Rolling Year Time Dummy Indexes and the Choice of Splicing Method

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Abstract: Multilateral time dummy hedonic methods suffer from revisions: extending the sample period, adding data and re-estimating the hedonic model leads to changes in previously published index numbers. A rolling year approach overcomes the revisions problem. We compare two splicing methods to update existing time series in a rolling year context: standard splicing and window splicing. The index obtained via window splicing is split into the index obtained via standard splicing and a component which depends upon long-run changes in average characteristics and parameter estimates. We also discuss a similar decomposition for the recently proposed time-product dummy or fixed effects index with a window splice and present an empirical illustration using New Zealand scanner data on consumer electronics.

Keywords: fixed effects, rolling window approach, splicing, time dummy method.

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1. Introduction

The time dummy hedonic approach to constructing quality-adjusted price indexes is well known and discussed at some length in the international CPI manual (ILO et al., 2004). The manual does not discuss other multilateral index number methods, such as the time-product dummy method and the GEKS method. During the last six years or so, quite a bit of theoretical and empirical research has been done on the use of multilateral methods for CPI purposes, which may be taken into account in the next version of the manual.

From a practical point of view, the biggest disadvantage of multilateral methods is perhaps that when the sample period is extended and data added, previously estimated index numbers change. A rolling window approach overcomes the revisions problem. In this paper we focus on rolling window time dummy methods and compare two splicing methods for updating the time series: standard movement splicing and an alternative method referred to as window splicing. Our aim is to investigate, using basic algebra, if window splicing would be a better choice than movement splicing.

Section 2 addresses the time dummy hedonic method and decomposes the index obtained with window splicing into two components: the index obtained with standard splicing and a component which depends on long-run changes in average characteristics and changes in the estimated parameters. Section 3 discusses a similar decomposition for the time-product dummy or fixed effects method with a window splice, proposed by Krsinich (2014). An empirical illustration using New Zealand scanner data on consumer electronics is provided in section 4. Section 5 concludes.

2. The rolling year time dummy hedonic method

The time dummy hedonic method applied to pooled data of three or more periods, is a multilateral approach that yields transitive quality-adjusted price indexes. Transitivity implies that the index is independent of the choice of base period and can be written in period-on-period chained form. Thus, by construction, the index does not suffer from chain drift. De Haan (2015) advocated the use of the multilateral time dummy method to deal with scanner data when sufficient price determining characteristics are available to the statistical agency.

Suppose we have price and characteristics data pertaining to periods $t = 0,...,T$. The estimating equation for the multilateral time dummy model is

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

where p_i^t is the price of item *i* in period *t*, z_{ik} is the quantity of the *k*-th characteristic $(k = 0,...,K)$ for item *i* and β_k is the corresponding parameter, δ^0 is the intercept term; D_i^t is a dummy variable which has the value 1 if item *i* is purchased in period *t* and 0 otherwise, and δ^t is the time dummy parameter; ε_i^t is an error term with an expected value of zero. The estimated parameters are denoted by $\hat{\delta}^0$, $\hat{\delta}^t$, and $\hat{\beta}_k$; the predicted prices are $\hat{p}_i^0 = \exp(\hat{\delta}^0)\exp[\sum_{k=1}^{K} \hat{\beta}_k z_{ik}]$ and $\hat{p}_i^t = \exp(\hat{\delta}^0)\exp(\hat{\delta}^t)\exp[\sum_{k=1}^{K} \hat{\beta}_k z_{ik}]$. The time dummy hedonic price index, $P_{TD}^{0,t} = \exp(\hat{\delta}^t) = \hat{p}_i^t / \hat{p}_i^0$, is quality-adjusted because changes in the characteristics are controlled for.

The sets of items observed are denoted by U^0 and U^t $(t = 1,...,T)$. Following Diewert (2004), we assume that equation (1) is estimated by Weighted Least Squares (WLS) regression where expenditure shares s_i^0 $(i \in U^0)$ and s_i^t $(i \in U^t)$ act as weights to reflect the items' economic importance. The time dummy index going from period 0 to period *t* can be written as (de Haan, 2010)

$$P_{TD}^{0,t} = \frac{\prod_{i \in U^t} (p_i^t)^{s_i^t}}{\prod_{i \in U^0} (p_i^0)^{s_i^0}} \exp\left[\sum_{k=1}^{K} \hat{\beta}_k \left\{ \sum_{i \in U^0} s_i^0 z_{ik} - \sum_{i \in U^t} s_i^t z_{ik} \right\} \right]. \qquad (2)$$

Notice that $\sum_{i \in U^0} s_i^0 z_{ik}$ and $\sum_{i \in U^t} s_i^t z_{ik}$ are the expenditure-share weighted averages of the (quantities of the) characteristics in periods 0 and *t*. Equation (2) shows that the time dummy index adjusts the ratio of weighted geometric average prices for changes in the weighted average characteristics.[1]

A problem with multilateral price indexes such as the time dummy index is that they suffer from revisions. When the sample period is extended, data for period $T + 1$ is added and the hedonic model is re-estimated, previously estimated indexes will change. Statistical agencies do not accept such revisions. A *rolling window approach* overcomes the revisions problem. The estimation window is shifted forward one period (keeping the length fixed at $T + 1$ periods), and the model is re-estimated on the data of periods

[1] De Haan and Krsinich (2014a) showed that the time dummy hedonic index can also be written as the ratio of weighted geometric averages of quality-adjusted prices.

$1,...,T+1$. Broadly speaking there are two ways of extending the existing time series for periods $1,...,T$ to period $T+1$: the standard splicing method, which we also refer to as a movement splice, and an alternative method introduced by Krsinich (2014), referred to as a window splice.[2]

To illustrate the two methods, suppose the length of the estimation window is 13 months. The *movement splice* works as follows: after moving forward the window one month and re-estimating the hedonic model, the most recent estimated month-on-month movement of the index is spliced on to the existing time series. The *window splice* splices the entire newly estimated 13-month series on to the index level pertaining to 12 months ago. For a formal description, we need some additional notation. In particular, we use (x) for results from the estimation window starting in period x. For example, $P_{TD}^{0,t}(0)$ is the weighted time dummy index going from period 0 to period *t*, estimated on the data of the sample period $0,...,T$. After moving forward the estimation window by one period, the time dummy index between periods 1 and *t* is denoted by $P_{TD}^{1,t}(1)$.

The standard *movement splice* extends the existing time series $P_{TD}^{0,1}(0)....P_{TD}^{0,T}(0)$ by multiplying $P_{TD}^{0,T}(0)$ by the movement $P_{TD}^{1,T+1}(1)/P_{TD}^{1,T}(1)$. That is, the time dummy index with a movement splice (TDMS) for the 'new' period $T+1$ and index reference period 0 is calculated as

$$P_{TDMS}^{0,T+1} = P_{TD}^{0,T}(0) \times \frac{P_{TD}^{1,T+1}(1)}{P_{TD}^{1,T}(1)} = P_{TD}^{0,T}(0) \times P_{TD}^{T,T+1}(1) = P_{TD}^{0,1}(0) \times P_{TD}^{1,T}(0) \times P_{TD}^{T,T+1}(1), \qquad (3)$$

using the transitivity property of a time dummy index. The TDMS index is also known as the rolling year time dummy index (RYTD). However, this name is ambiguous since window splicing is based on a rolling window approach as well.

The *window splice* method extends the time series by multiplying the (level of the) time dummy index for period 1, $P_{TD}^{0,1}(0)$, by the index going from period 1 to period $T+1$, $P_{TD}^{1,T+1}(1)$, based on the new estimation window. So the time dummy index with a window splice (TDWS) for period $T+1$ with index reference period 0 is calculated as

$$P_{TDWS}^{0,T+1} = P_{TD}^{0,1}(0) \times P_{TD}^{1,T+1}(1) = P_{TD}^{0,1}(0) \times P_{TD}^{1,T}(1) \times P_{TD}^{T,T+1}(1). \qquad (4)$$

[2] Ivancic, Diewert and Fox (2011) and de Haan and van der Grient (2011) used a rolling year standard splicing approach to updating GEKS indexes. De Haan and Krsinich (2014b) did the same for quality-adjusted GEKS indexes. Krsinich (2014) noted that her window splice approach is a simplified version of a suggestion by Melser (2011) for improving the splicing of the rolling year GEKS.

The difference between $P_{TDMS}^{0,T+1}$ given by (3) and $P_{TDWS}^{0,T+1}$ given by (4) is the use of $P_{TD}^{1,T}(0)$ rather than $P_{TD}^{1,T}(1)$ in the decomposition. That is, the standard splice measures the price change across the overlapping period $t=1,...,T$ of the two estimation windows based on the initially estimated model instead of the re-estimated model. In the words of Krsinich (2014): "the revised movement for back periods is not incorporated into the longer-term index movement".

To understand what the drivers of the difference between $P_{TDWS}^{0,T+1}$ and $P_{TDMS}^{0,T+1}$ are, we write the ratio of the two indexes, using expression (2), as

$$\frac{P_{TDWS}^{0,T+1}}{P_{TDMS}^{0,T+1}} = \frac{P_{TD}^{1,T}(1)}{P_{TD}^{1,T}(0)} = \frac{\exp\left[\sum_{k=1}^{K}\hat{\beta}_k(1)\left\{\sum_{i\in U^1} s_i^1 z_{ik} - \sum_{i\in U^T} s_i^T z_{ik}\right\}\right]}{\exp\left[\sum_{k=1}^{K}\hat{\beta}_k(0)\left\{\sum_{i\in U^1} s_i^1 z_{ik} - \sum_{i\in U^T} s_i^T z_{ik}\right\}\right]}$$

$$= \exp\left[\sum_{k=1}^{K}[\hat{\beta}_k(1) - \hat{\beta}_k(0)]\left\{\sum_{i\in U^1} s_i^1 z_{ik} - \sum_{i\in U^T} s_i^T z_{ik}\right\}\right]$$

$$= \exp\left[\sum_{i\in U^1} s_i^1[\hat{\lambda}_i(1) - \hat{\lambda}_i(0)] - \sum_{i\in U^T} s_i^T[\hat{\lambda}_i(1) - \hat{\lambda}_i(0)]\right], \qquad (5)$$

where $\hat{\beta}_k(0)$ and $\hat{\beta}_k(1)$ are the parameter estimates from the two estimation windows and with $\hat{\lambda}_i(0) = \sum_{k=1}^{K}\hat{\beta}_k(0)z_{ik}$ and $\hat{\lambda}_i(1) = \sum_{k=1}^{K}\hat{\beta}_k(1)z_{ik}$ for short. So, if the parameter estimates from the two estimation windows are the same for all the characteristics, the window splice and the standard splice will produce identical results. In practice this will not be the case, for two reasons. First, there are random disturbances. Second, the 'true' parameters may have changed. While this conflicts with the underlying assumption of fixed characteristics parameters, it does suggest that revising the regression coefficients is useful, in particular when the parameters exhibit structural changes.

Using (4) and transitivity of $P_{TD}^{0,T}$, the last movement of the TDWS index, i.e. $P_{TDWS}^{0,T+1}/P_{TDWS}^{0,T}$, can be decomposed as

$$\frac{P_{TDWS}^{0,T+1}}{P_{TDWS}^{0,T}} = \frac{P_{TDWS}^{0,T+1}}{P_{TD}^{0,T}(0)} = \frac{P_{TD}^{0,1}(0)\times P_{TD}^{1,T+1}(1)}{P_{TD}^{0,1}(0)\times P_{TD}^{1,T}(0)} = \frac{P_{TD}^{1,T+1}(1)}{P_{TD}^{1,T}(0)} = \frac{P_{TD}^{1,T+1}(1)}{P_{TD}^{1,T}(1)}\times\frac{P_{TD}^{1,T}(1)}{P_{TD}^{1,T}(0)}. \qquad (6)$$

The first component of (6) is identical to the index movement used in standard splicing; see equation (3). Because the month-on-month change from the standard splice depends on a single estimation window, it is relatively easy to interpret. In contrast, the month-on-month change from the window splice depends on two adjacent estimation windows, which hampers its interpretation. Furthermore, in some cases the second component of (6) may add 'noise', especially when the weighted characteristics in periods 1 and *T* are very different; see equation (5). In spite of these potential drawbacks we are in favor of the window splice because it revises the parameters between periods 1 and *T*.

Finally, it should be mentioned that any splicing method impairs transitivity, and chain drift in the linked multilateral index series cannot be completely ruled out. As long as the estimation window is long enough, say at least 13 months, this is unlikely to be a big problem.

3. The fixed effects index and splicing

Hedonic regression methods cannot be used if characteristics information is unavailable. The time-product dummy or *fixed effects* method replaces the unobservable 'constant' hedonic effects $\sum_{k=1}^{K}\beta_k z_{ik}$ in the time dummy hedonic model (1) by item-specific fixed values γ_i. If there are *N* different items across the sample period $0,...,T$, most of which will typically not be purchased in all time periods, the estimating equation for the fixed effects model becomes

$$\ln p_i^t = \delta^0 + \sum_{t=1}^{T}\delta^t D_i^t + \sum_{i=1}^{N-1}\gamma_i D_i + \varepsilon_i^t , \qquad (7)$$

where D_i is a dummy variable that has the value of 1 if the observation relates to item *i* and 0 otherwise. A dummy for item *N* is excluded ($\gamma_N = 0$) to identify the model. The parameter estimates are $\hat{\delta}^0$, $\hat{\delta}^t$ $(t = 1,...,T)$ and $\hat{\gamma}_i$ $(i = 1,..., N-1)$, and we set $\hat{\gamma}_N = 0$. The predicted prices are $\hat{p}_i^0 = \exp(\hat{\delta}^0)\exp(\hat{\gamma}_i)$ and $\hat{p}_i^t = \exp(\hat{\delta}^0)\exp(\hat{\delta}^t)\exp(\hat{\gamma}_i)$ for all *i*. Similar to the time dummy hedonic price index, the fixed effects index for period *t* is calculated as $P_{FE}^{0,t} = \exp(\hat{\delta}^t) = \hat{p}_i^t / \hat{p}_i^0$.[3]

As before, (x) indicates results from the estimation window that starts in period x. Using again the items' expenditure shares as weights in a WLS regression to estimate equation (7) on the pooled data of periods $t = 0,...,T$, the time-product dummy or fixed effects (FE) index for the last period *T* can be written as (de Haan and Hendriks, 2013)

[3] Following Aizcorbe, Corrado and Doms (2003), Krsinich (2014) also refers to the fixed effects index as a hedonic index, but this may be confusing. Hedonic methods explicitly use information on characteristics whereas the fixed effects method does not use any auxiliary information.

$$P_{FE}^{0,T}(0) = \frac{\prod_{i \in U^T} (p_i^T)^{s_i^T}}{\prod_{i \in U^0} (p_i^0)^{s_i^0}} \exp\left[\sum_{i \in U^0} s_i^0 \hat{\gamma}_i(0) - \sum_{i \in U^T} s_i^T \hat{\gamma}_i(0) \right]. \tag{9}$$

Unlike the hedonic time dummy method, the fixed effects method needs at least two observations across the estimation window for an item to be non-trivially included; items with only one observation are 'zeroed out', i.e. they do not affect the results. That is, indexes estimated on the pooled data set excluding items which are purchased during a single period only will be equal to the indexes estimated on the whole data set. In this sense, a fixed effects index is a *matched-item index*. One implication is that items which are purchased in period T but not in periods $0,...,T-1$ are implicitly omitted. Although the fixed effects of these new items can be estimated, the results are trivial in that the predicted (log of) prices lie exactly on the regression surface. Below, we outline what this means for the two splicing methods discussed in section 2.

Similar to equations (3) and (4) for the time dummy hedonic approach, the fixed effects indexes with a standard movement splice (FEMS) and a window splice (FEWS), respectively, for period $T+1$ and with reference period 0 are calculated as

$$P_{FEMS}^{0,T+1} = P_{FE}^{0,T}(0) \times \frac{P_{FE}^{1,T+1}(1)}{P_{FE}^{1,T}(1)} = P_{FE}^{0,T}(0) \times P_{FE}^{T,T+1}(1) = P_{FE}^{0,1}(0) \times P_{FE}^{1,T}(0) \times P_{FE}^{T,T+1}(1); \tag{10}$$

$$P_{FEWS}^{0,T+1} = P_{FE}^{0,1}(0) \times P_{FE}^{1,T+1}(1) = P_{FE}^{0,1}(0) \times P_{FE}^{1,T}(1) \times P_{FE}^{T,T+1}(1). \tag{11}$$

The only difference between $P_{FEMS}^{0,T+1}$ and $P_{FEWS}^{0,T+1}$ is the use of $P_{FE}^{1,T}(0)$ rather than $P_{FE}^{1,T}(1)$ in the above decompositions, similar to what we found for the time dummy hedonic method.

Krsinich (2014) argued that the FEWS method "is a form of implicit revision, incorporating not only the implicit price movements of new products being introduced, but also enables the fixed-effects estimates to be updated as more prices are observed for each product". To evaluate the effect of new items on FEMS and FEWS indexes, suppose first that a new item was introduced in period $T+1$. This item affects neither $P_{FEMS}^{0,T+1}$ nor $P_{FEWS}^{0,T+1}$ because it is observed only once in the estimation window (1), hence zeroed out, and unobserved in the estimation window (0). Suppose next that a new item was introduced in the previous period T. This item will typically be purchased in period $T+1$ as well; its price change from T to $T+1$ affects $P_{FE}^{T,T+1}(1)$ in equations (10) and (11) and therefore impacts on both $P_{FEMS}^{0,T+1}$ and $P_{FEWS}^{0,T+1}$. In addition, the FEWS method incorporates the effect of this item into the price movement for back periods through $P_{FE}^{1,T}(1)$ whereas the FEMS method does not 'revise' this longer-term price movement as $P_{FE}^{1,T}(0)$ is based on the previous estimation window.

To explain Krsinich's (2014) second point, it will be useful to write the FEWS index for period $T+1$ as

$$P_{FEWS}^{0,T+1} = \frac{P_{FE}^{1,T}(1)}{P_{FE}^{1,T}(0)} \times P_{FEMS}^{0,T+1}. \tag{12}$$

Using equation (9), the ratio of $P_{FE}^{1,T}(0)$ and $P_{FE}^{1,T}(1)$ in (12) can be expressed as

$$\frac{P_{FE}^{1,T}(1)}{P_{FE}^{1,T}(0)} = \exp\left[\sum_{i \in U^1} s_i^1 [\hat{\gamma}_i(1) - \hat{\gamma}_i(0)] - \sum_{i \in U^T} s_i^T [\hat{\gamma}_i(1) - \hat{\gamma}_i(0)]\right], \tag{13}$$

which is the fixed effects counterpart of the third expression of (5). For the item that was introduced in period *T*, the predicted price in period *T* from the regression ran on the window (0) equals $\hat{p}_i^T(0) = p_i^T = \exp(\hat{\delta}^0(0))\exp(\hat{\delta}^T(0))\exp(\hat{\gamma}_i(0))$. In other words, the fixed effect of this item – which belongs to U^T but not to U^1 – is trivially estimated by $\hat{\gamma}_i(0) = \ln p_i^T - \hat{\delta}^0(0) - \hat{\delta}^T(0)$. The FEWS method updates the trivial estimate $\hat{\gamma}_i(0)$ by the more realistic estimate $\hat{\gamma}_i(1)$. It also updates the fixed effects estimates for all the other items whereas the FEMS method is based on the previous fixed effects estimates.

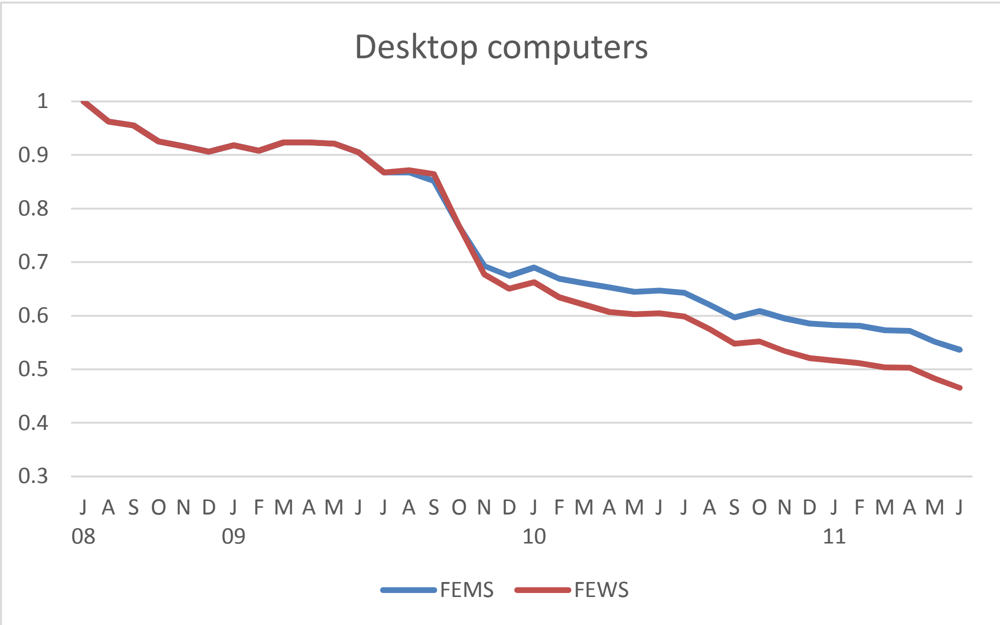
4. Empirical illustration

The choice between standard splicing and window splicing is particularly important for fixed effects indexes. For time dummy hedonic indexes we expect standard splicing to work reasonably well because here the issue of 'trivial estimates' for new items does not arise. In this empirical section we therefore focus on the differences between FEMS and FEWS indexes.

We use the same scanner data set that was used by Krsinich (2014) and de Haan and Krsinich (2014a;b). It contains monthly sales values and quantities, from mid 2008 to mid 2011, for 8 consumer electronics products: desktop computers, laptop computers, camcorders, digital cameras, DVD players and recorders, microwaves, portable media players, and televisions. The data was obtained from market research company GfK and is close to full coverage of the New Zealand market.

Chart 1 shows the rolling year (weighted) FEMS and FEWS indexes for desktop and laptop computers. For desktops, the FEWS index sits far below the FEMS index by the end of the sample period; the difference has been increasing gradually over time. For laptops, the difference is mall. The results for the 6 other products can be found in Chart A1 of the Appendix. For portable media players, FEWS sits above FEMS, and so we cannot say that the FEMS method necessarily produces 'upward biased' indexes.

Chart 1: Rolling year fixed effects indexes for computers



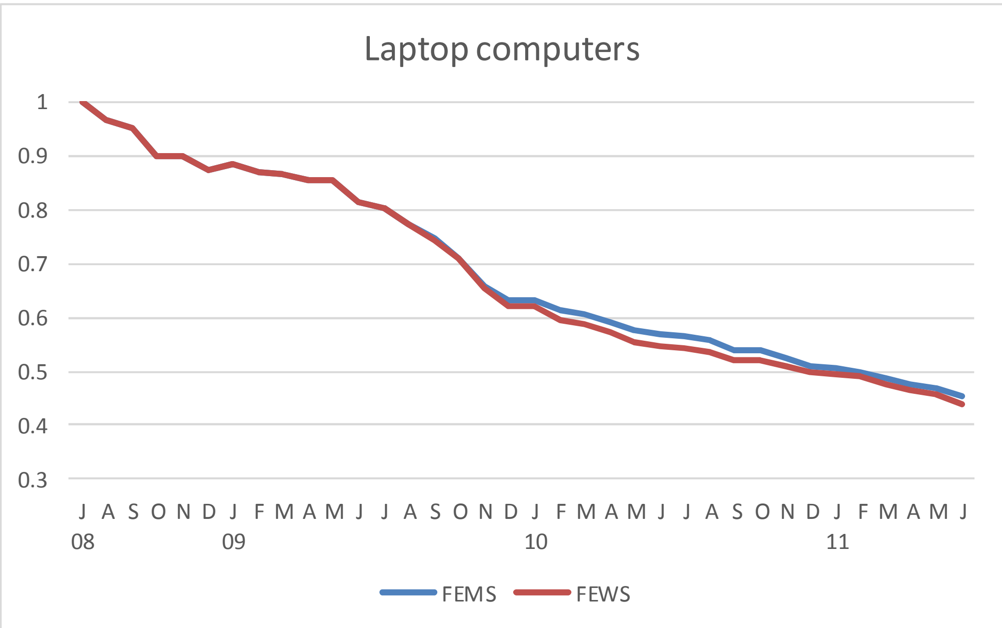
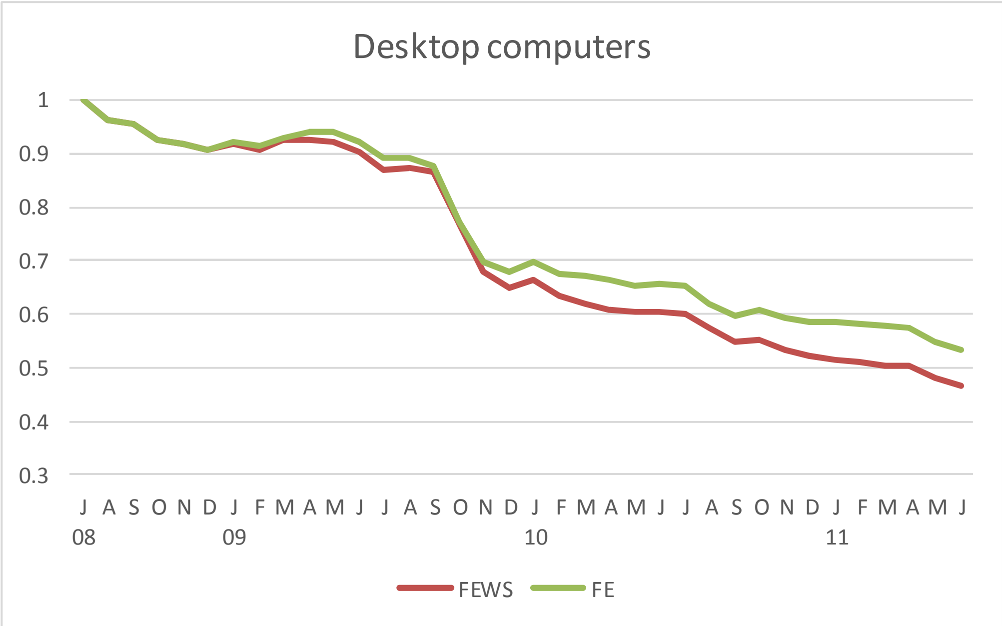
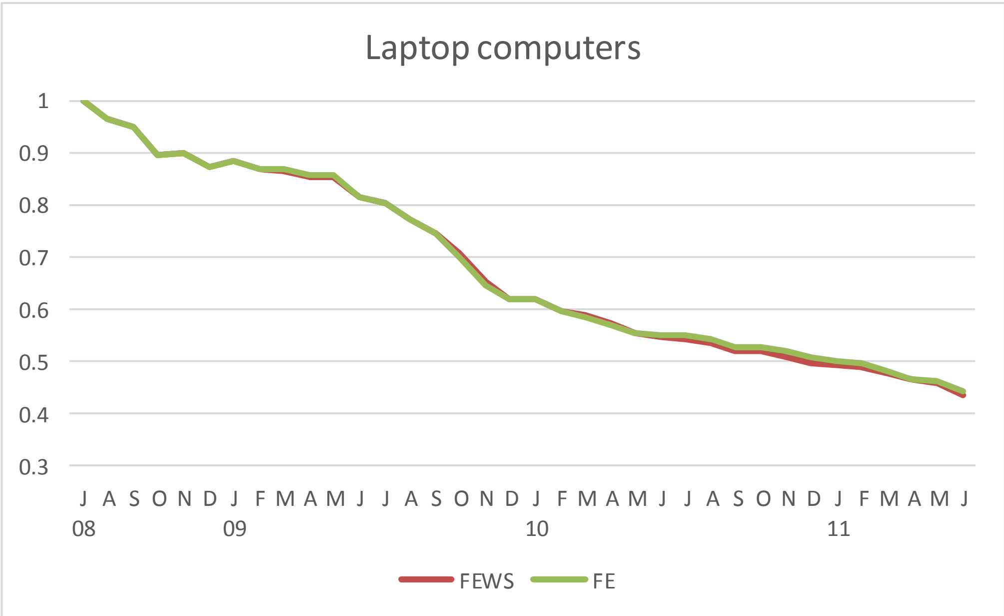


Chart 2 compares the FEWS index with the (revisable) weighted fixed effects index that is estimated on the data of the whole sample period, i.e. without splicing. For desktops, the FEWS index sits below the overall index, but for laptops the difference is very small. This seems to be a more general result; Chart A2 in the appendix shows that the FEWS indexes for the other products are either below or similar to the overall fixed effects indexes.

Chart 2: Fixed effects and FEWS indexes for computers





The items in our data set were defined by the combination of brand, model and a large number of product characteristics. If instead items would have been identified by barcode, product churn in terms of new and disappearing items would have been higher. It is unlikely though that the trends of the FEMS and FEWS indexes would have been affected much. Importantly, as can be seen from Charts 1 and A1, the volatility of the FEWS and FEMS indexes is virtually the same. There is no reason to expect that the use of barcode-level data would have changed this finding.

5. Conclusions

Window splicing incorporates the revised movement for back periods into longer-term index movements through updating of the regression coefficients; this is true for time dummy hedonic as well as time-product dummy or fixed effects indexes. In this sense, window splicing is ‘better’ than standard splicing.

We agree with Krsinich (2014) that, in contrast to the FEMS method, the FEWS method incorporates “the implicit price movements of new products being introduced” with a one period lag. Also, we did not find evidence of FEWS producing more volatile indexes than FEMS. Thus, we would definitely prefer window splicing over standard splicing when using a fixed effects approach to measuring aggregate price change in the absence of item characteristics.

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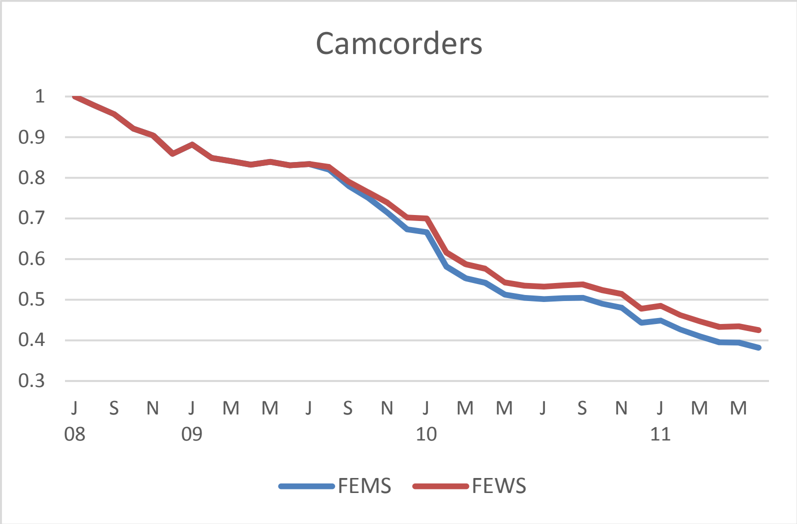
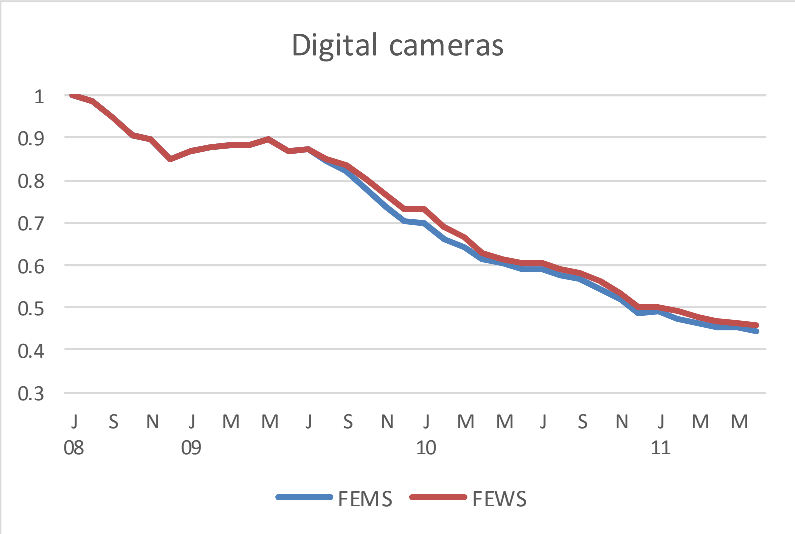
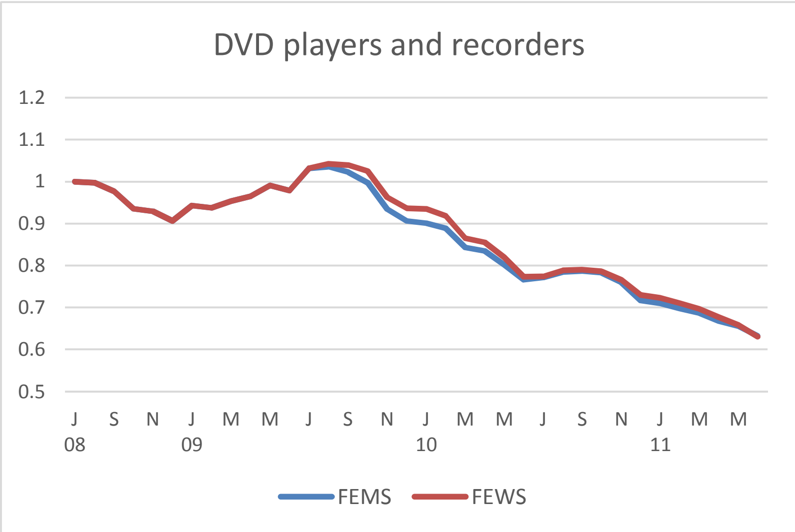
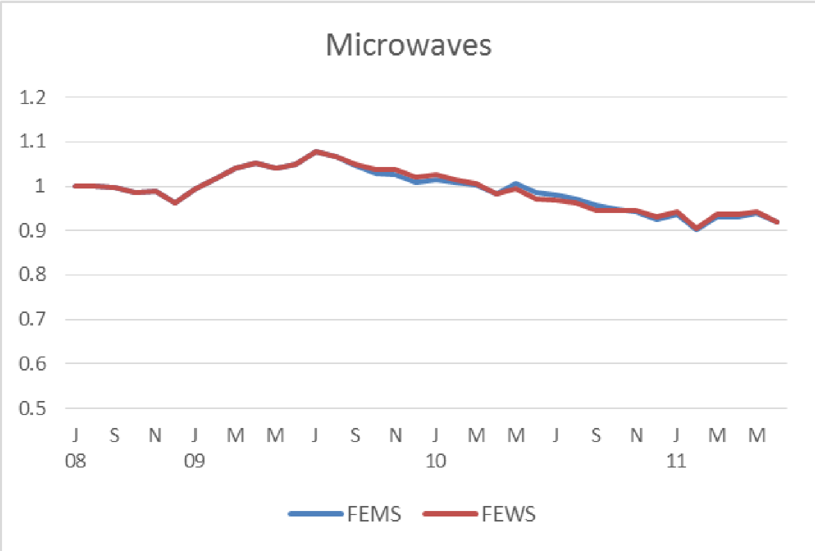
Appendix

Chart A1: Rolling year fixed effects indexes








Microwaves
1.2
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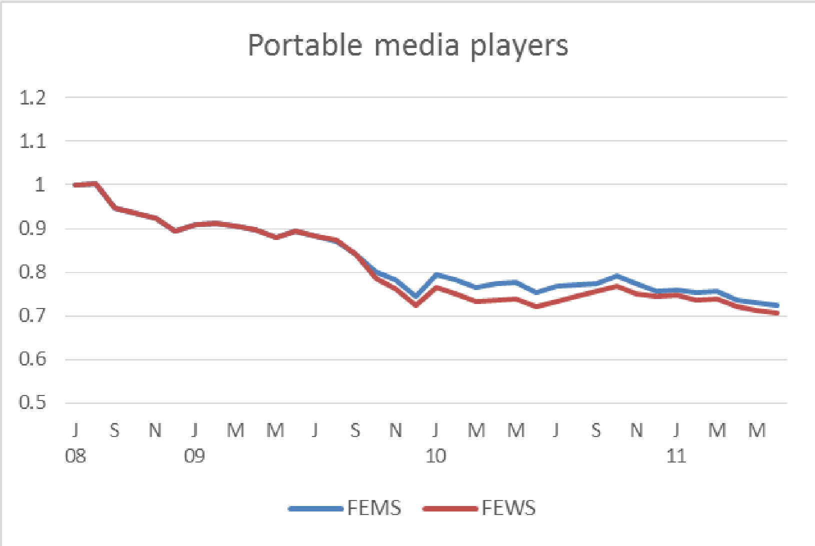
FEMS
FEWS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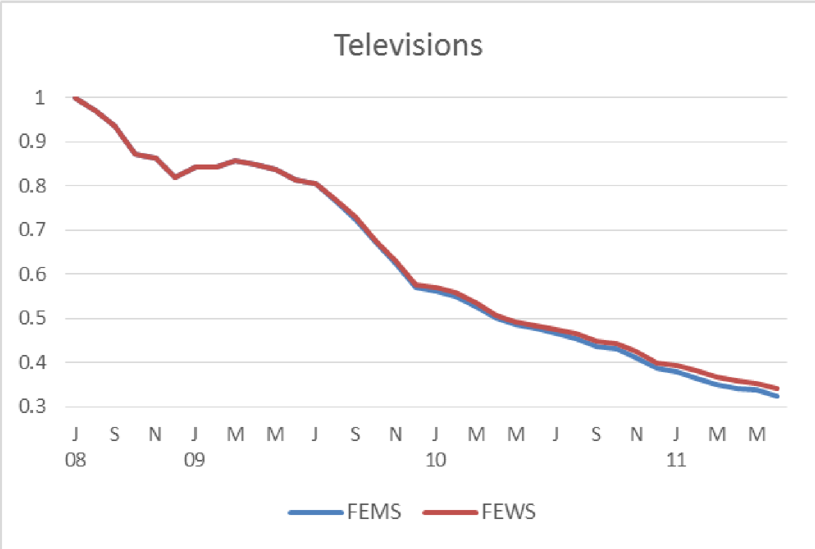
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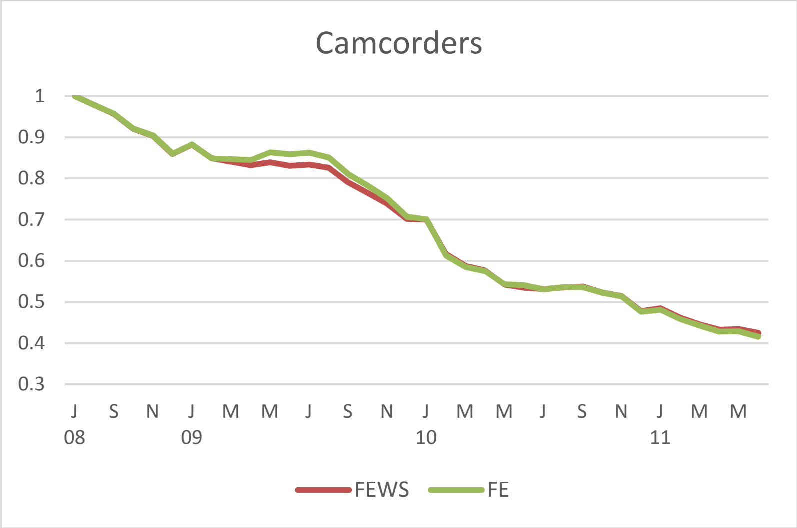
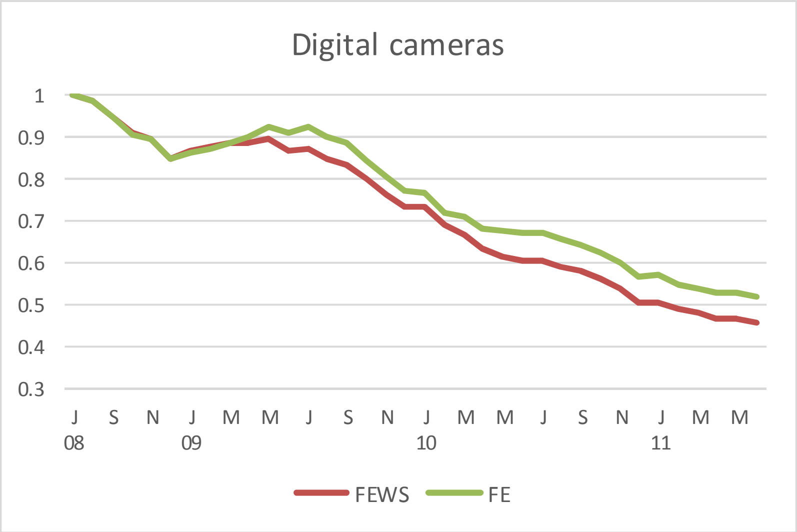
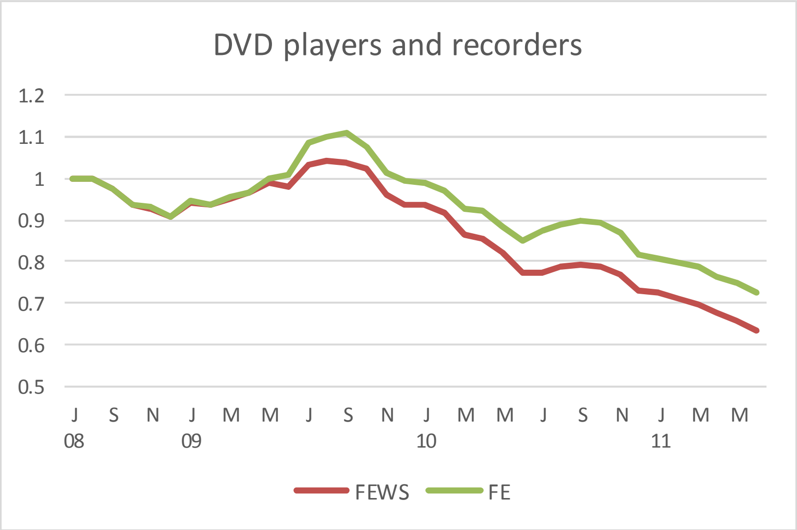
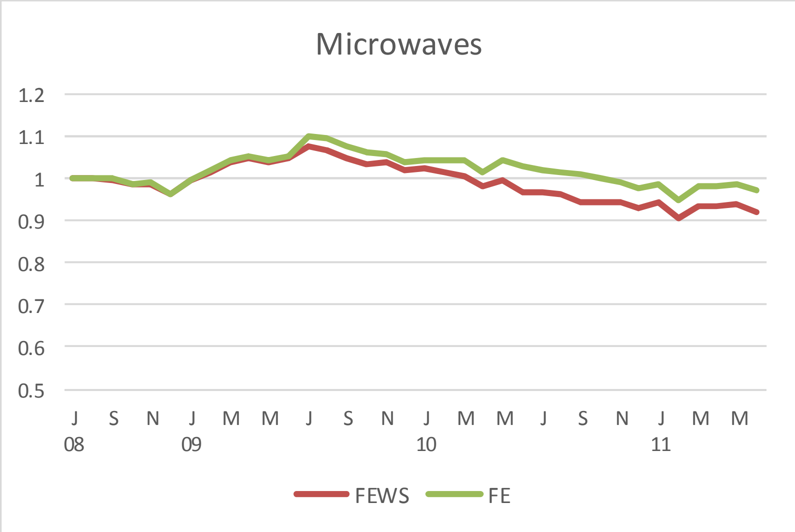
0.7
0.6
0.5
0.4
0.3
J S N J M M J S N J M M J S N J M M
08 09 10 11
FEMS
FEWS

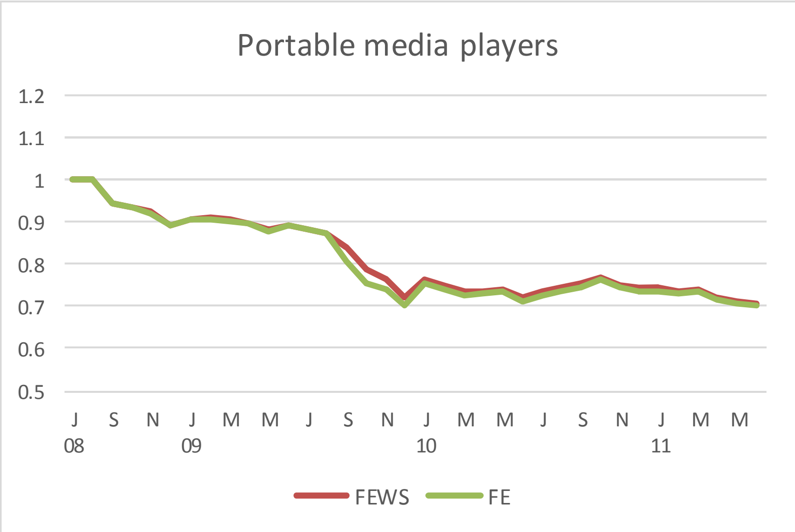
Chart A2: Fixed effects and FEWS indexes

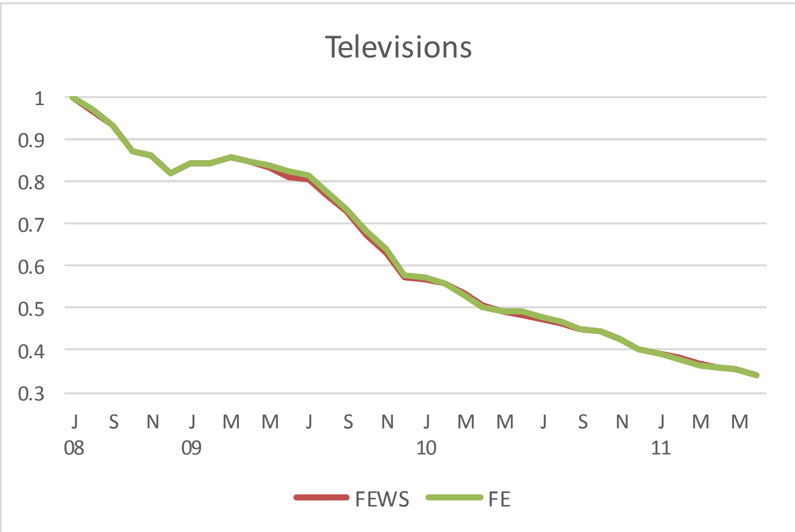







Microwaves
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
J S N J M M J S N J M M J S N J M M
08 09 10 11
FEWS
FE


Portable media players
1.2
1.1
1
0.9
0.8
0.7
0.6
0.5
J S N J M M J S N J M M J S N J M M
08 09 10 11
FEWS
FE


Televisions
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
J S N J M M J S N J M M J S N J M M
08 09 10 11
FEWS
FE