^0 - \overline{D}_l^t) + \sum_{m=1}^{M} \hat{\beta}_m (\overline{D}_m^0 - \overline{D}_m^t) \right] \qquad (2)$$

Where $\overline{D}_l^t = \sum_{i \in S_t} D_{il} / N^t$ is the sample mean of the dummy variable for category l of the L main effects and $\hat{\beta}_l$ is the estimated parameter for category l of the L main effects. And similarly for the M second-order interactions.

3.2 The window-splice

Because a product needs two observations to be non-trivially included in the fixed-effects index, a window-splice is used to incorporate implicit revisions alongside the latest period's movement. This approach also enables the fixed-effects estimates to be updated for all the other products observed within the estimation window.

Krsinich (2014) gives the intuition for how the window-splice works.

De Haan (2015) fomulates the fixed-effects index with a standard 'movement-splice'[5] as follows

$$P_{FEMS}^{0,T+1} = P_{FE}^{0,T}(0) \times P_{FE}^{T,T+1}(1) \qquad (3)$$

Where $P_{FE}^{s,t}(x)$ is the fixed-effects index from time s to t, on an estimation window of length $T+1$, starting at time x

Using the same notation he then formulates the fixed-effects with a window-splice as

$$P_{FEWS}^{0,T+1} = P_{FE}^{0,1}(0) \times P_{FE}^{1,T+1}(1) \qquad (4)$$

and shows in his equation (12) that the FEWS index can then be expressed in terms of the FEMS index as

$$P_{FEWS}^{0,T+1} = \frac{P_{FE}^{1,T}(1)}{P_{FE}^{1,T}(0)} \times P_{FEMS}^{0,T+1} \qquad (5)$$

The ratio of $P_{FE}^{1,T}(0)$ and $P_{FE}^{1,T}(1)$ is the 'implicit revision factor', which can be expressed (eqn (13), de Haan, 2015) as

$$\frac{P_{FE}^{1,T}(1)}{P_{FE}^{1,T}(0)} = \exp\left[\sum_{i \in U^1} s_i^1 [\hat{\gamma}_i(1) - \hat{\gamma}_i(0)] - \sum_{i \in U^T} s_i^T [\hat{\gamma}_i(1) - \hat{\gamma}_i(0)] \right] \qquad (6)$$

Where:

$\hat{\gamma}_i(t)$ is the predicted fixed-effect for product i estimated on the window starting at period t,

s_i^t is the expenditure share of product i in period t

and U^t is the set of products observed in period t

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[5] ie the standard approach to splicing, for example in the RYGEKS of Ivancic et al (2011)

4. Empirical results

4.1 Daily online data for New Zealand consumer electronics

First, we look at the impact of not explicitly adjusting for new products entering, and old products disappearing from, the market. To do this we compare the performance of the daily chained Jevons[6] index to the (unweighted) daily FEWS index for three New Zealand consumer electronics products, using 15 months of daily web-scraped online data for a major New Zealand retailer shared with us by the Billion Prices Project.

An index based on the unadjusted average daily price is included, to give an indication of the change in quality of products being sold over time.

Figure 1 shows the chained Jevons index, the (unweighted) FEWS index and the average price index as daily indexes in the left hand column. We derive monthly indexes from these daily indexes in the right hand column, to more clearly show the underlying trends of the daily indexes.

Note that this data is in its raw form, and hasn't been through the usual processing / cleaning processes applied by PriceStats for their published inflation indicators. Therefore these results are indicative only, with their main purpose being to compare across price index methods. Also, there was a lapse in data collection for almost two months from early february to late march 2013, which is why the price indexes are flat for these periods.

Table 1 in the appendix summarises the number and turnover of distinct products in the data.

Figure 1. Daily and monthly indexes from BPP consumer electronics online data

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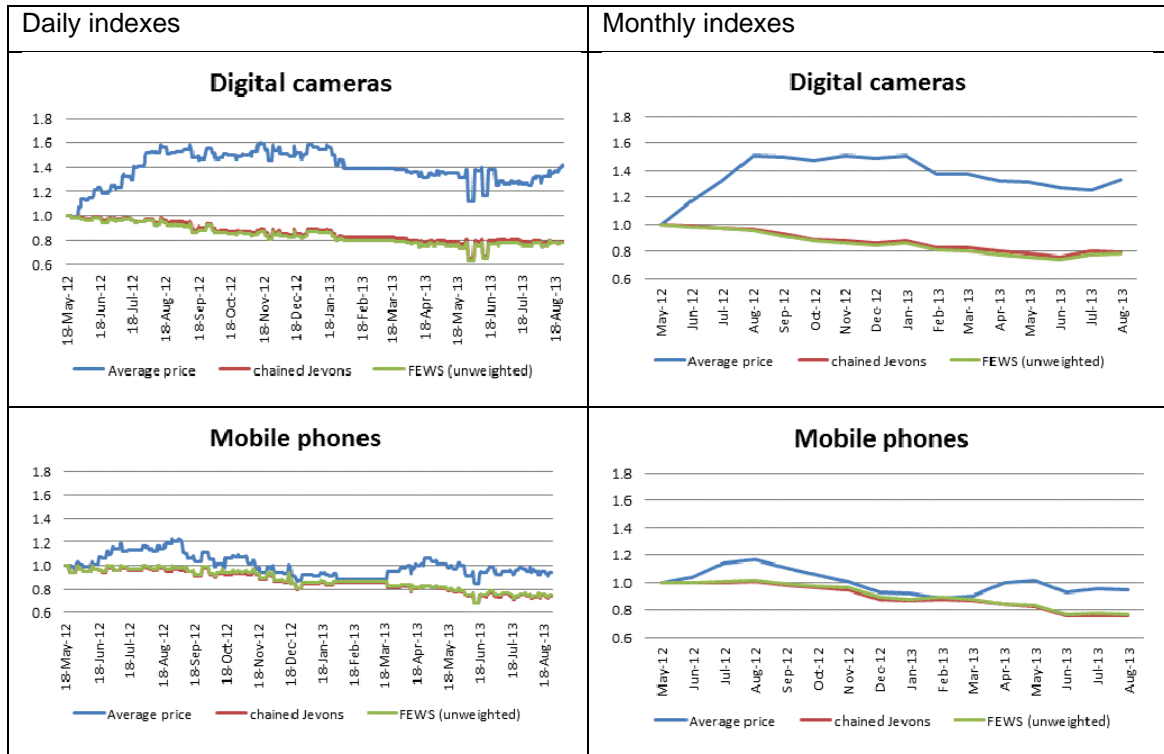
[6] The chained Jevons is the method currently used by BPP and PriceStats to calculate price indexes from the online data.
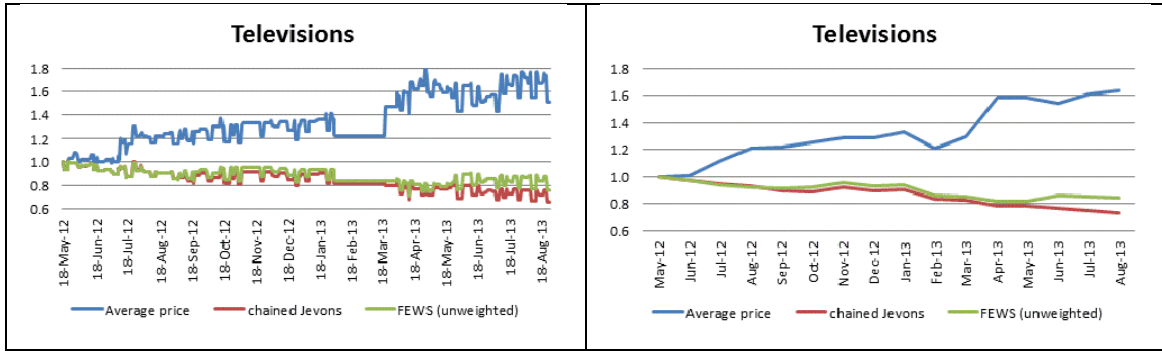
Over the 15 months from May 2012 to August 2013, the chained Jevons and unweighted FEWS indexes are very similar for both digital cameras and mobile phones.

For televisions, they sit very closely for the first, year, before starting to drift apart between May and June 2013. This implies that the implicit price movements of new and/or disappearing televisions during this time differed from those of matched products.

4.2 Monthly scanner data for New Zealand consumer electronics

Monthly-aggregated scanner data for New Zealand consumer electronics products, from market research company GfK, was used to test the effect of quantities on the price indexes.
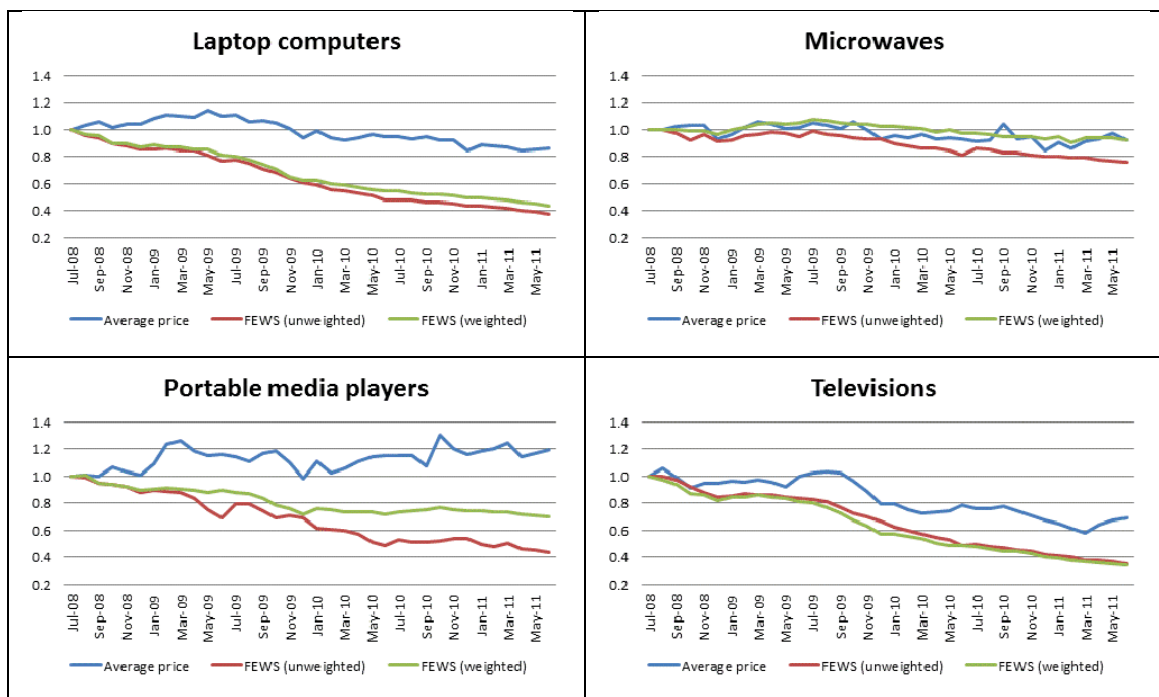
Figure 2 shows weighted and unweighted FEWS indexes, alongside the weighted average price indexes, for eight consumer electronics product categories.

Table 2 in the appendix summarises the number and turnover of distinct products in the data.

Figure 2. Monthly indexes from GfK consumer electronics scanner data
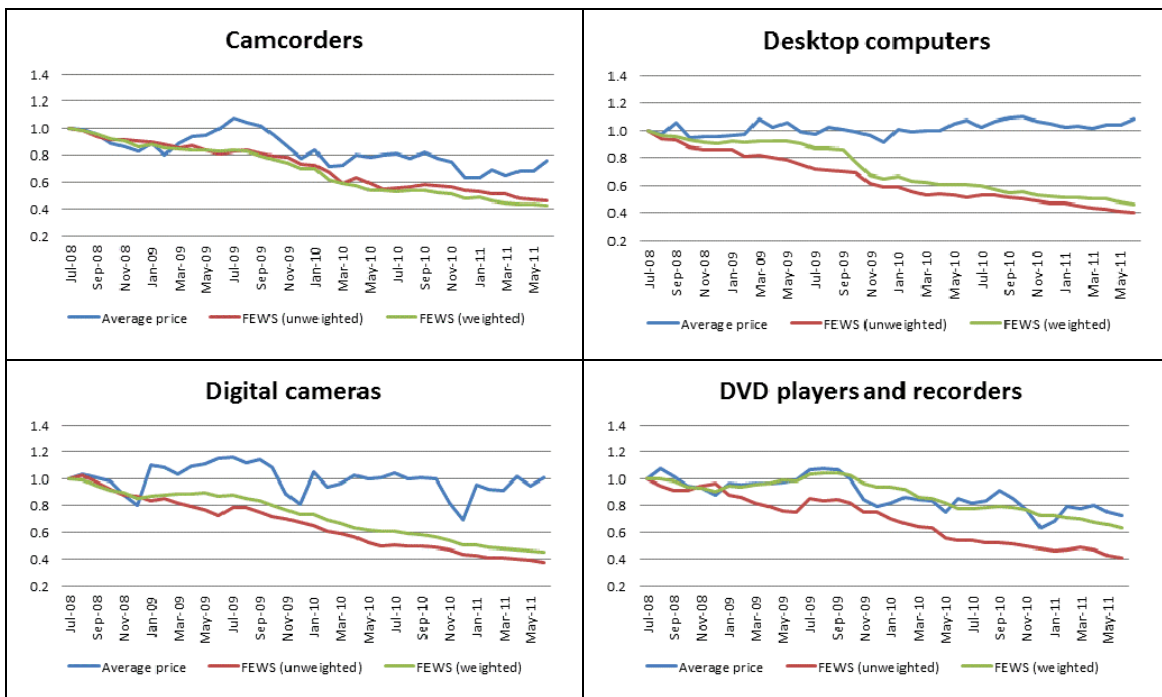
Interestingly, the quantities make little difference for five of the eight product categories: camcorders; desktop computers; digital cameras; laptop computers; and televisions.

For the other three product categories however – DVD players and recorders; microwaves; and portable media players – the omission of quantities causes a significant downward bias to the indexes.

Camcorders and, for part of the 3 year period, televisions are the only product categories for which the exclusion of weights causes an upwards bias though in both cases this is relatively small.

Note that the televisions category – for which the exclusion of quantities is making very little difference over this three-year-period – contributes almost half the expenditure weight of the aggregate consumer electronics group in the New Zealand CPI.

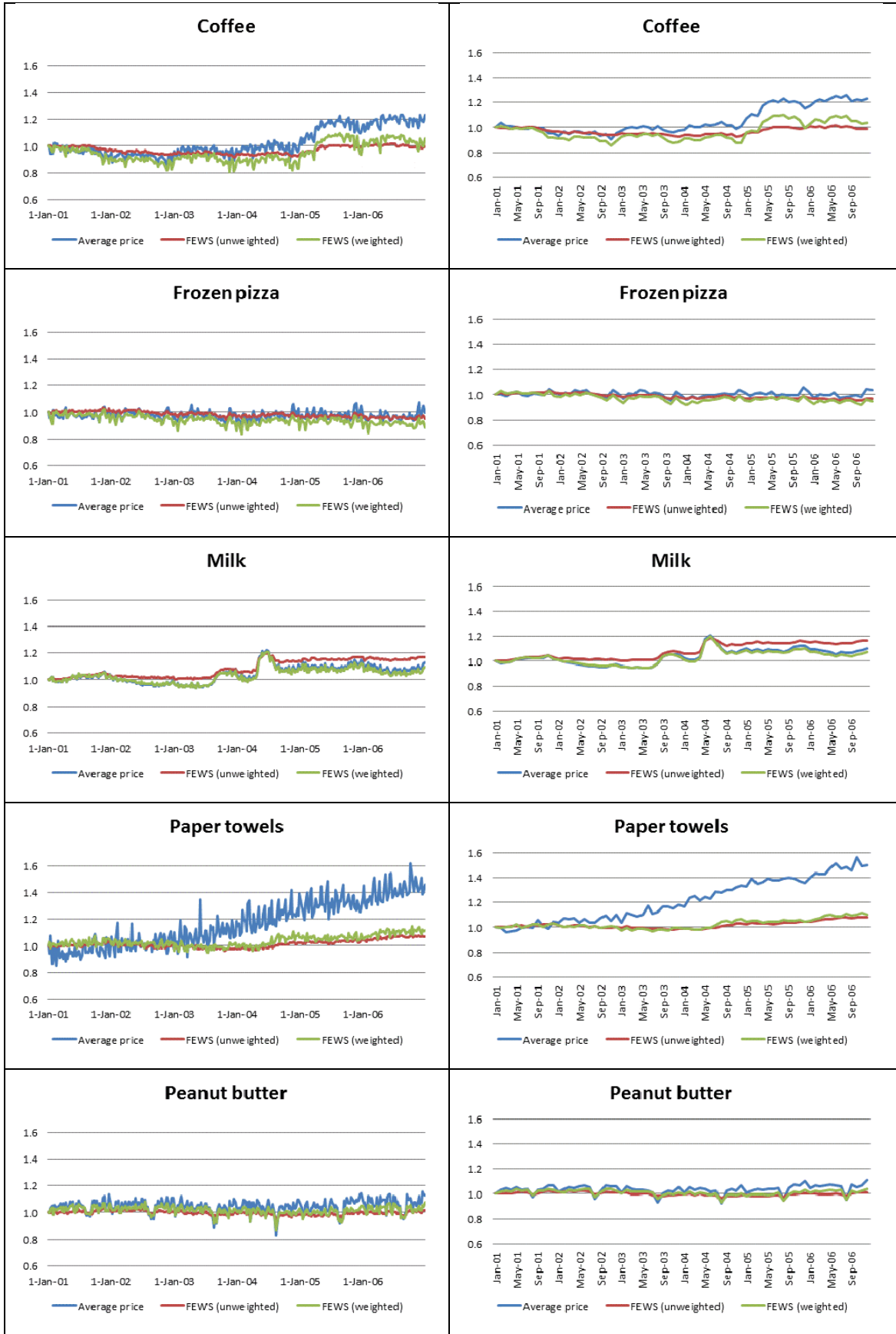### 4.3 Weekly scanner data for US supermarket products

Scanner data for US supermarket products, from IRI marketing, was used to test the effect of quantities on the price indexes for a selection of supermarket products. Figure 3 shows weighted and unweighted FEWS indexes, alongside the weighted average price indexes, for six product categories.

Weekly indexes are shown in the left-hand column, and in the right hand column are monthly indexes derived from the weekly indexes, which show the seasonality of the indexes more clearly.

Because an outlet identifier is available in the data, we incorporate this with the product identifier in the FEWS index to control for the effect of outlet on price. Table 3 in the appendix summarises the number and turnover of distinct product-by-outlet combinations in the data.

Figure 3. Weekly and monthly indexes from IRI supermarket scanner data

Weekly indexes	Monthly indexes

Coffee (left and right panels)

Frozen pizza (left and right panels)

Milk (left and right panels)

Paper towels (left and right panels)

Peanut butter (left and right panels)

Legend (all panels): Average price — FEWS (unweighted) — FEWS (weighted)
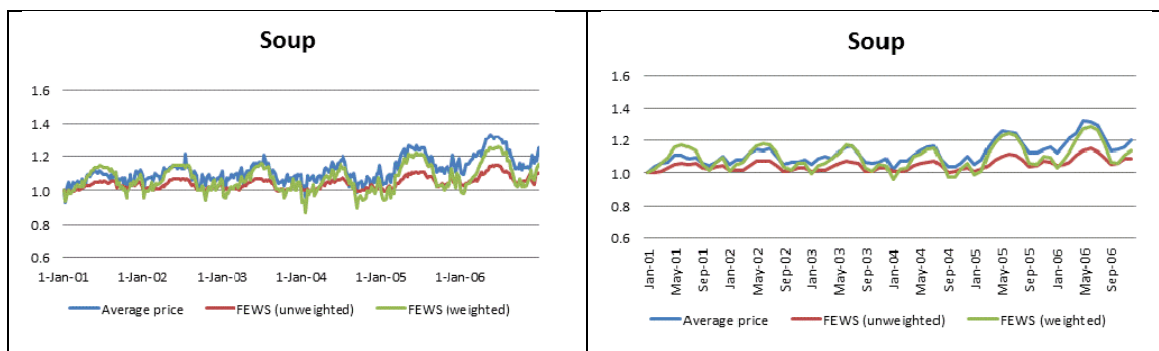
Perhaps the most striking feature of these comparisons is that the inclusion of quantities results in more pronounced seasonality in the price indexes, but doesn't seem to affect the longer term trend significantly for most of the product categories.

Soup, in particular, shows a very regular and strong seasonality in both the average price and weighted FEWS indexes, which is dampened in the unweighted FEWS.

Of the six product categories, milk is the only one where there appears to be a systematic drift between the weighted and unweighted FEWS results over the 6 years.

5. Conclusion

Online data offers potential for very timely and high-frequency price indexes for products where retailers have an online presence.

Two apparent problems with online data, however, are its lack of characteristics for quality adjustment, and quantities.

We have shown that the fixed-effects (FE) index exploits the longitudinal dimension of the data to implicitly quality-adjust price indexes equivalently to fully-interacted time dummy (TD) hedonic indexes which explicitly incorporate all price-determining characteristics of the products.

The use of a window-splice enables an implicit revision factor to be incorporated when splicing on the most recent period's movement to the unrevisable index.

So a combination of a fixed-effects index with a window-splice enables fully quality-adjusted unrevisable price indexes for data such as online data where characteristics are not available.

Empirical testing of the effect of not having quantities in the data show that, for supermarket products, the effect is relatively small. For consumer electronics, the effect varies.

From the perspective of an official statistics agency, the use of online data is very promising. Given the potential for drift in the online indexes due to the lack of quantities, and coverage differences, the most promising approach would seem to be some form of hybrid one. High-frequency timely indexes derived from online data could be calibrated to the less-frequent official measures derived from more comprehensive data such as scanner data or traditionally field-collected data.

With both online and scanner data for New Zealand consumer electronics we now have the potential to test this approach for the consumer electronics component of the New Zealand CPI, and this is the intended direction of our research using the online data being shared with us by PriceStats.

Appendix

Table 1. Descriptive statistics for Billion Prices Project online data

	Total distinct product specs over the entire 15 months	Average daily number of product specs	Average yearly match rate[7]
Digital cameras	192	94	0.45
Mobile phones	159	60	0.15
Televisions	161	51	0.15

Table 2. Descriptive statistics for GfK scanner data

	Total distinct product specs over the entire 3 years	Average monthly number of product specs	Average yearly match rate
Camcorders	603	88	0.33
Desktop computers	1411	150	0.02
Digital cameras	2039	289	0.22
DVD players and recorders	1380	202	0.24
Laptop computers	4100	432	0.03
Microwaves	877	152	0.26
Portable media players	1149	161	0.16
Televisions	2319	341	0.21

Table 3. Descriptive statistics for IRI scanner data

	Total distinct product-by-outlets over the entire 6 years	Average weekly number of product-by-outlets	Average yearly match rate
Coffee	5359	2578	0.81
Frozen pizza	2210	1192	0.86

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[7] Calculated as the average of two year-on-year match rates relative to the start and end of the 15 month period.

Milk	5034	2697	0.88
Paper towels	898	399	0.83
Peanut butter	388	239	0.90
Soup	1920	1048	0.88

References

Allison, PD (2005). *Fixed-effects regression methods for longitudinal data using SAS*. Cary, NC: SAS Institute Inc.

de Haan, J (2015). *Rolling year time dummy indexes and the choice of splicing method*. Unpublished draft, 28 March 2015.

de Haan, J, & Hendriks, R (2013, November). *Online data, fixed effects and the construction of high-frequency price indexes*. Paper presented at the 2013 Economic Measurement Group, Sydney, Australia.

de Haan, J, & Krsinich, F (2014a). Scanner data and the treatment of quality change in non-revisable price indexes. *Journal of Business & Economic Statistics* (forthcoming).

de Haan, J, & Krsinich, F (2014b, August). *Time-dummy hedonic and quality-adjusted unit value indexes: Do they really differ?* Paper to be presented at the conference of the Society for Economic Measurement, Chicago.

Ivancic, L, Diewert, WE, & Fox, KJ (2011). *Scanner data, time aggregation and the construction of price indexes*. Journal of Econometrics, *161*(1), 24–35.

Krsinich, F (2011, May). *Measuring the price movements of used cars and residential rents in the New Zealand consumers price index*. Paper presented at the 12th meeting of the Ottawa Group, Wellington, New Zealand.

Krsinich, F (2014). *Fixed effects with a window splice – non-revisable quality-adjusted price indexes with no characteristic information*. Paper presented at the meeting of the group of experts on consumer price indices, 26-28 May 2014, Geneva, Switzerland.

Krsinich F (2015, May). *Implementation of consumer electronics scanner data in the New Zealand CPI*. Paper being presented at the 14th meeting of the Ottawa Group, Tokyo.

Statistics New Zealand (2014). *Measuring price change for consumer electronics using scanner data*. Available from www.stats.govt.nz