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Rolling-Time-Dummy House Price Indexes: Window Length, Linking and Options for Dealing with Low Transaction Volume

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Rolling-time-dummy (RTD) is a hedonic method used by a number of countries to compute their official house price indexes (HPIs). The RTD method requires less data and is more adaptable than other hedonic methods, which makes it well suited for computing higher frequency HPIs (e.g., monthly or weekly). In this article, we address three key issues relating to RTD. First, we develop a method for determining the optimal length of the rolling window. Second, we consider variants on the standard way of linking the current period with earlier periods, and show how the optimal linking method can be determined. Third, we propose three ways of modifying the RTD method to make it more robust to periods of low transaction volume. These modifications could prove useful for countries using the RTD method in their official HPIs.

Key words: House price index; hedonic quality adjustment; optimal window length; optimal chain linking; higher frequency indexes; low transaction volume.

1. Introduction

The housing market and the broader economy are closely connected. While it is true that economic booms and recessions can trigger booms and busts in the housing market, the causation can also run in the opposite direction. The global financial crisis of 2007–2010 was a case in point. For central banks to effectively maintain financial stability, it is therefore important to have reliable and timely house price indexes (HPIs).

To effectively distinguish between genuine price changes and compositional differences, HPIs are typically computed using hedonic methods. The hedonic approach entails estimating shadow prices on the characteristics of properties (such as floor area, age, and location) so as to ensure that quality is held fixed when measuring price changes from one period to the next. For example, Eurostat recommends that countries in Europe should compute their official HPIs using hedonic methods (Eurostat 2016).

A number of hedonic methods for constructing HPIs have been proposed in the literature (see Hill 2013, for an overview). One hedonic method that has been attracting increased attention in recent years is the rolling-time-dummy (RTD) method. It was first

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proposed by Shimizu in 1998 as part of a project entitled Construction of Property Price Indexes using Big Data 1998–2002 at Reitaku University (Shimizu et al. 2003, 2010).

The RTD method has four desirable properties. First, it is relatively simple to compute and interpret. Second, it requires less data than some other hedonic methods, such as the hedonic imputation or average characteristics methods. This is because it pools the data of multiple periods when estimating the characteristic shadow prices, which allows them to be measured with greater accuracy. RTD is particularly useful for smaller countries that have less data. In Europe, it is used by Croatia, Cyprus, France, Ireland and Portugal to construct their official HPIs (Hill et al. 2018). Japan has recently decided to compute its official residential and commercial property price indexes using the RTD method (Shimizu and Diewert 2019). Also, Brunei Darussalam (https://www.ambd.gov.bn/SiteY/o20AssetsY/o20Y/o20News/RPPI-Technical-Notes.pdf), Peru and Thailand (see https://www.bot.or.th/App/BTWS_STAT/statistics/DownloadFile.aspx?file = EC_EI_008_S2_ENG.PDF) are using RTD, and Indonesia is about to start using it (see Rachman 2019). RTD's effectiveness with smaller data sets means that it is also a good candidate for computing higher frequency indexes, such as monthly or weekly.

Third, an index provider using the RTD method can choose the length of the rolling window. A longer window increases the robustness of the index, which can be important when the data set is small, while a shorter window increases the current market relevance of the index. Index providers can trade off these two aspects when choosing the window length. In Europe, France and Portugal use a two-quarter rolling window, In Europe, Cyprus and Croatia use the RTD method with a four-quarter window, and Ireland a 12-month window, while France and Portugal employ a two-quarter window (see Hill et al. 2018). Note that the two-period RTD is also referred to as the adjacent-period method (Triplett 2004) or as the chained two-period time-dummy method. These choices are consistent with the idea that smaller countries should choose longer windows.

Fourth, an RTD index is not revised when new periods are added to the data set. This avoids confusion among users. By contrast, the time-dummy method violates the non-revisability criterion.

In this article, we address three key issues relating to the RTD hedonic method. First, there is the question of how one determines the optimal window length for any given data set? We develop an approach for answering this question and use it to compute the optimal window length for weekly HPIs in Sydney and Tokyo.

Second, the standard version of the RTD method links the current period to the period directly preceding it. It turns out this is just one of many ways that the HPI can be computed from the estimated hedonic model. We compare a number of other ways of linking in the current period, and develop an approach for determining which linking method is optimal. Our approach is then again tested on Sydney and Tokyo data. As similar linking issues arise in the scanner-data literature, we then briefly discuss the parallels between the HPI and scanner-data literatures.

Third, periods of low transaction volume can generate weak links in the RTD HPI, potentially undermining the integrity of the whole time series. We propose three ways of modifying the RTD method to make it more robust to weak links. We illustrate the problem using Sydney data. These modifications could prove useful for countries using the RTD method in their official HPIs.

Our focus is on weekly indexes. A trade-off exists between reliability and timeliness when choosing the frequency of a house price index. Higher frequency indexes, such as weekly indexes, are useful when timeliness is important, for example, when central banks make their monetary policy decisions. However, it should be noted that transaction prices are often available only after a time lag of many weeks or even months (see, for example, Shimizu et al. 2016). In such cases, a weekly index has less appeal. Higher frequency indexes, such as weekly indexes, may therefore need to be computed using list price data, which are available without any lag directly from property listing websites.

2. The Rolling Time Dummy (RTD) Method

2.1. The Standard Version

The RTD method estimates a hedonic model that includes the data of a fixed number of time periods, with time dummies included for each period (except the base period). Price indexes are derived from the estimated coefficients on these time dummies. The model is then moved forward one-period and re-estimated. The overall RTD price index is constructed by chaining together the prices indexes from these rolling windows.

More specifically, consider the standard version of the RTD method with a window length of $k + 1$ periods, as defined in Shimizu et al. (2010) and O'Hanlon (2011). Supposing that the first period in the window is period t, the first step is to estimate a semilog hedonic model as follows:

$$\ln p_{\tau h} = \sum_{c=1}^{C} \beta_c z_{\tau ch} + \sum_{s=t+1}^{t+k} \delta_s d_{\tau sh} + \varepsilon_{\tau h}, \tag{1}$$

where h indexes the housing transactions that fall in the rolling window, $p_{\tau h}$ the transaction price of property h in time period τ (where $t \leq t \leq t + k$), c indexes the set of available characteristics of the transacted dwellings, and ε is an identically, independently distributed error term with mean zero. The characteristics of the dwellings are given by the $z_{\tau ch}$, while $d_{\tau sh}$ is a dummy variable that equals 1 when $\tau = s$, and zero otherwise.

Estimating this model using ordinary least-squares, the change in the price index from period $t + k-1$ to period $t + k$ is then calculated as follows:

$$\frac{P_{t+k}}{P_{t+k-1}} = \frac{\exp(\hat{\delta}^t_{t+k})}{\exp(\hat{\delta}^t_{t+k-1})}, \tag{2}$$

where $\hat{\delta}$ denotes the least squares estimate of δ. A superscript t is included on the estimated δ coefficients to indicate that they are obtained from the hedonic model with period t as the base (i.e., $P_t = 1$). As can be seen from Equation (2), the hedonic model with period t as the base is only used to compute the change in house prices from period $t + k-1$ to period $t + k$. The window is then rolled forward one period and the hedonic model is re-estimated. The change in house prices from period $t + k$ to period $t + k + 1$ is now computed as follows:

$$\frac{P_{t+k+1}}{P_{t+k}} = \frac{\exp(\hat{\delta}^{t+1}_{t+k+1})}{\exp(\hat{\delta}^{t+1}_{t+k})}, \tag{3}$$

where now the base period in the hedonic model is period $t+1$. The price index over multiple periods is computed by chaining these bilateral comparisons together as follows:

$$\frac{P_{t+k+1}}{P_t} = \left[\frac{\exp(\hat{\delta}^{t-k}_{t+1})}{\exp(\hat{\delta}^{t-k}_{t})}\right]\left[\frac{\exp(\hat{\delta}^{t-k+1}_{t+2})}{\exp(\hat{\delta}^{t-k+1}_{t+1})}\right] \times \cdots \times \left[\frac{\exp(\hat{\delta}^{t+1}_{t+k+1})}{\exp(\hat{\delta}^{t+1}_{t+k})}\right]. \tag{4}$$

An important feature of the RTD method is that once a price change P_{t+k}/P_{t+k-1} has been computed, it is never revised. Hence when data for a new period $t+k+1$ becomes available, the price indexes P_t, P_{t+1}, . . ., P_{t+k} are already fixed. The sole objective when re-estimating the hedonic model to include period $t+k+1$ is to compute P_{t-k+1}/P_{t+k}.

2.2. Linking Variants on the RTD Method

Instead of always focusing on the last two estimated δ coefficients in each hedonic model, an alternative would be to focus on the last and third last coefficients. In this case, the price change from period $t+k-1$ to period $t+k$ could be calculated as follows:

$$\frac{P_{t+k}}{P_{t+k-1}} = \left(\frac{P_{t+k-2}}{P_{t+k-1}}\right)\frac{\exp(\hat{\delta}^{t}_{t+k})}{\exp(\hat{\delta}^{t}_{t+k-2})}, \tag{5}$$

where as has been noted above both P_{t+k-1} and P_{t+k-2} are already fixed by the time the data for period $t+k$ becomes available. Another alternative is the following:

$$\frac{P_{t+k}}{P_{t+k-1}} = \left(\frac{P_{t+k-3}}{P_{t+k-1}}\right)\frac{\exp(\hat{\delta}^{t}_{t+k})}{\exp(\hat{\delta}^{t}_{t+k-3})}, \tag{6}$$

and more generally,

$$\frac{P_{t+k}}{P_{t+k-1}} = \left(\frac{P_{t+k-j}}{P_{t+k-1}}\right)\frac{\exp(\hat{\delta}^{t}_{t+k})}{\exp(\hat{\delta}^{t}_{t+k-j})}, \tag{7}$$

where $j \leq k$. In Equation (5), the hedonic model is used to link each new period with two periods earlier. In Equation (6), each new period with three periods earlier, while in Equation (7), each new period with j periods earlier. In other words, given a window length of $k+1$ periods, there are k distinct ways of linking period $t+k$ with the earlier periods. Each will give a different answer, and one cannot say ex-ante that one is better than another.

Another possibility is to compute the geometric mean of these k sets of results as follows:

$$\frac{P_{t+k}}{P_{t+k-1}} = \prod_{j=1}^{k}\left[\left(\frac{P_{t+k-j}}{P_{t+k-1}}\right)\left(\frac{\exp(\hat{\delta}^{t}_{t+k})}{\exp(\hat{\delta}^{t}_{t+k-j})}\right)\right]^{1/k}. \tag{8}$$

This method uses each single-period link in turn to generate k distinct estimates of P_{t+k}/P_{t+k-1}, and then takes the geometric mean of these estimates.

A weighted geometric mean could also be computed, with more recent periods being given more weight. For example, the weights could decline geometrically as follows:

$$\frac{P_{t+k}}{P_{t+k-1}} = \prod_{j=1}^{k} \left\{ \left[\left(\frac{P_{t+k-j}}{P_{t+k-1}} \right) \left(\frac{\exp(\hat{\delta}^{t}_{t+k})}{\exp(\hat{\delta}^{t}_{t+k-j})} \right) \right]^{\frac{(1-\lambda)\lambda^{j-1}}{1-\lambda^{k}}} \right\}, \tag{9}$$

where $0 < \lambda < 1$. The idea here is that price index comparisons between closer together periods may be more accurate then comparisons between further apart periods.

There are close similarities here with the literature on constructing monthly or weekly price indexes for consumer goods using scanner data. Focusing on the case of monthly indexes, price indexes in this literature are often computed using a 13-month rolling window. The price index itself in each window is not necessarily computed using a hedonic method. Nevertheless, the same issue arises regarding how the current period should be linked to earlier periods. In this literature, the standard linking method used by the RTD method in Equation (2) is sometimes referred to as a *movement* splice (see, for example, De Haan 2015, and Chessa et al. 2017). Other possibilities considered are a *window* splice which links the new month in by comparing it with the corresponding month one year earlier (Krsinich 2016), and a mean splice, which is analogous to the geometric mean in Equation (8) (Diewert and Fox 2020). These methods are all discussed in De Haan et al. (2020). In addition, Melser (2018) proposes a weighted mean splice. Melser's method is similar in spirit to our weighted mean described in Equation (9), although the context is rather different. His weighted mean splice is a solution to a logarithmic weighted least squares problem focused on transitivizing bilateral price indexes. The weights are derived from the product overlaps between adjacent periods. No such equivalent weights exist in our context.

2.3. *Low Transaction Periods*

Many data sets exhibit pronounced seasonal fluctuations in the number of transactions. For example, each year in Sydney the number of transactions falls very significantly in December and January (see Subsection 5.6). This period of low transaction volume could create problems potentially causing a level shift or drift in the overall RTD price index. A weekly price index over this period will contain an unusually high level of noise. For example, suppose the price index for week 51 of 2020 contains a large positive random error. This will have a permanent impact on the RTD price index, causing it to drift upwards.

We consider three ways of mitigating the effect of low transactions volume on RTD house price indexes. Our starting point is that the desired window length is known and that special action is deemed necessary for any period that has less than N transactions.

2.3.1. Method 1

When computing the price index for period $t+k$, if any of earlier periods that are supposed to be in the window have less than N transactions, then these periods are deleted and replaced by the most recent available earlier period that has at least N transactions. If period $t+k$ has less than N transactions, the RTD method is still used to compute P_{t+k}/P_{t+k-1} (or $P_{t+k}/P_{\mathrm{t+k-2}}$ if period $t+k-1$ has less than N transactions). But period $t+k$ is then not used to compute the price indexes of later periods.

An example should help clarify the rule. Suppose the window length is set at three weeks, and that 2020, weeks 51, 52, and 2021 week 1 have less than N transactions.

Current period	**Periods included in the rolling window**
2020w50:	(2020w48, 2020w49, 2020w50)
2020w51:	(2020w49, 2020w50, 2020w51)
2020w52:	(2020w49, 2020w50, 2020w52)
2021w1:	(2020w49, 2020w50, 2021w1)
2021w2:	(2020w49, 2020w50, 2021w2)
2021w3:	(2020w50, 2021w2, 2021w3)
2021w4:	(2021w2, 2021w3, 2021w4)

The linking structure in this example is graphed in Figure 1. 2020w51, 2020w52, 2021w1 and 2021w2 are all linked into the price index via 2020w50. From then on, normal chronological chaining as described in Subsection 2.1 resumes.

In the scenario described above, the three-week rolling window price indexes are calculated as follows:

$$\frac{P_{2020w51}}{P_{2020w50}}=\frac{\exp\left(\hat{\delta}^{2020w49}_{2020w51}\right)}{\exp\left(\hat{\delta}^{2020w49}_{2020w50}\right)},\ \frac{P_{2020w52}}{P_{2020w50}}=\frac{\exp\left(\hat{\delta}^{2020w49}_{2020w52}\right)}{\exp\left(\hat{\delta}^{2020w49}_{2020w50}\right)},\ \frac{P_{2020w1}}{P_{2020w50}}=\frac{\exp\left(\hat{\delta}^{2020w49}_{2020w1}\right)}{\exp\left(\hat{\delta}^{2020w49}_{2020w50}\right)},$$

$$\frac{P_{2021w2}}{P_{2020w50}}=\frac{\exp\left(\hat{\delta}^{2020w49}_{2021w2}\right)}{\exp\left(\hat{\delta}^{2020w49}_{2020w50}\right)},\ \frac{P_{2021w3}}{P_{2021w2}}=\frac{\exp\left(\hat{\delta}^{2020w50}_{2021w3}\right)}{\exp\left(\hat{\delta}^{2020w50}_{2021w2}\right)},\ \frac{P_{2021w4}}{P_{2021w3}}=\frac{\exp\left(\hat{\delta}^{2021w2}_{2021w4}\right)}{\exp\left(\hat{\delta}^{2020w2}_{2020w3}\right)}.$$

In these equations, the superscript denotes the base week in each hedonic model and the subscript denotes the week of the estimated δ parameter.

The overall price index with 2020w50 normalized to 1 is then constructed as follows:

$$1,\frac{P_{2020w51}}{P_{2020w50}},\frac{P_{2020w52}}{P_{2020w50}},\frac{P_{2020w1}}{P_{2020w50}},\frac{P_{2021w2}}{P_{2020w50}},\frac{P_{2021w2}}{P_{2020w50}},\frac{P_{2021w3}}{P_{2021w2}},\frac{P_{2021w2}}{P_{2020w50}},\frac{P_{2021w3}}{P_{2021w2}},\frac{P_{2021w4}}{P_{2021w3}},\ldots$$

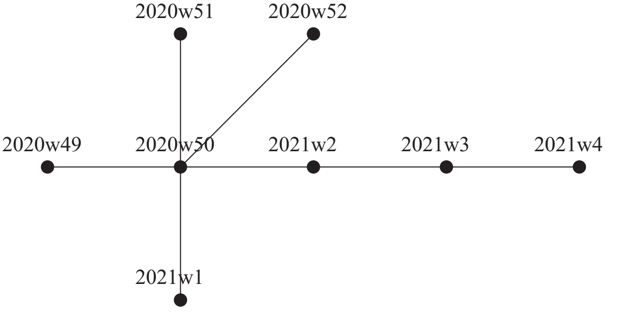

Fig. 1. The linking structure of method 1.

As can be seen the lack of data for 2020w51, 2020w52 and 2021w1 does not contaminate the longer time series RTD price index after 2021w1.

2.3.2. Method 2

When a period has fewer than N transactions, more transactions are drawn from the preceding period until the threshold N is reached. The chronologically closest transactions from the previous period are used first. If there are enough transactions in the last three days of the preceding period to reach the N threshold, then only these last three days are added to the current period, when computing the current period price index. These three days are still also included in the previous period.

As an example, suppose that each of 2020w51, 2020w52 and 2021w1 has more than $N/2$ and less than N transactions. The RTD rolling window would now be constructed as follows:

Current period	**Periods included in the rolling window**
2020w50:	(2020w48, 2020w49, 2020w50)
2020w51:	(2020w49, 2020w50, 2020w51^{+})
2020w52:	(2020w50, 2020w51^{+}, 2020w52^{+})
2021w1:	(2020w51^{+}, 2020w52^{+}, 2021w1^{+})
2021w2:	(2020w52^{+}, 2021w1^{+}, 2021w2)
2021w3:	(2021w1^{+}, 2021w2, 2021w3)
2021w4:	(2021w2, 2021w3, 2021w4)

The “+” superscripts above denote that the week is being supplemented with data from the previous week. Once each week with less than N transactions has been supplemented with transactions from the previous week, the RTD price index is computed in the standard way described in Subsection 2.1.

2.3.3. Method 3

Our third alternative approach is to not compute an index for a period with less than N transactions. Instead it is merged with the next period. If together these two periods reach the N transaction threshold, then they are treated as a single period. If together they still do not reach the N transaction threshold, then again no index is computed until the next period becomes available, d so on.

As an example, again suppose that each of 2020w51, 2020w52 and 2021w1 has more than $N/2$ and less than N transactions. The RTD rolling window would now be constructed as follows:

Current period	**Periods included in the rolling window**
2020w50:	(2020w48, 2020w49, 2020w50)
2020w51:	Missing
2020w51-w52:	(2020w49, 2020w50, 2020w51-w52)
2021w1:	Missing
2021w1-w2:	(2020w50, 2020w51-w52, 2021w1-w2)
2021w3:	(2020w51-w52, 2021w1-w2, 2021w3)
2021w4:	(2021w1-w2, 2021w3, 2021w4)
2021w5:	(2021w3, 2021w4, 2021w5)

All three methods ensure that periods of low transaction volume do not contaminate the index in later periods. Method 1 computes price indexes for each low transaction week using whatever transaction data are actually available. Method 2 supplements the data for low transaction weeks with data from the previous week (or more if required), while method 3 merges low transaction weeks and treats them as a single period if each individually does not contain enough transactions. Which method is best depends on the needs of users. If it is important that a price index is computed for every period (here weeks) then either method 1 or 2 should be used. Method 1 will better capture actual price movements during low transaction periods unless they become too distorted by noise arising from small sample sizes. Overall we prefer Method 1. We illustrate the impact of its use on the Sydney data set in Subsection 5.6.

3. Quarterly Benchmarks

3.1. The Hedonic Imputation Method

The hedonic imputation method is an alternative to the RTD method (see, for example Diewert 2011 and Hill 2013). We use the hedonic imputation method here as a reference index for assessing the performance of different versions of the RTD method.

The hedonic imputation approach estimates a separate hedonic model for each period:

$$\ln p_{t,h} = \beta_t \cdot z_{t,h} + \varepsilon_{t,h}, \tag{10}$$

where for convenience β_t and $z_{t,h}$ now both denote vectors. The hedonic model is then used to impute prices for individual houses. For example, let $\hat{p}_{t+1,h}(z_{t,h})$ denote the imputed price in period $t+1$ of a house with the characteristic vector $z_{t,h}$ sold in period t. This price is imputed by substituting the characteristics $z_{t,h}$, into the estimated hedonic model of period $t+1$ as follows:

$$\hat{p}_{t+1,h}(z_{t,h}) = \exp\left(\sum_{c=1}^{C} \hat{\beta}_{c,t+1} z_{c,t,h}\right). \tag{11}$$

With these imputed prices it is now possible to construct a matched sample, thus allowing standard price index formulas to be used. See Silver and Heravi (2007), Diewert et al. (2009), and Rambaldi and Rao (2013) for a discussion of some of the advantages of the hedonic imputation method.

$$\text{Geometric–Paasche Imputation}: \; P^{PI}_{t,t+1} = \prod_{h=1}^{H_{t+1}} \left[\left(\frac{\hat{p}_{t+1,h}}{\hat{p}_{t,h}(z_{t+1,h})}\right)^{1/H_{t+1}}\right] \tag{12}$$

$$\text{Geometric–Laspeyres Imputation}: \; P^{LI}_{t,t+1} = \prod_{h=1}^{H_{t}} \left[\left(\frac{\hat{p}_{t+1,h}(z_{t,h})}{\hat{p}_{t,h}}\right)^{1/H_{t}}\right] \tag{13}$$

$$\text{Törnqvist Imputation}: \; P^{TI}_{t,t+1} = \sqrt{P^{PI}_{t,t+1} \times P^{LI}_{t,t+1}} \tag{14}$$

In a comparison between periods t and $t+1$, the Geometric-Laspeyres index focuses on the H_t houses that sold in the earlier period t. Similarly the Geometric-Paasche index focuses on the H_{t+1} houses that sold in the later period $t+1$. These price indexes give equal weight to each house sold (see De Haan (2010) for a discussion on alternative weighting schemes). By taking the geometric mean of Geometric-Paasche and Geometric-Laspeyres, the Törnqvist index gives equal weight to both periods. The Geometric-Paasche, Geometric-Laspeyres and Törnqvist indexes above are of the double imputation variety, meaning that both prices in each price relative are imputed. A single imputation approach by contrast imputes only one price in each pair (since the actual price is always available for one of the two periods being compared). There has been some discussion in the literature over the relative merits of the two approaches (see, for example De Haan 2004; Hill and Melser 2008). Empirically we try both approaches. The resulting price indexes are virtually indistinguishable. Hence to simplify the presentation, we focus here only on double imputation price indexes. The hedonic imputation method allow the characteristic shadow prices to update each period.

In the context of weekly indexes, the hedonic imputation method is unlikely to work well since the sample sizes in many weeks may be too small to justify estimating a separate hedonic model each week. However, in our context, quarterly hedonic imputation will provide a useful benchmark for weekly RTD indexes.

3.2. *The Time-Dummy Method*

We also use the time-dummy index as a reference for assessing the performance of RTD weekly indexes. The time-dummy method is the limiting case of the RTD method where the window length is the same as the number of periods in the comparison. One disadvantage of the time-dummy method is that it violates non-revisability, with the effect that whenever a new period is added to the data set, all past price indexes are subject to change.

$$\ln p_{\tau h} = \sum_{c=1}^{C} \beta_c z_{\tau c h} + \sum_{t=2}^{T} \delta_t d_{\tau t h} + \varepsilon_{\tau h}. \tag{15}$$

The price index for period t relative to period 1 is then calculated as follows:

$$\frac{P_t}{P_1} = \exp\left(\hat{\delta}_t\right). \tag{16}$$

3.3. *A Performance Criterion for Weekly Indexes Derived from Quarterly Indexes*

We propose a criterion here for determining the optimal window length and linking method for weekly RTD indexes, by comparing them with reference quarterly hedonic indexes. We consider two reference quarterly hedonic indexes: these are the hedonic imputation method and the time-dummy method described above. We focus on these two methods because they are quite different (i.e., one re-estimates the hedonic model every quarter while the other does not re-estimate at all). Using these quarterly indexes as benchmarks should avoid biasing the results towards any particular window length.

Empirically we find that the quarterly hedonic imputation and time-dummy methods approximate each other closely. By contrast for weekly RTD indexes, if we allow the window length to vary between two and 53 weeks, the range of possible results becomes much larger (see Subsection 5).

The greater sensitivity of weekly indexes to the choice of hedonic method makes them a more interesting focus of analysis than quarterly indexes. The choice of window length really matters for weekly RTD indexes. Furthermore, the greater robustness of quarterly indexes is a property we can exploit to discriminate between competing weekly RTD indexes.

The first step of our criterion for assessing the performance of alternative weekly RTD indexes is to construct a quarterly index from each weekly index. This can be done in the following way. Let $t = 1, \ldots, T$ indexing the quarters in the data set, and $v = 1, \ldots, V$ the 13 weeks in a quarter. A quarterly price index $P^{w}_{t,t+1}$ is obtained from a weekly price index as follows:

$$P^{w}_{t,t+1} = \prod_{v=1}^{13} \left(\frac{P_{t+1,v}}{P_{t,v}} \right)^{1/13}, \tag{17}$$

where $P_{t,v}$ denotes the level of the weekly price index in quarter t, week v. Each element $P_{t+1,v}/P_{t,v}$ in (17) is a price index comparing a particular week with another week one quarter later. In other words, each of these elements is a price index calculated at a quarterly frequency. A total of 13 such indexes can be computed in each quarter. By taking the geometric mean of these 13 quarterly frequency price indexes, we obtain an overall quarterly price index, which can be interpreted as the quarterly equivalent of the original weekly index.

Once the quarterly version of the weekly index has been constructed, its performance can be measured by comparing it with a reference quarterly index. Here we make the comparison using a metric proposed by Diewert (2002, 2009).

$$X = \frac{1}{T-1} \sum_{t=1}^{T-1} \left[\left(\frac{P^{w}_{t,t+1}}{P^{quart}_{t,t+1}} \right) + \left(\frac{P^{quart}_{t,t+1}}{P^{w}_{t,t+1}} \right) - 2 \right].$$

The smaller the value of the X metric, the more similar are the two indexes.

Given a reference quarterly index, we can then vary the length of the RTD rolling window and observe how it affects the X metric. We prefer whichever window length generates the smallest X metric. An important question then is how robust is the optimal window length to the choice of reference quarterly index? If it is reasonably robust, then the selected window length is optimal in the sense that it generates a weekly RTD index that is the most consistent with our reference quarterly indexes. Similarly, holding the window length fixed at 53 weeks, we can observe how changing the RTD linking method affects the X metric. Again, we prefer the linking method with the smallest X metric.

4. The Data Sets

4.1. The Sydney Data Set and Hedonic Model

We use a data set obtained from Australian Property Monitors that consists of prices and characteristics of houses sold in Sydney (Australia) for the years 2003–2014. For each house, we have the following characteristics: the actual sale price, time of sale, postcode, property type (i.e., detached or semi), number of bedrooms, number of bathrooms, land area, exact address, longitude and latitude. (We exclude all townhouses from our analysis since the corresponding land area is for the whole strata and not for the individual townhouse itself.)

For a robust analysis, it was necessary to remove some outliers. This is because there is a concentration of data entry errors in the tails of the distribution, caused for example by the inclusion of erroneous extra zeroes. These extreme observations can distort the results. Complete data on all our hedonic characteristics are available for 433,202 observations. To simplify the computations, we also merged the number of bathrooms and number of bedrooms into broader groups (one, two, and three or more bathrooms; one or two, three, four, five or more bedrooms).

Using weekly periods, the hedonic model for Sydney is estimated with a rolling window ranging between two weeks and 53 weeks. The window is then rolled forward one period and the hedonic model re-estimated. Hence in the case of the two-week window, a total of 711 hedonic models are estimated, covering the time interval from January 2003 to December 2014.

The hedonic model estimated for Sydney is semilog and contains the following five characteristics:

(1) number of bedrooms,
(2) number of bathrooms,
(3) log of land area,
(4) house type (detached, or semi), and
(5) postcode.

All these variables with the exception of land area take the form of dummy variables.

4.2. The Tokyo Data Set and Hedonic Model

The Tokyo data set covers the metropolitan area (621 square kilometers), and the analysis period is approximately 30 years between January 1986 and June 2016. The data set includes previously-owned condominiums published Shukan Jyutaku Joho (Residential Information Weekly) published by RECRUIT, Co. This magazine provides information on the characteristics and asking prices of listed properties on a weekly basis. Moreover, Shukan Jutaku Joho provides time-series data on housing prices from the week they were first posted until the week they were removed as a result of successful transactions. We only use the price in the final week because this can be safely regarded as sufficiently close to the contract price.

The available housing characteristics include floor space and age. The convenience of public transportation from each housing location is represented by travel time to the central business district (CBD), and time to the nearest station. City codes and a railway dummy to indicate along which railway/subway line a housing property is located are also available.

The hedonic model for Tokyo is estimated over 242,233 observations. The functional form is semilog. The explanatory variables used here are:

(1) log of floor area,
(2) age,
(3) time to nearest station,
(4) time to Tokyo central station (included as a quadratic), and
(5) city code.

5. Results

5.1. The Sensitivity of the Results to the Choice of Window Length

The spreads of the weekly RTD hedonic price indexes for Sydney and Tokyo as the window length is varied between two and 53 weeks are shown in Figures 2 and 3. It can be seen that the weekly indexes are quite sensitive to the choice of window length.

5.2. The Sensitivity of the Results to the Choice of Linking Method

Holding the window length fixed at 53 weeks, the sensitivity of a weekly RTD method to the choice of linking method is shown for Sydney and Tokyo in Figures 4 and 5. It can be seen that the variation in the RTD price indexes from varying the linking method is smaller than the variation resulting from changing the window length. However, the spread is still significant.

5.3. A Quarterly Index as a Benchmark

The hedonic imputation and time-dummy methods generate very similar quarterly price indexes. The results are shown in Figures 6 and 7. These results indicate that at a quarterly frequency, we have quite a good idea of what the right answer is. Hence, these quarterly indexes can be used as a benchmark for discriminating between competing weekly indexes.

5.4. How RTD Index Performance Depends on Window Length

Here we focus on the standard RTD linking method described in Subsection 2.1. For this case, the *X* metric for each RTD window length for Sydney with the hedonic imputation index as the reference quarterly index is shown in Figure 8. The *X* metric is minimized when the RTD

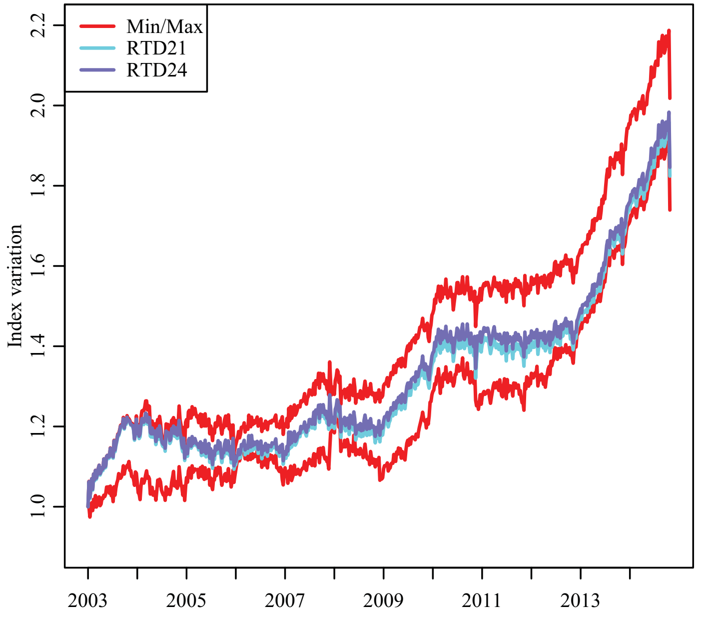

Fig. 2. The impact of varying the window length on weekly RTD house price indexes for Sydney.
Note: RTD21 and RTD24 denote the 21- and 24-week RTD price indexes for Sydney. Min and max denote the lower and upper bounds on all the RTD price indexes with windows ranging between two and 53 weeks.

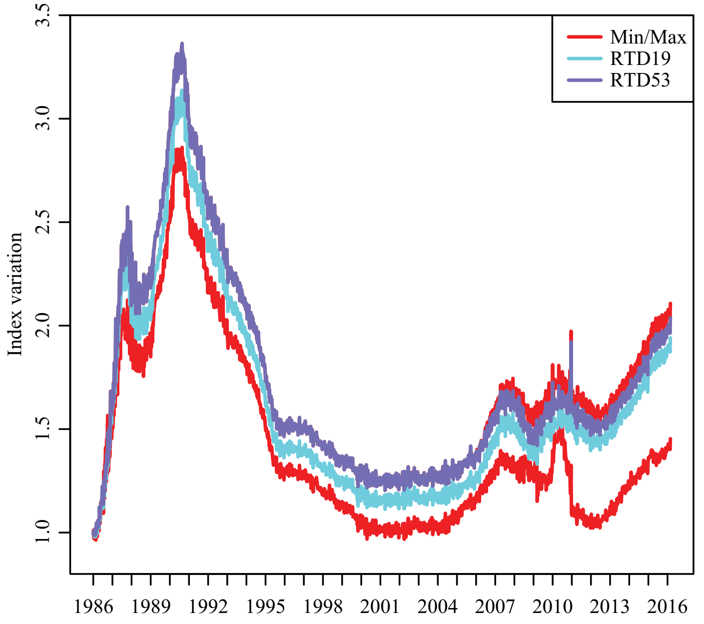

Fig. 3. The impact of varying the window length on weekly RTD house price indexes for Tokyo.
Note: RTD19 and RTD53 denote the 19- and 53-week RTD price indexes for Tokyo. Min and max denote the lower and upper bounds on all the RTD price indexes with windows ranging between two and 53 weeks.

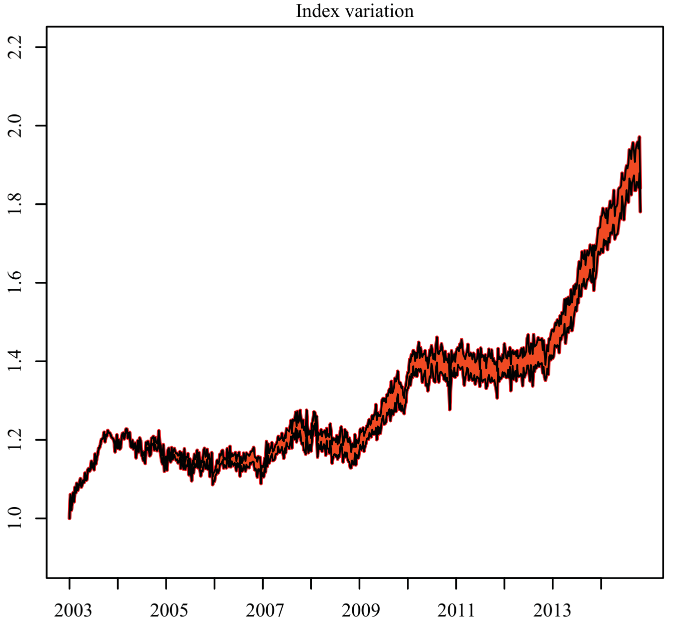

Fig. 4. The impact of varying the linking method on weekly RTD house price indexes with a 53-week window for Sydney.
Note: This graph shows the range of RTD price indexes for Sydney resulting from using different single-period linking methods. With the window length fixed at 53 weeks, there are 52 ways of doing single-period linking.

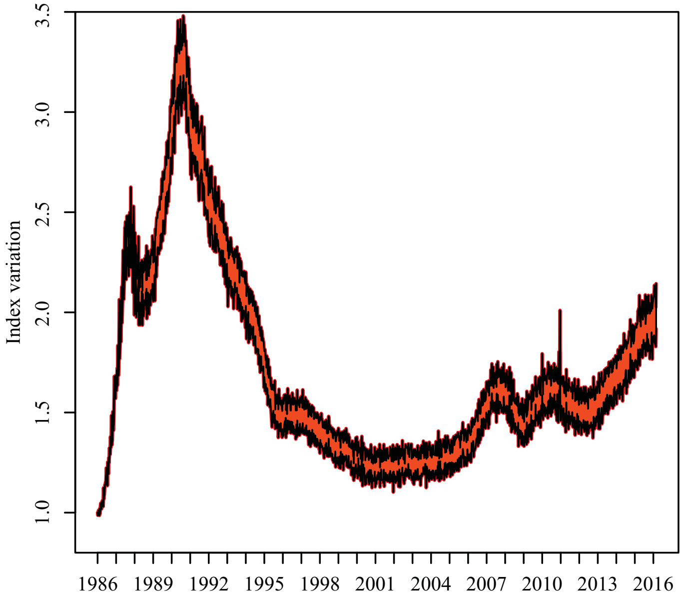

Fig. 5. The impact of varying the linking method on weekly RTD house price indexes with a 53-week window for Tokyo.
Note: This graph shows the range of RTD price indexes for Tokyo resulting from using different single-period linking methods. With the window length fixed at 53 weeks, there are 52 ways of doing single-period linking.

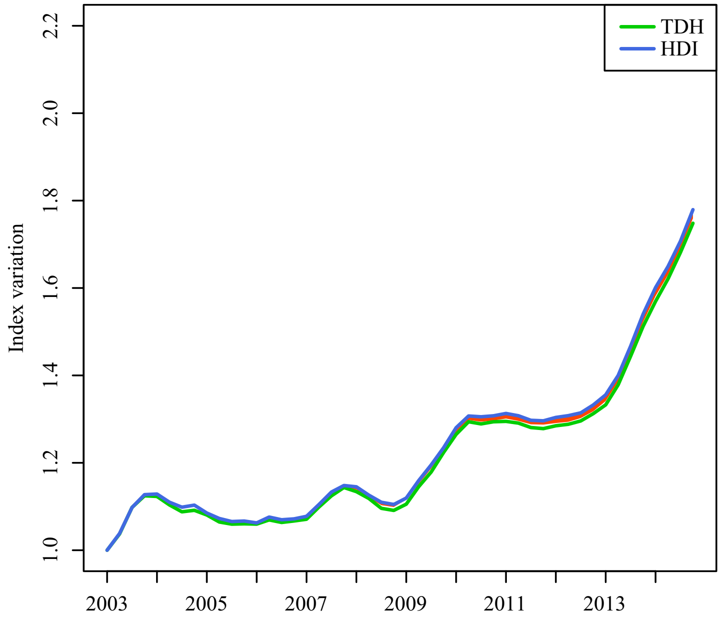

Fig. 6. Quarterly hedonic imputation and time-dummy house price indexes for Sydney.
Note: TDH and HDI here denote quarterly time-dummy hedonic and hedonic double imputation price indexes for Sydney. As can be seen, the two indexes closely approximate each other.

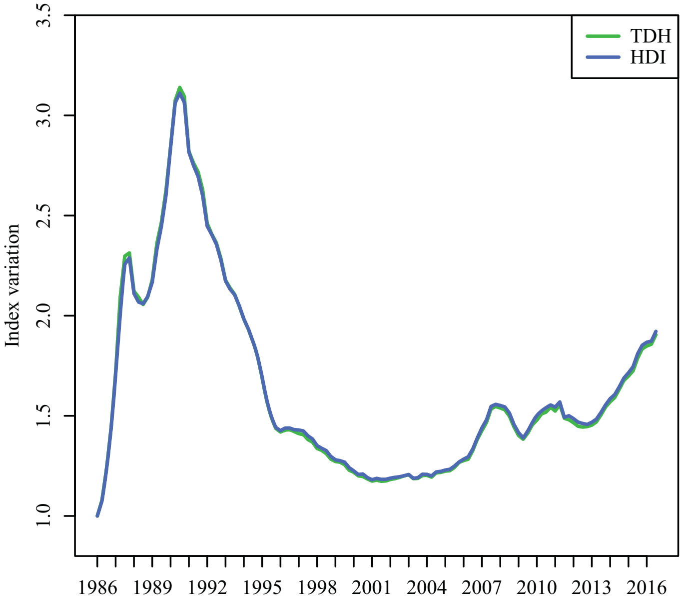

Fig. 7. Quarterly hedonic imputation and time-dummy house price Indexes for Tokyo.
Note: TDH and HDI here denote quarterly time-dummy hedonic and hedonic double imputation price indexes for Tokyo. As can be seen, the two indexes closely approximate each other.

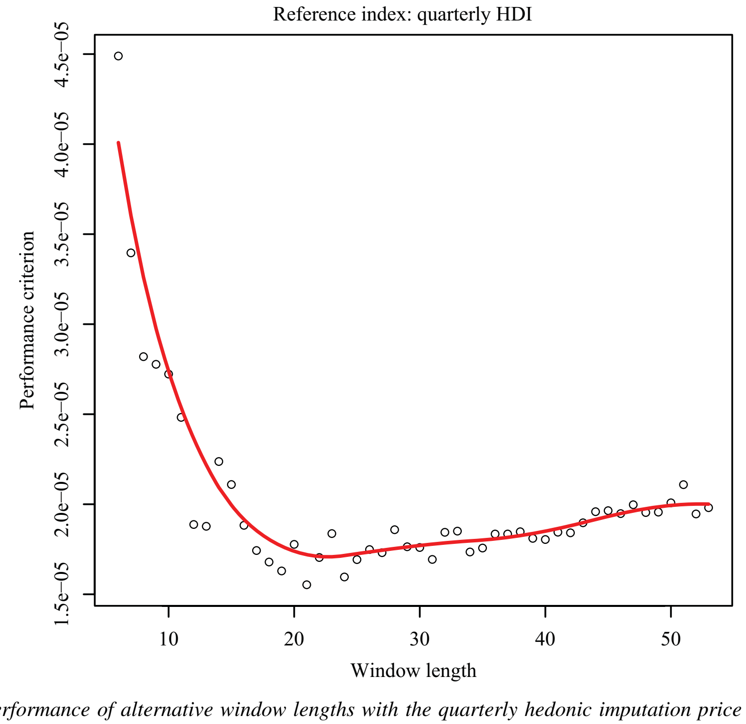

Fig. 8. Performance of alternative window lengths with the quarterly hedonic imputation price index as the reference: Sydney
Note: This graph shows which window length generates a weekly RTD price index that most closely approximates a quarterly hedonic imputation index. For Sydney the optimal window length here is 21 weeks. The red curve represents a fitted curve obtained by a local-linear smoother.

window length is 21 weeks. The same answer is obtained when the time-dummy index is used as the reference quarterly index as shown in Figure 15 in the Appendix (Section 7).

For Tokyo, when the hedonic imputation index is used as the reference quarterly index, the X metric is minimized by an RTD window length of 18 weeks, as shown in Figure 9. When the time-dummy index is used as the reference quarterly index, the results for Tokyo are not so clear, as shown in Figure 16, in the Appendix.

The optimal window length may also depend on the linking method. To illustrate this point, we recompute the optimal window length for Sydney, where now the linking is done using the geometric mean linking method as described in Equation (8). Using the quarterly hedonic imputation method as the benchmark, the optimal window length is now 19 weeks (see Figure 10). This is quite similar to the optimal window length of 21 weeks obtained using single-period linking.

In summary, we find that for Sydney the optimal RTD window length is between 19 and 21 weeks depending on the linking method used. For Tokyo, according to the quarterly hedonic imputation benchmark, the optimal window length is 18 weeks.

5.5. How RTD Index Performance Depends on the Linking Method

Now instead, we hold the RTD window length fixed at 53 weeks and compare the impact on the X metric of varying the linking method used by the RTD method. With a 53 week window, there are 52 ways of linking a new period to a single previous period, as described in Equation (6). For Sydney, the X metric corresponding to each of these 52 ways of

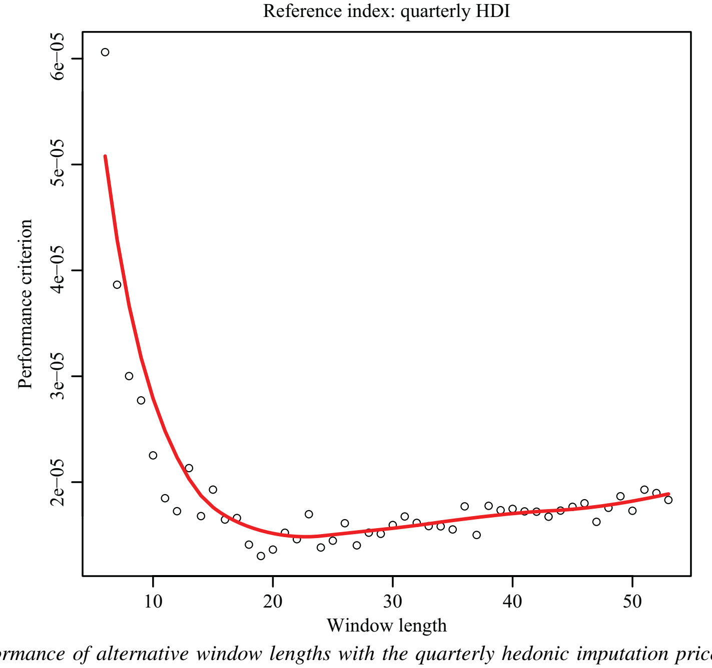

Fig. 9. Performance of alternative window lengths with the quarterly hedonic imputation price index as the reference: Tokyo.

Note: This graph shows which window length generates a weekly RTD price index that most closely approximates a quarterly hedonic imputation index. For Tokyo the optimal window length here is 18 weeks. The red curve represents a fitted curve obtained by a local-linear smoother.

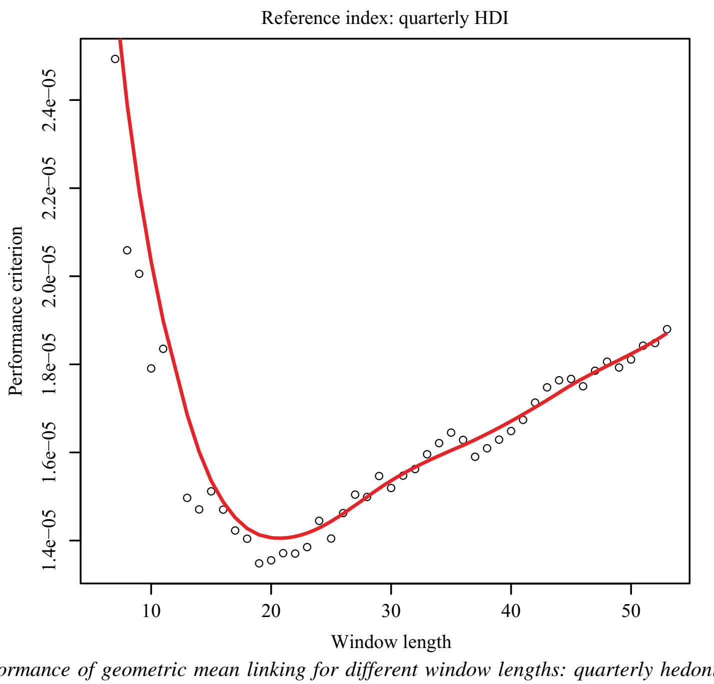

Fig. 10. Performance of geometric mean linking for different window lengths: quarterly hedonic imputation benchmark for Sydney.

Note: This graph shows which window length generates a weekly RTD price index that most closely approximates a quarterly hedonic imputation index when the current period is linked in using the geometric linking method in Equation (8). For Sydney the optimal window length here is 19 weeks. The red curve represents a fitted curve obtained by a local-linear smoother.

linking is shown in Figure 11 for the case where the quarterly hedonic imputation index is used as the reference. Corresponding results with the quarterly time-dummy index as the reference are shown in Figure 17.

In addition to these 52 single period linking methods, we also consider three average linking methods.

(1) **Geomean52** is the geometric mean of the 52 single period linking methods as described in Equation (8).
(2) **Geomean20** is the geometric mean of the 20 chronologically closest single period linking methods.
(3) **lambda = 0.95** is the weighted geometric mean method with $\lambda = 0.95$ as described in Equation (9).

When the quarterly hedonic imputation method is used as the reference index the optimal linking method links week t to week $t-16$ (see Figure 11). Linking through the period 16 weeks earlier even slightly outperforms the average linking methods (1), (2) and (3).

When the quarterly time-dummy method is used as the reference index, the optimal link for week t is with week $t-13$ (see Figure 17 in the Appendix). In this case, linking through the period 13 weeks earlier slightly outperforms methods (1) and (3), but is about equivalent to taking the geometric mean of the chronologically most recent 20 single-week links.

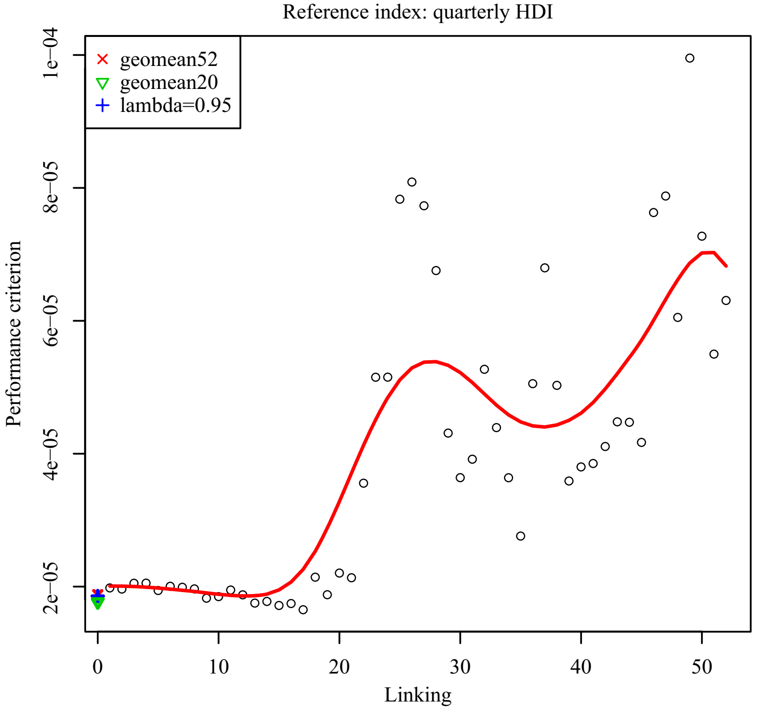

Fig. 11. Performance of alternative linking methods: quarterly hedonic imputation benchmark for Sydney.
Note: This graph shows the performance for Sydney (relative to a quarterly hedonic imputation index) of different single-period linking methods, Geomean52, Geomean20, and the weighted geomean method in (9) with Λ set to 0.95 (see values indicated at left-hand side of graph). The best performing method is single-period linking with 16 weeks earlier.

The corresponding results for Tokyo are shown in Figures 12 and 18. For the singleweek links, in both Figures 12, (where the quarterly hedonic imputation index is used as a benchmark) and Figure 18 in the Appendix (where the quarterly time-dummy index is used as the benchmark), the X metric is minimized by linking week t with week $t-12$ (i.e., linking the current week with 12 weeks earlier).

For Tokyo in Figure 12 the averaging methods (1), (2) and (3) perform equivalently to linking through 12 weeks earlier. In Figure 18, method (1) (i.e., the geometric mean of the 52 single-period lining methods) outperforms all the single-period linking methods.

5.6. The Low Transaction Method Illustrated Using Weekly Sydney Data

Here we focus specifically on low-transaction method 1, as described in Subsection 2.3. Setting the minimum number of observations per week to 250, we can see from Figure 13 that every year the last week in December and the first week in January fail to attain this threshold.

Setting the window length to seven weeks, the standard RTD method exhibits a slight upward drift compared with low transaction method 1, as can be seen in Figure 14. Towards the end of our sample, the cumulative size of this upward drift is 8.9%. The size and direction of drift will differ depending on the country or city and frequency of the index. Drift is most likely to be a problem for smaller countries without much data.

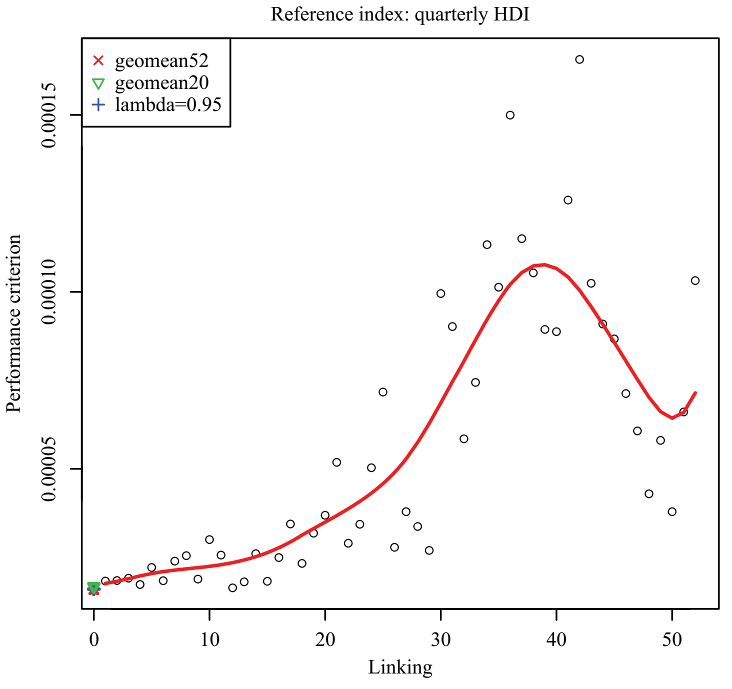

Fig. 12. Performance of alternative linking methods: quarterly hedonic imputation benchmark for Tokyo.
Note: This graph shows the performance for Tokyo (relative to a quarterly hedonic imputation index) of different single-period linking methods, Geomean52, Geomean20, and the weighted geomean method in Equation (9) with λ set to 0.95 (see values indicated at left-hand side of graph). The best performing method is single-period linking with 12 weeks earlier.

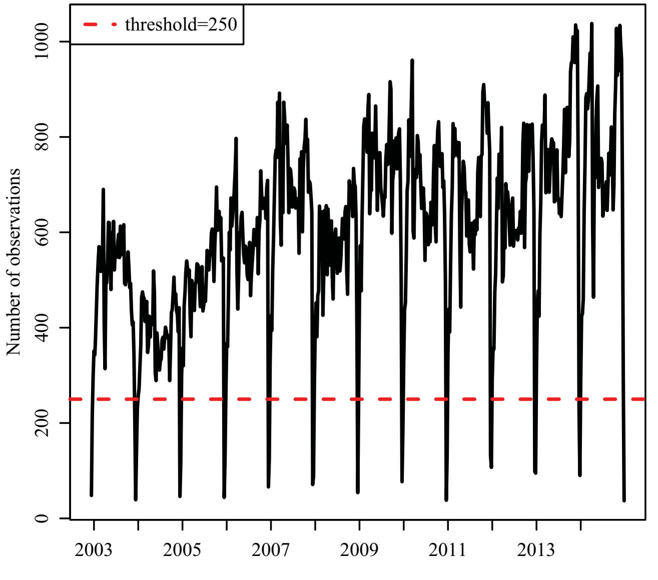

Fig. 13. Weekly observations versus the 250 observation threshold: Sydney.
Note: This graph shows the weekly number of transactions in Sydney. The low point each year is the last week in December and the first week in January. When implementing low transaction method 1, a threshold of 250 transactions per week is used.

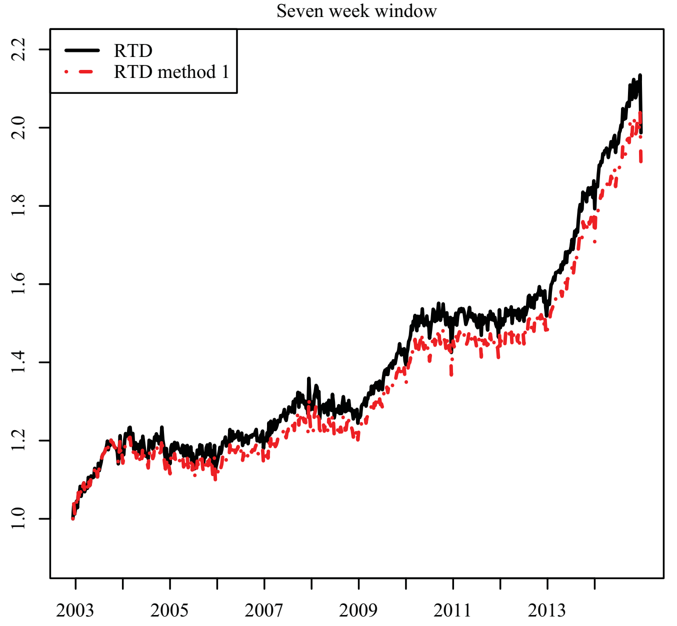

Fig. 14. Comparing the standard seven-week RTD index with the low transaction method 1 Index.
Note: RTD here is a standard weekly RTD price index computed with a seven-week window. RTD method 1 is the modified method where weeks with less than 250 transactions are treated seperatly as explained in Subsection 2.3. Failure to adjust for low transaction weeks seems to cause a slight upward drift in the RTD index.

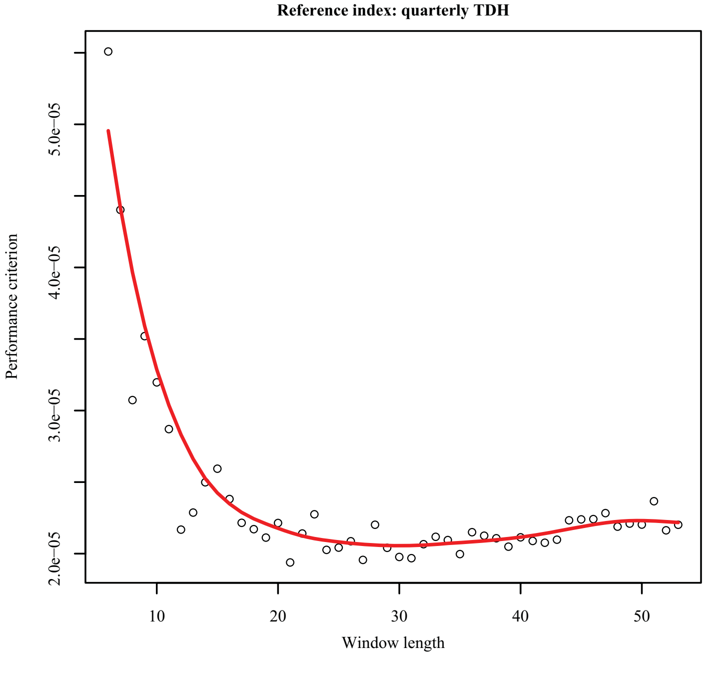

Fig. 15. Performance of alternative window lengths with the quarterly time-dummy price index as the reference: Sydney.
Note: This graph shows which window length generates a weekly RTD price index that most closely approximates a quarterly time-dummy hedonic index. For Sydney, the optimal window length here is 21 weeks.

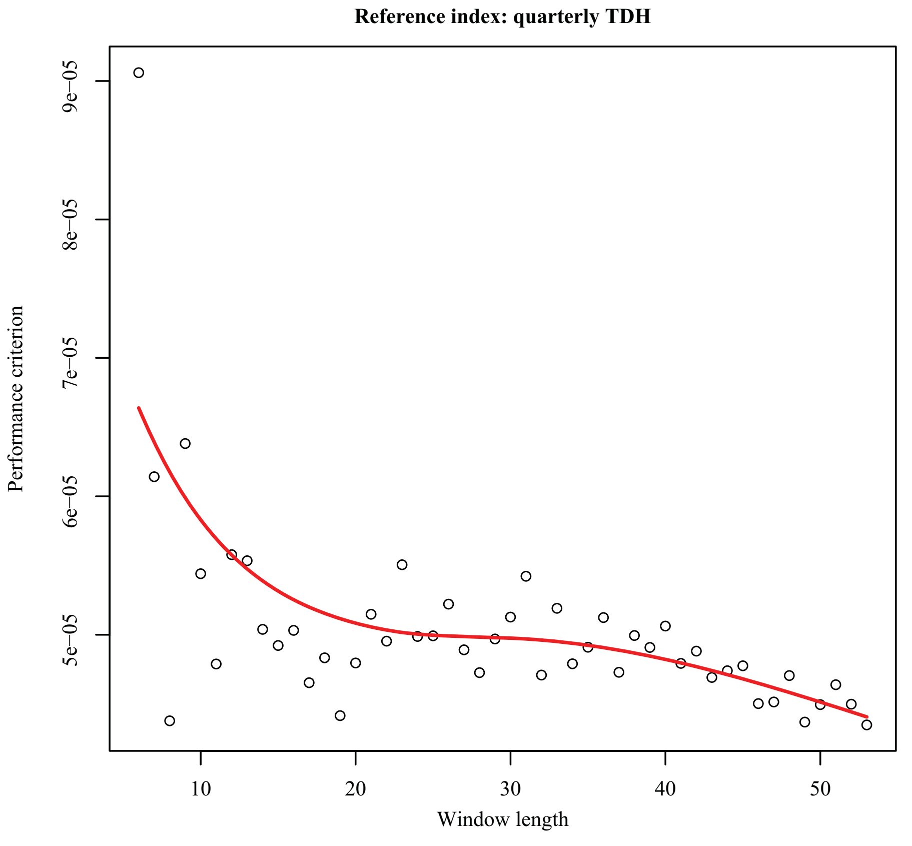

Fig. 16. Performance of alternative window lengths with the quarterly time-dummy price index as the reference: Tokyo.
Note: This graph shows which window length generates a weekly RTD price index that most closely approximates a quarterly hedonic imputation index. For Tokyo, the optimal window length here is 53 weeks.

6. Conclusion

We have considered two dimensions over which RTD HPIs can differ. These are the window length and the method used for linking the current period to earlier periods. We have proposed a new criterion for determining the optimal window length and linking method. This method, which relies on using a lower frequency index to assess the performance of higher frequency indexes, works well for weekly indexes, using quarterly indexes as a benchmark. It remains to be seen how well it will work on lower frequency indexes, such as quarterly indexes, using say yearly indexes as the benchmark.

Focusing on weekly indexes, we find that for the Sydney data set, the optimal window length is between 19–21 weeks. For the Tokyo data set the optimal window length is about 18 weeks.

We show that it is possible to improve on the standard linking method used by the RTD method. The linking method that performs best on the Sydney data set links the current week with a period between 13–16 weeks earlier. For Tokyo, linking the current week with the period 12 weeks earlier performs best. Geometric averaging of the single-period linking methods performs about the same as the best of the single-period linking methods.

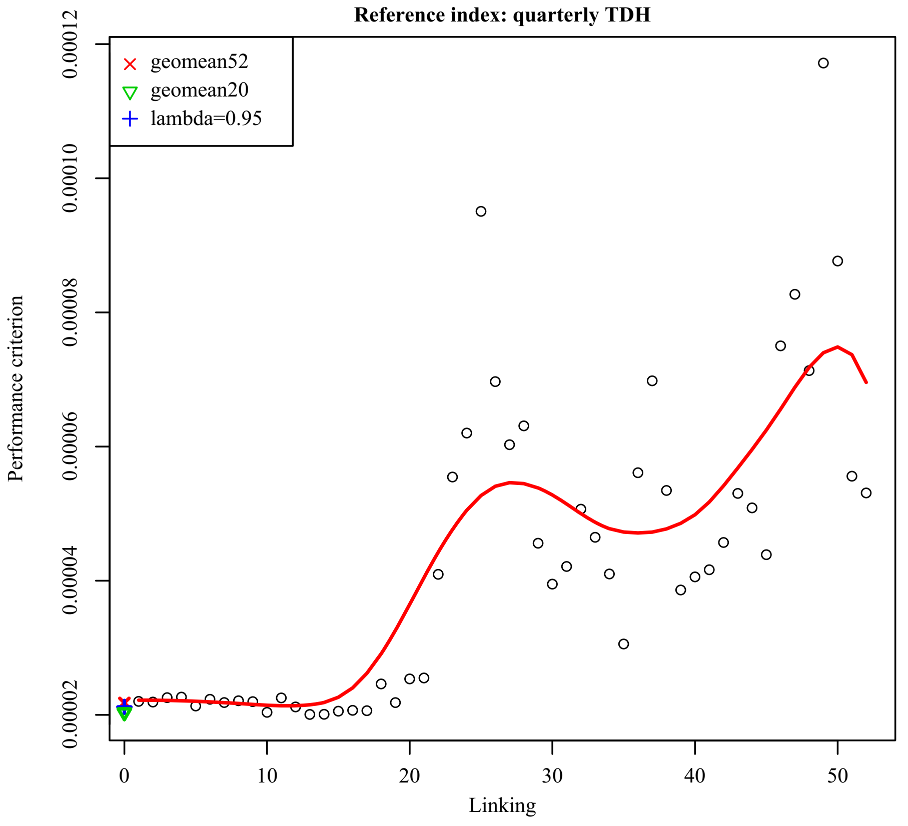

Fig. 17. Performance of alternative linking methods with standard RTD linking: quarterly time-dummy benchmark for Sydney.

Note: This graph shows the performance for Sydney (relative to a quarterly time-dummy hedonic index) of different single-period linking methods, Geomean52, Geomean20, and the weighted geomean method in Equation (9) with Λ set to 0.95 (see values indicated at left-hand side of graph). The best performing method is single-period linking with 13 weeks earlier.

We have also considered how the RTD method can be adjusted to mitigate the distorting effects of low transaction periods on house price indexes. Method 1 (in Subsection 2.3) in particular could prove useful for countries in Europe and the rest of the world that compute their official HPIs using the RTD method.

Finally there is the question of whether weekly indexes are indeed useful. In our opinion the answer is yes that they are a useful complement to lower frequency indexes, as long as there are enough transactions per week to allow the construction of hedonic indexes and the time lag for obtaining the necessary price data is not too long. In many countries to avoid such long time lags it may be necessary to construct weekly house price indexes using list price data, as our Tokyo index does. What then of a daily HPI? A daily repeat-sales HPI index has been constructed by Bollerslev et al. (2016) using US data. We doubt that it would be feasible to construct a daily RTD index in most countries. A different approach that compensates for the low rate of transactions by imposing more econometric structure on the model is probably needed for daily indexes.

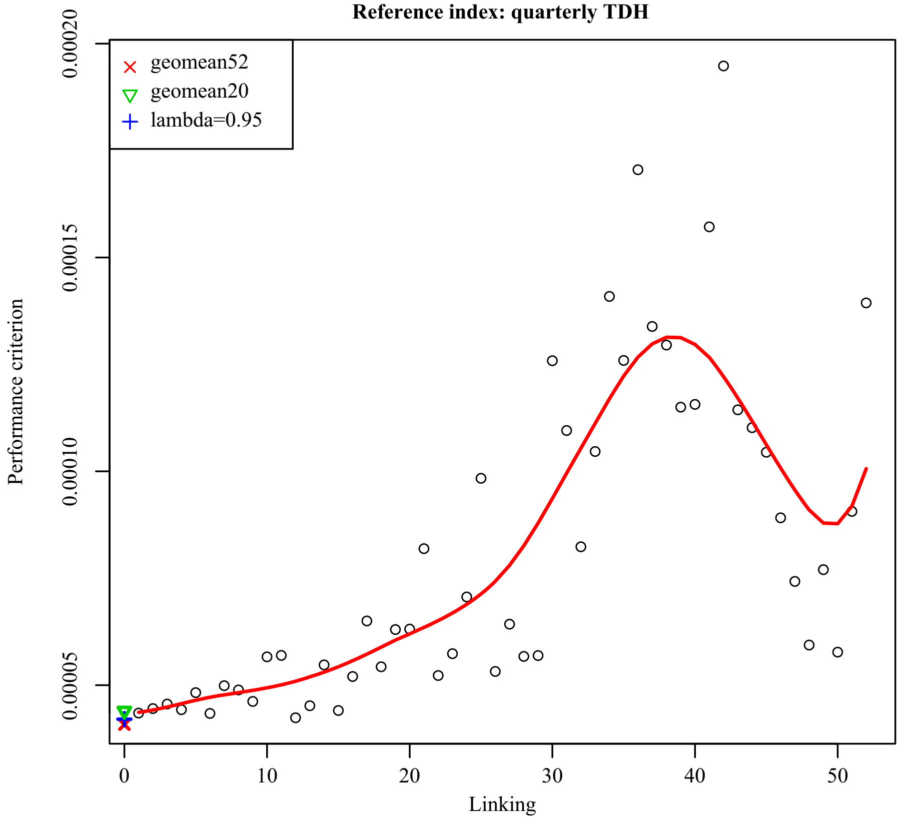

Fig. 18. Performance of alternative linking methods with standard RTD linking: time-dummy benchmark for Tokyo.

Note: This graph shows the performance for Tokyo (relative to a quarterly time-dummy hedonic index) of different single-period linking methods, Geomean52, Geomean20, and the weighted geomean method in (9) with Λ set to 0.95 (see values indicated at left-hand side of graph). The best performing method is Geomean52.

7. Appendix: Results Obtained Using the Quarterly Time-Dummy Index As the Reference

As a robustness check, here we recompute all the results derived using the quarterly hedonic imputation method as a benchmark. Now instead, we use the quarterly time-dummy method as the benchmark. In most cases, the results are very similar to those obtained using the hedonic imputation method.

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