Using the rolling year time-product dummy method for quality adjustment in the case of unobserved characteristics

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Frances Krsinich[1]

Senior Researcher, Prices Unit, Statistics New Zealand
P O Box 2922
Wellington, New Zealand
frances.krsinich@stats.govt.nz

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Abstract

This paper will discuss the use of the rolling year time-product dummy (RYTPD) method in situations where characteristics are unavailable for explicitly incorporating into hedonic regression models.

This builds on results from two earlier pieces of work. Krsinich (2011) used a fixed-effects hedonic model (ie a pooled time-product dummy(TPD) method) to benchmark the performance of the current matched-sample approach to estimating the rental index for New Zealand, where there are few observed characteristics in the longitudinal rental data. More recently, de Haan and Krsinich (2012) extended the RYGEKS method to impute price movements for new and disappearing items using hedonic regression. Results from applying this 'imputation Tornqvist' (IT) RYGEKS to New Zealand consumer electronics scanner data were compared with a range of other methods. The RYTPD was the best performing of the methods that do not explicitly incorporate characteristics.

It will be argued that the RYTPD is a viable method in situations where characteristics are unobserved, such as supermarket scanner data. Unlike matched-model approaches, the RYTPD appears to be doing some imputation for new and disappearing items, though in production a more sophisticated splicing approach will be required to deal with the lagged capturing of price movements for new items.

Introduction

Scanner data and its challenges

The potential benefits of using scanner data to measure price change include:

- improved accuracy, due to greater coverage of transactions and availability of real-time quantities
- ability to use existing administrative-type data sources
- improved treatment of seasonal commodities
- ability to account for commodity and product substitution between reweights.

However, traditional index formulae do not work well in the context of scanner data.

Prices and quantities are recorded for products identified at the finest level of specification corresponding to the barcode – this is referred to as the item[2] level – and at this level there is a significant level of churn. That is, many new items are being sold, and old items are no longer being sold, each month or quarter.

This churn means that fixed-based indexes quickly become unrepresentative. However, high-frequency chaining of superlative indexes, such as the Tornqvist, suffer from chain-drift bias due to the ‘spiking’ of prices and quantities due, in part, to discounting. This chain-drift can be particularly significant for supermarket products where consumers are more likely to stockpile when goods are discounted.

Work to date on scanner data methods

The rolling year GEKS (RYGEKS) method developed by Ivancic et al (2011) uses all matched items’ prices and quantities and is shown to be free of chain-drift. It appropriately adjusts for any change in the quality composition of the matched items. Using a rolling estimation window with the splicing-on of the movement for the most-recent period means it does not require revision.

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[2] For consistency with de Haan and Krsinich (2012)

However, because the RYGEKS uses matched items only (items existing in both the periods relating to each bilateral index) then any pure price change associated with new or disappearing items (ie unmatched items) is not reflected in the index.

For example, if a new item is introduced at a low price relative to its characteristics, then this is a price decrease which will not be identified in the RYGEKS index.

De Haan and Krsinich (2012) introduced an extension of the RYGEKS method based on bilateral time dummy hedonic indexes, rather than the superlative indexes such as the Tornqvist or Fisher that the RYGEKS is based upon. This method is called the imputation Tornqvist RYGEKS (ITRYGEKS). It is shown that the method implicitly imputes price movements for the unmatched items by using the predicted prices from the time dummy hedonic models.

The ITRYGEKS was applied to New Zealand consumer electronics scanner data – to show that incorporating the price movements of unmatched items tends to result in a lower price index than that shown by the RYGEKS. That is, the introduction and disappearance of items corresponds to a net quality increase that is not reflected by the RYGEKS.

Other methods were also compared with the ITRYGEKS. The conclusion was that, for the New Zealand consumer electronics products investigated:

- the monthly chained Tornqvist suffers from chain-drift, though less significantly than for supermarket products
- the rolling year time dummy hedonic index (RYTD) tends to sit fairly close to the ITRYGEKS
- the rolling year time-product dummy index (RYTPD) tends to sit closer to the ITRYGEKS than the RYGEKS does.

Data without characteristics

The ITRYGEKS has been shown to be a good benchmark index in its ability to appropriately reflect price movements for unmatched items, but it can only be applied to data where a full range of characteristics exist to estimate the time dummy hedonic indexes required for its calculation.

Unlike the New Zealand consumer electronics research scanner data, supermarket scanner data tends to have very limited information on the characteristics of products at the item level. At the most, weight, size, or volume may be recorded in the data, along with free-text descriptors of the item.

De Haan and Krsinich (2012) found that the rolling year time-product dummy index (the RYTPD) tends to sit closer to the ITRYGEKS than the RYGEKS does. The RYTPD is a method that only requires the item identifiers, rather than explicit information on characteristics, so this warrants further investigation as a method to be used for supermarket scanner data.

The RYTPD is similar to a time dummy hedonic index in that it models the log of price against time dummies and the parameters estimated for time are used to derive the index. Where it differs is that, rather than explicitly including characteristics in the model, the RYTPD includes 'product dummies' corresponding to each item. This is a fixed-effects approach to the hedonic estimation, which is effectively using each item as its own control. Allison (2005) explains fixed-effects methods as follows:

> (p2)… by using [fixed-effects] it is possible to control for all possible characteristics of the individuals [or, in the case of scanner data, items] 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 [ie item] 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.

When thinking more carefully about the potential of the RYTPD method, it was realised that because of fixed-effects estimation's requirement for at least two observations, the current splicing approach of RYTPD – where just the most recent month's movement is spliced onto the index each month – will be omitting the price movements of new items each month after the initial 12 months. This is because, by definition, the new items have only one observation in the month they appear.

In response to this, a modified splicing approach is considered, which incorporates the movement from the start of the window.

The use of RYTPD for other price measurement situations

There are other situations where a time-product dummy, or fixed-effects, approach is useful for price measurement where characteristics are lacking. Krsinich (2011) explains the use of a fixed-effects hedonic index for benchmarking the performance of the New Zealand rental price measure, which currently uses a matched-sample estimation approach on longitudinal data from an area-based probability sample survey.

The only characteristics in the data are region and number of bedrooms, so the longitudinal nature of the data was taken advantage of, to produce a fixed-effects hedonic index. The current matched-sample rental index matched this benchmark relatively closely, implying that any bias due to pure price movement of new and disappearing rentals is of little practical significance.

However, questions were raised about the appropriateness of the fixed-effects formulation – in particular, could the price movements for new and disappearing items be being omitted as for the matched-sample approach?

In response to these concerns, a result from Aizcorbe et al (2003) was extended to show that the implicit imputation for the price movement of a new rental dwelling is the movement from the average of the quality-adjusted rents of continuing dwellings in the previous period, to the quality adjusted rent of the new dwelling in the current period. Some questions still remain – in particular whether an assumption about characteristics' parameters being fixed over time is addressed sufficiently by using chained yearly-pooled estimation windows. Further work is underway.

Any other price measurement situation where we have repeated price information across time, for products whose characteristics do not change, could use the time-product dummy, or fixed-effects, approach.

Theoretical work is being done (de Haan, 2013) to formulate what the implicit imputation of the time-product dummy approach is, to determine its potential for use where Dutch online data is obtained by web-scraping. This will also be directly relevant for the price indexes produced by the Billion Prices Project, where quality adjustment approaches are currently being considered (Cavallo, 2012).

The purpose of this paper and its structure

This paper presents work in progress. Theoretical work is underway to clarify, in particular, what is being imputed for unmatched items in a time-product dummy index. The research discussed in this paper has been exploratory, employing an iterative approach and exploiting the rich scanner data available for New Zealand consumer electronics. Unexpected results have suggested new directions for investigation. In particular, the results from a lagged RYTPD versus a RYTPD with a modified splicing approach have raised new questions.

It is hoped that by presenting the empirical results at this early stage, members of the Ottawa Group will contribute to the research by offering suggestions and ideas.

Results from New Zealand consumer electronics scanner data

The GfK consumer electronics scanner data

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 is very close to full-coverage of the New Zealand market, and contains sales values and quantities aggregated to quarterly levels for combinations of brand, model, and up to six characteristics.

A much more detailed dataset was recently 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, microwaves, televisions, and portable media players. Monthly sales values and quantities are disaggregated by brand, model, and around 40 characteristics.

This data has been used to investigate the performance of different index methods, as discussed in Krsinich (2011) and de Haan and Krsinich (2012).

The RYTPD index with standard splicing

In de Haan and Krsinich (2012) the ITRYGEKS was applied to the consumer electronics scanner data. It was shown that the RYGEKS is generally biased upwards for these products, by not incorporating the price movements of new and disappearing items.

That is, for most of the eight products, there is a net quality increase due to the introduction and disappearance of consumer electronics items that matched-model approaches such as the RYGEKS are not able to reflect.

However, the drawback of the ITRYGEKS method is that it requires extensive information on characteristics to estimate the bilateral time dummy hedonic indexes that are the inputs to the RYGEKS stage of the index calculation. While this level of detail exists on the GfK consumer electronics scanner data, generally it is not available in supermarket scanner data – the main area of focus for most official statistics agencies considering incorporating scanner data into production for their CPIs. The rolling year time-product dummy method (the RYTPD) models the log of price against dummy variables for time and the item identifiers themselves, rather than explicit characteristics. This is a fixed-effects approach, where each item is effectively acting as its own control.

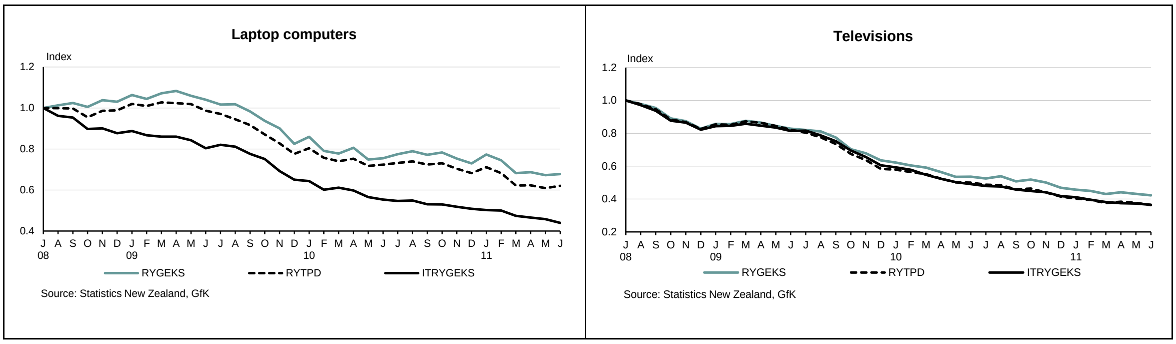
It was found that, in the case of the consumer electronics products, the RYTPD tended to sit closer to the ITRYGEKS benchmark than the RYGEKS, which suggests that the implicit imputations for new and disappearing items associated with the RYTPD may be closer to those of the ITRYGEKS than the RYGEKS.

Figure 1 shows how the RYTPD compares with both the RYGEKS and the ITRYGEKS for two of the consumer electronics products – laptop computers and televisions.[3] Although the RYTPD is not explicitly incorporating any characteristics, it sits significantly closer to the benchmark ITRYGEKS than the RYGEKS index does.

[3] Note the different scale on the y-axis for each product, so the differences between each method can be seen more clearly.

Figure 1

RYTPD compared with RYGEKS and ITRYGEKS – laptop computers and televisions



The RYTPD does not consistently perform better than the RYGEKS though. Figure 2 shows that for portable media players, the RYTPD is no closer to the ITRYGEKS benchmark than the RGEKS, and for microwaves it actually performs less well.

Figure 2

RYTPD compared with RYGEKS and ITRYGEKS – portable media players and microwaves

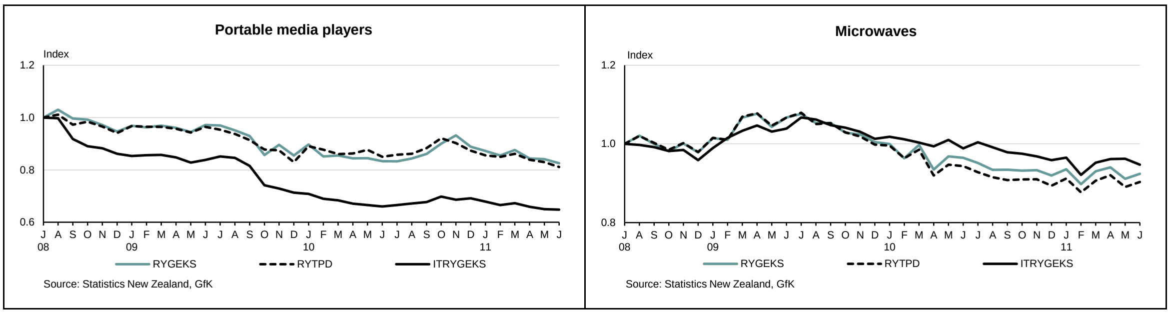


Figure 3 shows the average difference from the ITRYGEKS[4] of each of the RYGEKS and RYTPD indexes – for each of the eight consumer electronic products investigated.[5]

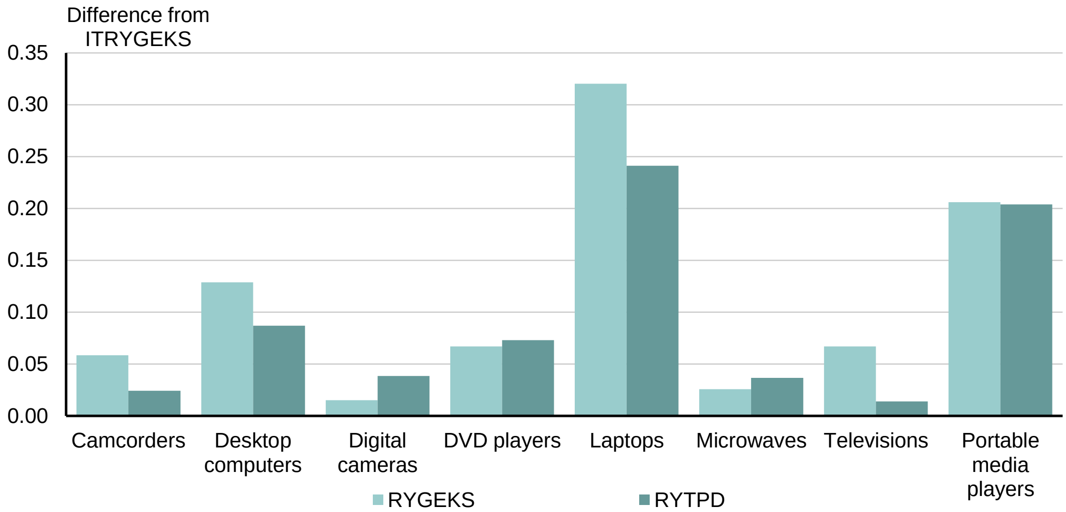
The RYTPD sits closer to the ITRYGEKS on average for most of the products. For three products the RYTPD performs less well than the RYGEKS – digital cameras, DVD players and recorders, and microwaves. For portable media players (also shown in figure 2) the methods perform equally well.

[4] For each product, this is defined as the arithmetic average across all months of the absolute differences from the ITRYGEKS index (divided by the ITRYGEKS to standardise the measure across products).

[5] Strictly speaking, microwaves are not a consumer electronics product but, as a lower technology product, they provide a useful contrast to the other products when comparing the performance of different methods.

Figure 3

Difference from ITRYGEKS – RYGEKS and RYTPD



Source: Statistics New Zealand, GfK

Note that expenditure is very different across the different products – table 1 shows the relative expenditure shares.[6]

Table 1

Expenditure shares across the eight consumer electronics products investigated

Product	Average expenditure share
Camcorders	0.02
Desktop computers	0.06
Digital cameras	0.08
DVD players and recorders	0.04
Laptop computers	0.26
Microwaves	0.03
Televisions	0.44
Portable media players	0.07

So – while it is important to compare methods at the product level to look for explanations in how the comparisons differ for different types of products, it should be noted that some products will ultimately have a much greater impact on the consumers price index than others.

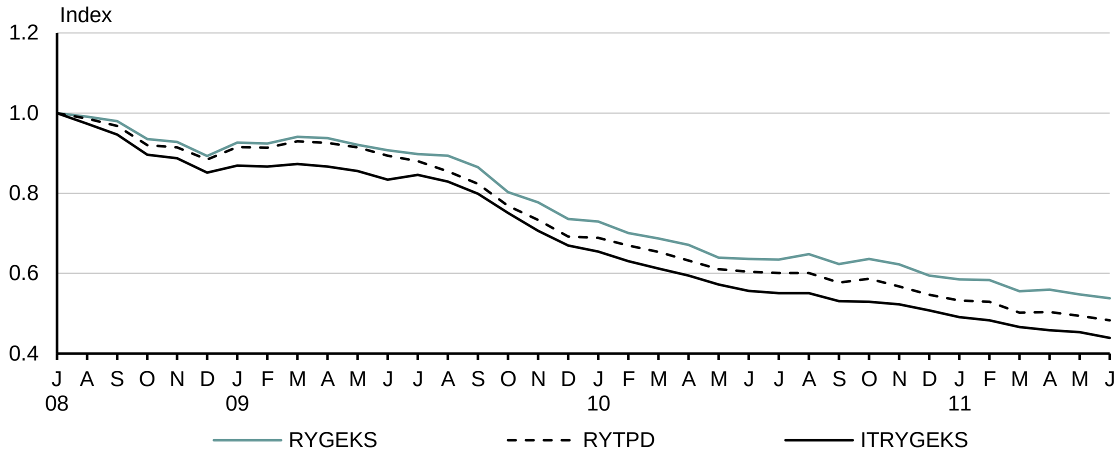
Figure 4 shows the RYGEKS, RYTPD, and ITRYGEKS aggregated across the eight products to a quasi[7] ‘consumer electronics’ level, using the monthly expenditure weights from the scanner data and a Tornqvist aggregation. At this level, the relative performance of the methods for the highly-weighted televisions (44 percent) and laptop computers (26 percent) dominate, and the

[6] Calculated as the average of the monthly expenditure shares.
[7] ‘Quasi’ because these eight products do not cover the entire range of consumer electronics products.

RYTPD method performs significantly better than the RYGEKS against the ITRYGEKS benchmark.

Figure 4

RYGEKS, RYTPD, and ITRYGEKS indexes at the aggregated consumer electronics level



Source: Statistics New Zealand, GfK

Figure 4 suggests the RYTPD is doing something to reflect the price movements of new and disappearing items.

But, since the RYTPD method is not incorporating the price movements for new items past the first estimation window, either this improvement is due only to incorporating disappearing items, or there is some other explanation.

To reiterate, the reason price movements for new items are not being incorporated in the RYTPD is that the fixed-effects estimation requires at least two observations for an item to be added into the estimation.

Because the current splicing is of the most-recent month's movement only, the effect of new items will be consistently being omitted for all months after the first 12 months of the initial 13-month window.

Rather than splicing on just the most-recent month, the movement across the most-recent 13-month estimation window can be incorporated into the index calculation. This is a very simplified version of a suggestion by Melser (2011) for improving the splicing of the RYGEKS.

This modified splicing of the RYTPD – referred to as the RY'TPD – gives significantly improved results but not for the reasons expected. To explain this clearly requires first looking at the results of **lagging** the RYTPD calculation.

The RYTPD lagged by 1 month and 6 months

A straightforward way to test the effect of not including price movements for new items in the RYTPD (past the initial 12 months of the first estimation window) is to lag the RYTPD. That is, the movement for a given month (t) is taken from an estimation window that extends past month t. This ensures there will be more than one observation for the new items and they will therefore be incorporated into the fixed-effects estimation.

While this approach is not appropriate for production, it does provide a benchmark against which other methods can be compared.

The RYTPD was lagged by 1 month (the RYTPD_lag1m) and 6 months (the RYTPD_lag6m).

Figure 5 shows the results of lagging the RYTPD for both laptops and televisions.

Unexpectedly, it makes very little difference. For laptop computers, the 6-month lagged RYTPD is marginally closer to the ITRYGEKS in the middle of the three-year period. For televisions, the lagged RYTPD indexes actually perform slightly less well. Does this imply that it is the **disappearing** items that have the most significantly different price movements from matched items, and that these therefore drive the difference between the RYGEKS and the ITRYGEKS? Or perhaps the implicit imputation of the RYTPD for new items is not working as effectively as for the disappearing items. This requires further investigation.

Figure 5

RYTPD lagged by 1 month and 6 months – laptop computers and televisions

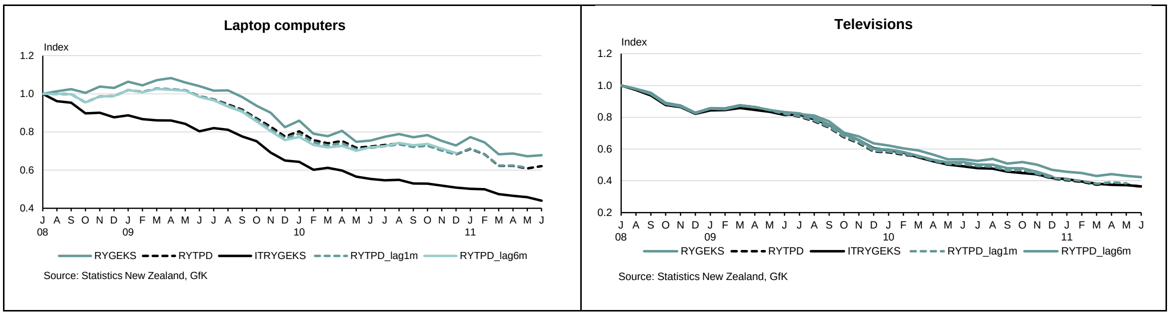
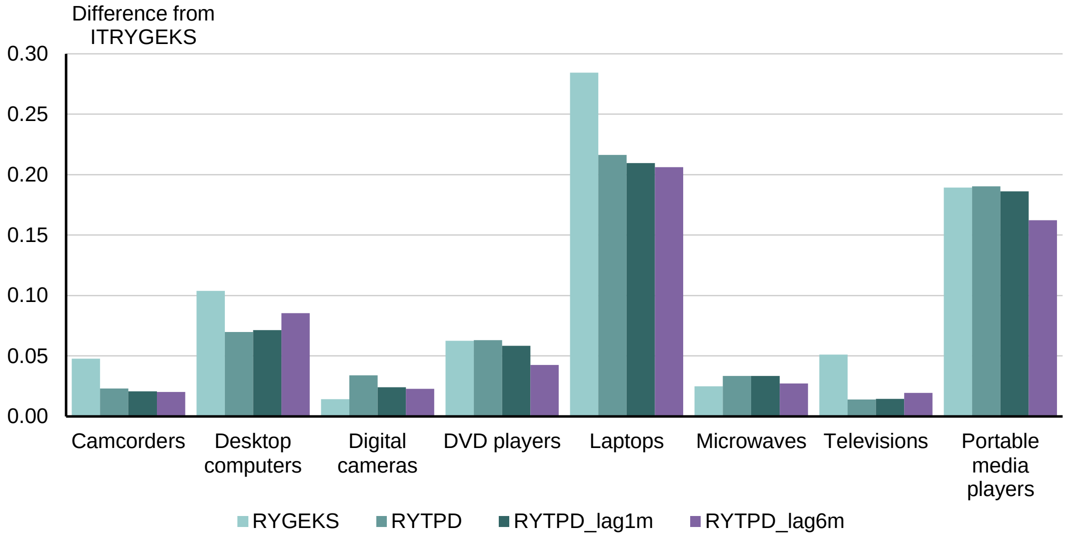


Figure 6 summarises the difference from the ITRYGEKS of the unlagged and both the lagged RYTPD indexes, for each product. While lagging improves the RYTPD marginally for most products, one exception is the highly-weighted televisions, where the 6-month lagged RYTPD performs less well than either the original spliced RYTPD or the 1-month lagged RYTPD.

Figure 6

Difference from ITRYGEKS of RYTPD lagged by 1 month and 6 months



Source: Statistics New Zealand, GfK

The RYTPD with modified splicing

When first considering how to incorporate price movements for new items in the RYTPD index, it was realised that, if the movement for the full window was used rather than that for the most-recent month, this would ensure the inclusion of the price movements for new items in each month up to the most-recent one. That is, while new items' price movements for the most-recent month will not be reflected, those items' movements will be incorporated in the index estimated across the next estimation window, so any biases will not accumulate over time.

In fact, this modified splicing gives significantly better results than the lagged RYTPD indexes shown above. This implies there is some other improvement that is due to the modification of the splicing, not just the inclusion of the new items' movements.

This is a very recent result and the implications are still being considered. The initial hypothesis is that the modified splice is better reflecting the implicit[8] parameters for price-determining characteristics, which are gradually changing over time.

Figure 7 shows the effect of modifying the splicing approach of the RYTPD (the RY'TPD) for laptop computers and portable media players. For both these products, the RY'TPD performs significantly better than the original spliced RYTPD. Note that, by construction, both the RYTPD methods are the same over the initial 13-month window.

[8] Implicit because the RYTPD doesn't estimate parameters for characteristics directly, but rather it estimates parameters corresponding to each distinct bundle of characteristics corresponding to an item.

Figure 7

Modified splice RY'TPD compared with original splice RYTPD and ITRYGEKS – laptop computers and portable media players

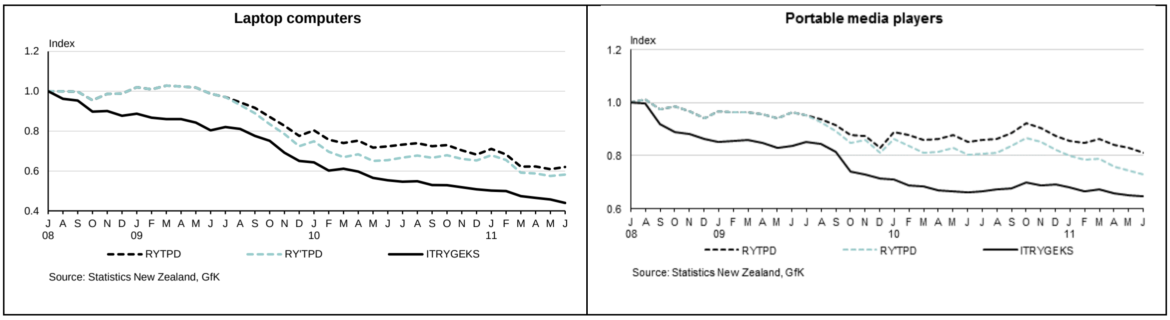
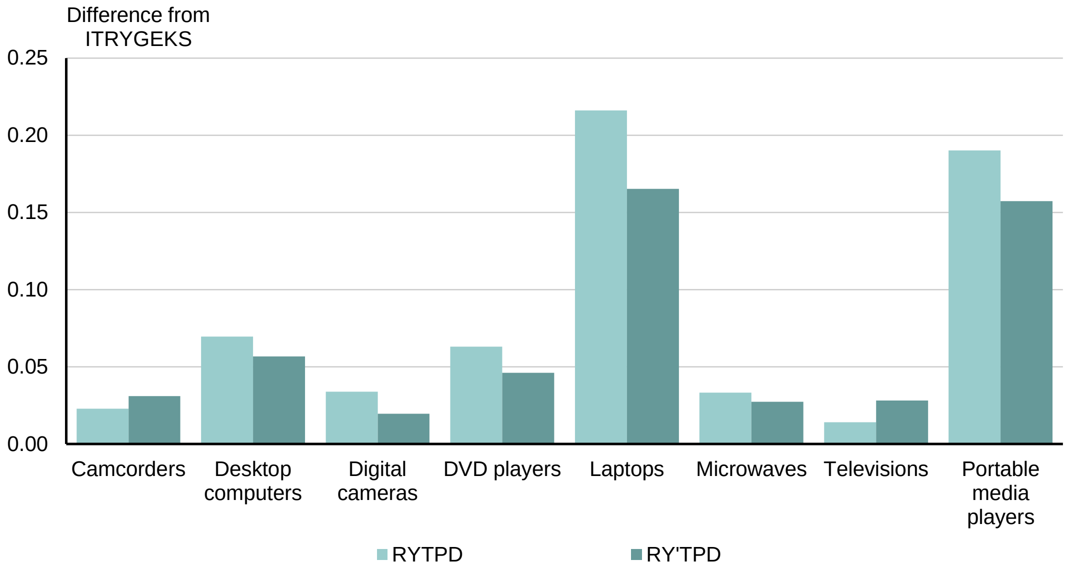


Figure 8 summarises the difference from ITRYGEKS for the modified splice RY'TPD for each product, along with the original spliced RYTPD. Other than for televisions and camcorders, the modified splice RY'TPD performs better than the original spliced RYTPD on average, particularly for laptop computers and portable media players.

Figure 8

Average difference from ITRYGEKS – for RYTPD and RY'TPD



Source: Statistics New Zealand, GfK

A revisable RYTPD

An even better approach to splicing the RYTPD is possible if revisions are allowed. This revised RYTPD (RYTPD_rev) is based on the most-recent full window of data, with monthly movements before that based on the most up-to-date estimation window possible.

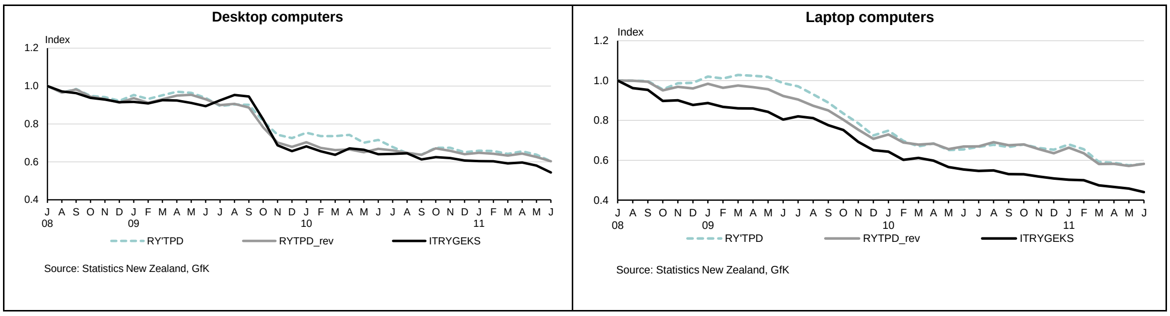
The revised RYTPD_rev index equals the modified splice RY'TPD at the end of the index by construction, with the potential for improved earlier monthly movements.

While this is not a viable production method for a CPI, which cannot be revised, it could be the benchmark method against which to test other production-friendly methods – where lack of characteristics means that an ITRYGEKS benchmark is not possible.

Figure 9 shows that for both desktop and laptop computers the revised RYTPD_rev sits noticeably closer to the ITRYGEKS than the modified splice RY'TPD in the earlier months of the three-year period investigated.

Figure 9

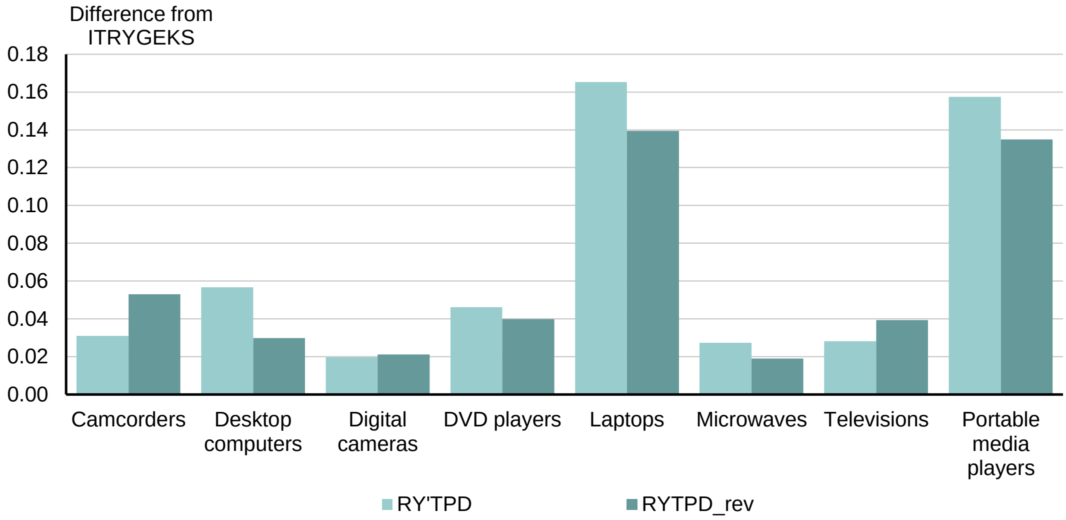
Revised splice RYTPD_rev compared with modified splice RY'TPD and ITRYGEKS



At the individual product level the average improvement of the RYTPD_rev over the RY'TPD can be significant (see figure 10). The RYTPD_rev performs better on average than the RY'TPD, for all products except camcorders, digital cameras, and televisions.

Figure 10

Average difference from ITRYGEKS – for modified splice RY'TPD and revised splice RYTPD_rev



Source: Statistics New Zealand, GfK

Summary of all methods

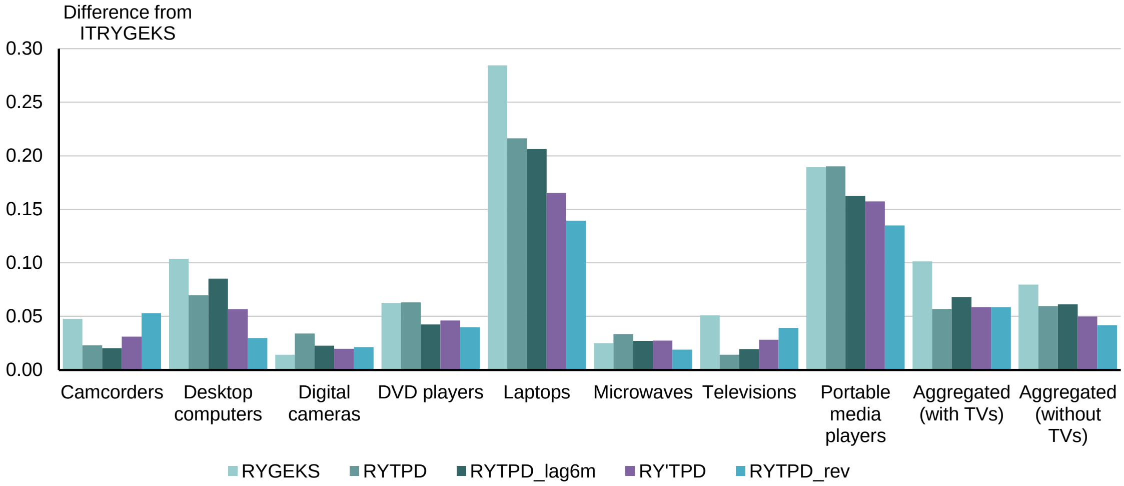
Figure 11 shows the performance of all the methods[9] looked at, illustrated by the average difference from the benchmark ITYGEKS, for all products and at the aggregated consumer electronics level – both including and excluding the highly-weighted televisions, for which the comparisons across methods tend to be different from the other products.

Of the methods that can be put into production – RYGEKS, RYTPD, and RY'TPD – the RY'TPD performs the best for all products except camcorders and televisions.

For all products, except camcorders, digital cameras and televisions, the revised RYTPD_rev is the best performing of all the methods which suggests that, in the absence of characteristics, this may be the best benchmark method against which to assess the performance of methods that can be put into production.

Figure 11

Average difference from ITRYGEKS – all methods



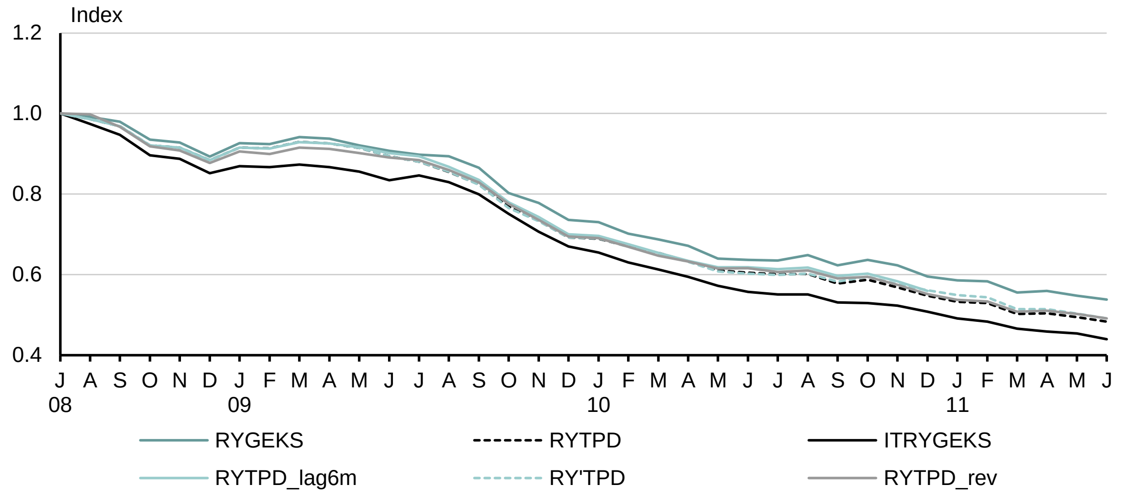
Source: Statistics New Zealand, GfK

Figure 12 shows the indexes at the aggregate 'consumer electronics' level. At this level, there is not much difference between the RYTPD, the RY'TPD, or the RYTPD_rev, though all are a distinct improvement over the RYGEKS.

Figure 12

All methods at the aggregated consumer electronics level, including televisions

[9] Excluding the RYTPD_1m, because the RYTPD_6m illustrates the effect of lagging more thoroughly.

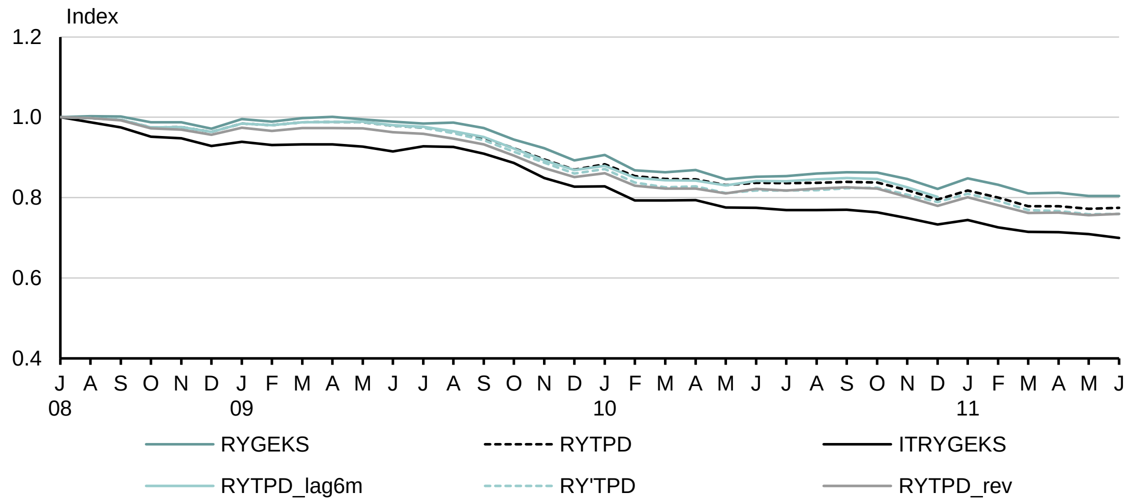


Source: Statistics New Zealand, GfK

The aggregate consumer electronics-level indexes shown in figure 12 are dominated by the highly-weighted televisions, for which the comparison across methods is different than for other products. Figure 13 shows the aggregated consumer electronics-level index with televisions excluded. As summarised in figure 11, there is a distinct improvement over the RYGEKS by all the RYTPD indexes, with the RY’TPD noticeably better than the RYTPD, and the RYTPD_rev closer again to the ITRYGEKS benchmark.

Figure 13

All methods at the aggregated consumer electronics level, excluding televisions



Source: Statistics New Zealand, GfK

Issues for further investigation

Whether disappearing items are more influential than new items

The RYTPD with standard splicing – which, by construction, is not incorporating any implicit imputations for new items, only disappearing items – sits closer to the ITRYGEKS than the RYGEKS does. When the RYTPD is lagged to incorporate new items it does not move the RYTPD much closer to the ITRYGEKS. Is this because the price movements of the disappearing items are of more significance than the price movements of the new items? Or is there some reason why the RYTPD is able to impute more effectively for disappearing than for new items?

Further improvement of the modified splicing for RYTPD

The RY'TPD with a very simple modified splicing performs significantly better than the original spliced RYTPD. The performance of a more sophisticated splicing approach such as that suggested by Melser (2011) should be investigated.

Modifying the splicing for the ITRYGEKS

Given the effect of modifying the splicing of the RYTPD, what would the effect be of similarly modifying the splicing of the ITRYGEKS? This may be a better benchmark index where characteristics are available to run the time-dummy hedonic models.

The time-product dummy index equals the fully-interacted time dummy index

In earlier work associated with the analysis presented in Krsinich (2011),[10] it was demonstrated that a time-product dummy (TPD) index, using item identifiers constructed as the combination of all the categorical characteristics, gives exactly the same result as a fully-interacted time dummy (TD) index based on the corresponding categorical characteristics.

Is it possible that the implicit imputation done by the RY'TPD might be an improvement over that of the ITRYGEKS(TD), given that it corresponds to a fully-interacted hedonic model rather than a main-effects hedonic model?

Recent attempts to test this by running ITRYGEKS indexes based on fully-interacted TD indexes, to compare with the ITRYGEKS(TD), failed – due to the sheer size of estimation models. It is intended to pursue this, though, by running some test scenarios based on fewer characteristics.

The ITRYGEKS based on a rolling-year time dummy index equals the rolling-year time dummy index

Another potentially useful result is that the ITRYGEKS based on the rolling-year time dummy index (ie the indexes from the 13-month pooled TD indexes, rather than all the bilateral TD indexes corresponding to the 13-month window) gives the same result as the RYTD index. That is, the ITRYGEKS(RYTD) equals the RYTD.

This is presumably because the RYGEKS procedure adds nothing to the RYTD, which already incorporates all the available information symmetrically.

There may be potential to combine this result with the above result (ie that the TPD equals the fully-interacted TD) to show the RYTPD converges to an ITRYGEKS based on a fully-interacted time dummy index under particular conditions.

[10] But not included in Krsinich (2011).

Conclusions

The RY'TPD performs better than the RYGEKS where characteristics are unobserved

Where characteristics are unobserved, the ITRYGEKS method cannot be used. In this situation the modified splice RY'TPD index seems likely to be preferable to an RYGEKS index. Empirical results indicate that the RY'TPD's implicit imputation for unmatched items is closer to that of the ITRYGEKS than that of the RYGEKS.

Results vary across different products

As with earlier work on methods for scanner data (Krsinich 2011, de Haan and Krsinich 2012), the comparisons across methods can vary for different products, even within consumer electronics. This suggests that caution should be applied when extrapolating conclusions about how different methods compare for different products, such as those from supermarkets.

Televisions are influential but unusual

Televisions – by far the most highly expenditure-weighted of the eight consumer electronics products looked at – tend to behave differently from the other products. For televisions, neither the lagging nor the modified splicing of the RYTPD perform better than the original spliced RYTPD. Understanding why the results are different for televisions is likely to give more general insight into what determines the performance of the different methods.

Appendix: Full results for all consumer electronics products

Figure 14

Methods that could be put into production – RYGEKS, RYTPD and RY'TPD – compared with the benchmark ITRYGEKS

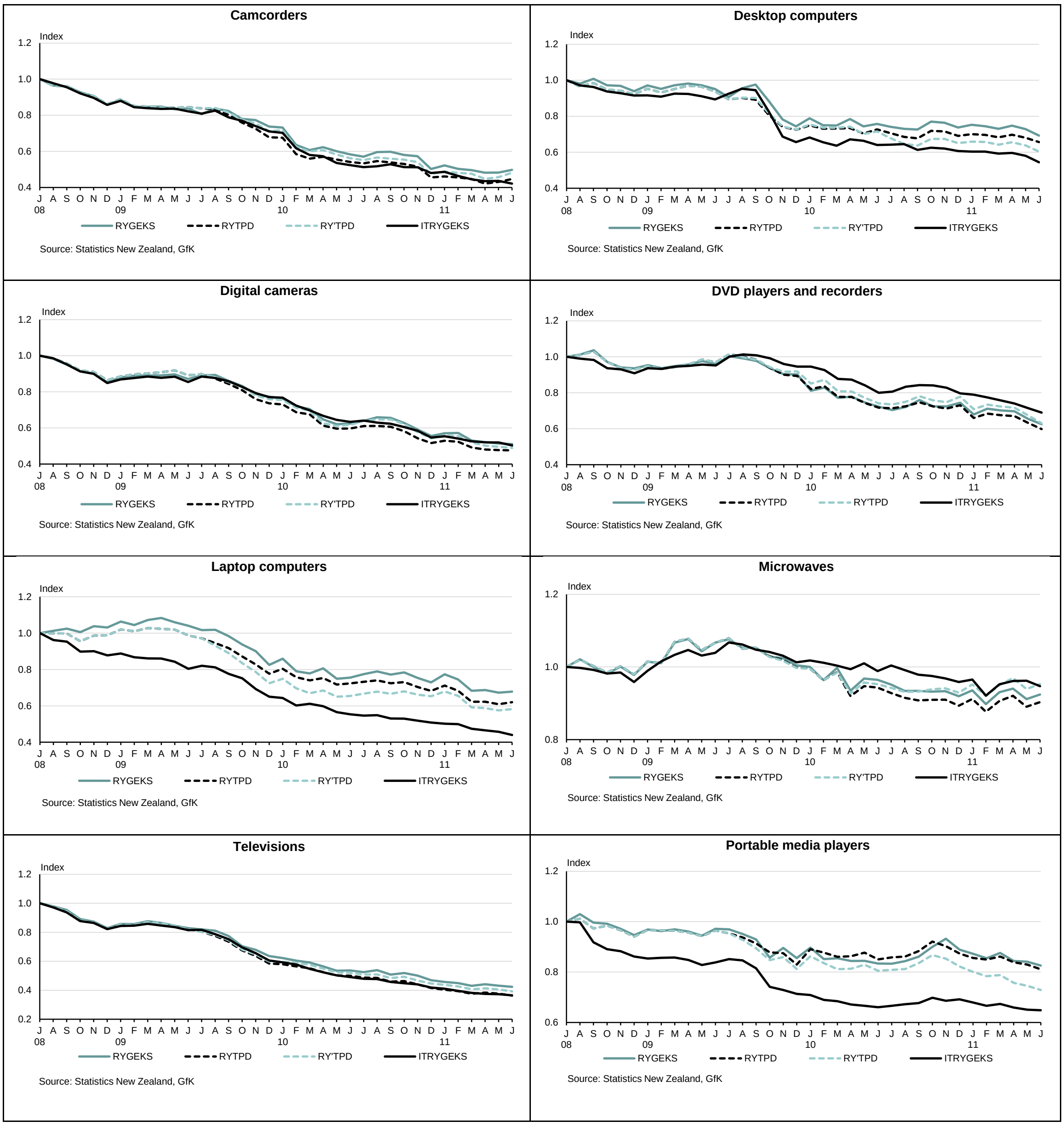
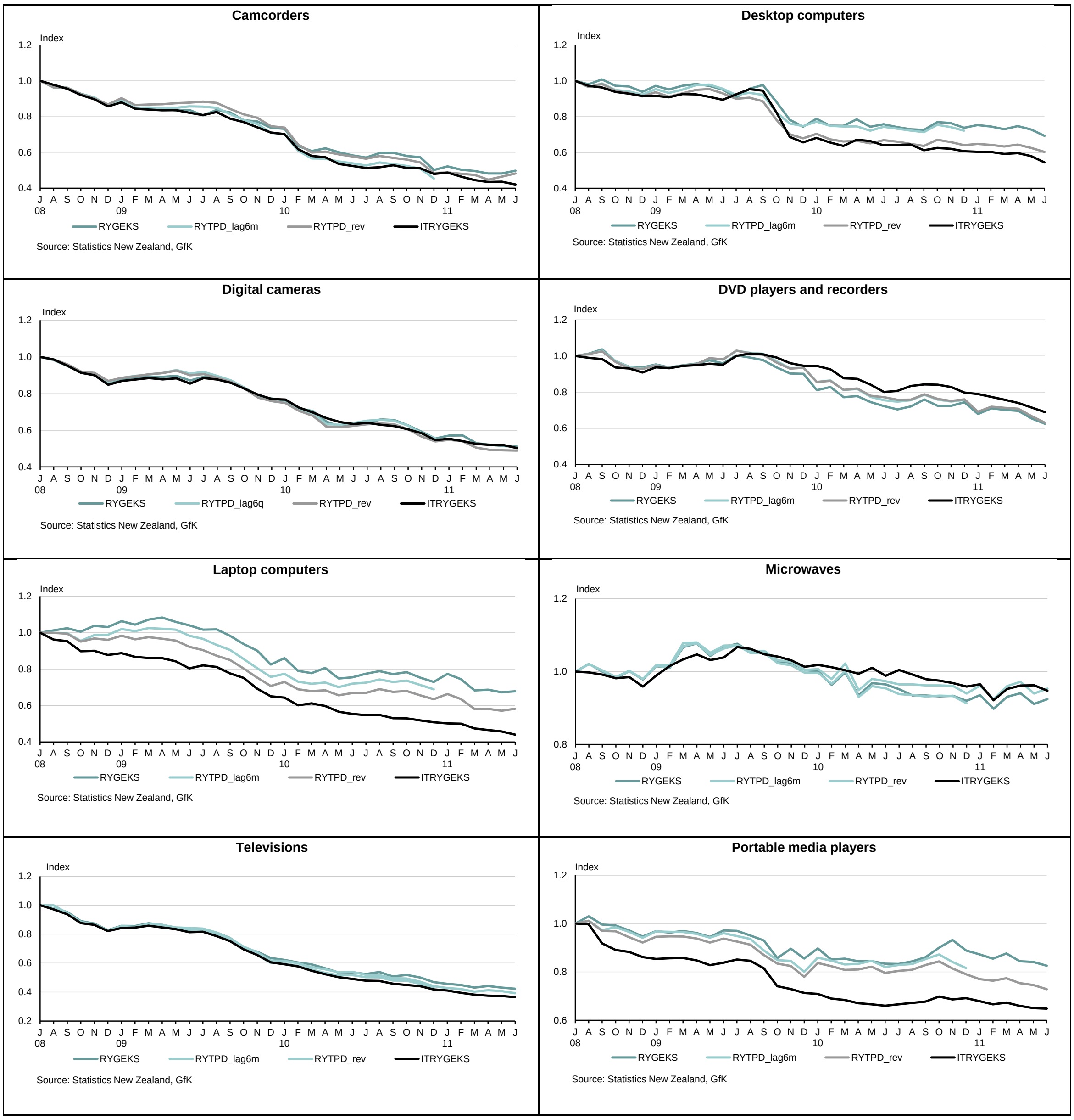


Figure 15

Non-production benchmark methods – RYTPD_lag6m and RYTPD_rev – compared with RYGEKS and ITRYGEKS



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