

Scholz, Hill and Rambaldi: “Weekly Hedonic House Price Indexes” – Discussion

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Structure of the presentation

1. Introduction
2. Hedonic Imputation and Index Quality
3. Empirical Application
4. Conclusion

“A spline is a numeric function that is piecewise-defined by polynomial functions, and which possesses a high degree of smoothness at the places where the polynomial pieces connect.” Source: Wikipedia, The Free Encyclopedia.

1. Introduction

- The **hedonic imputation method** provides a flexible way of constructing **quality-adjusted house price indexes**.
- The interplay of this well-known method with the **increasing number of recorded residential property transaction prices** and the advances in computing power and econometric techniques offers new opportunities in **constructing higher frequency indexes (at the weekly or even daily level)** and in deepening the knowledge about the real estate asset class.
- However, the **hedonic imputation method** becomes **unreliable at higher frequencies**, since then even in large data sets there may **not be enough price observations in each period**.
- As a consequence **computational and statistical problems occur** (e.g., no observations for some postcodes).

1. Introduction

- In this article Scholz, Hill and Rambaldi (Scholz et al.) show how the **reliability of weekly hedonic indexes can be improved by replacing postcode dummies by a geospatial spline** and then using a Kalman filter.
- This approach has **two advantages**.
 - First, the **dimensionality of the model is reduced**. Replacing postcode dummies by values from the geospatial spline function at each location in the data set **very significantly reduces the number of parameters** that need to be estimated, **and the number of covariance restrictions** that must be imposed to make the Kalman filter operational.
 - Second, the small number of observations in each period causes larger variability in **estimated parameters (shadow prices) which should not change too much** from one week to another. Estimation of a dynamic linear model with the **Kalman filter interconnects those parameters over time**.

2. Hedonic Imputation and Index Quality

- In this paper, Scholz et al. use the hedonic imputation method and model the hedonic equation in two different ways:
 - (i) in a **semi-parametric generalised additive model (GAM)** and
 - (ii) a **linear varying coefficient (dynamic) model**.

- The idea behind this is to estimate in each period t the **semilog GAM model with a parametric part** based on the physical characteristics Z (including an intercept) **and a fully nonparametric function** $g_t(\cdot)$ defined on the geospatial data (latitudes z_{lat} and longitudes z_{long}):
 - (1) $y = Z \beta_t + g_t(z_{lat}, z_{long}) + \varepsilon$, where $y = \ln p$.

2. Hedonic Imputation and Index Quality

- It is well known that the information of the **location of the individual dwellings is a main explanatory variable** and price driver in a hedonic context. As an alternative to a function $g_t(\cdot)$ defined on longitudes and latitudes often the use of **postcode dummies** is proposed:
 - (2) $y = Z \beta_t + D \delta_t + \varepsilon$,
 - where D is a matrix of postcode dummies containing the location information.
- Scholz et al. propose the **combination of both methods** in the following way.
 - First, they **estimate (1) for the weekly frequency and extract each time the estimated locational component \bar{g}_t** .
 - In a second step they **include this estimate of the spline function in (2) as a constructed variable** replacing all the postcode dummies.

2. Hedonic Imputation and Index Quality

– The Kalman filter can now **interrelate the spline surfaces over time**:

- (3) $y = Z \beta_t + \bar{g}_t \gamma_t + \varepsilon$,

- where γ is a scalar coefficient that can now vary over time and thus shift the whole spline surface up or down.

– In addition, Scholz et al. have **replaced a large number of parameters** (they have around 250 postcodes in their data set) by a single parameter, what is a great gain in parsimony.

– Using the estimated hedonic models **imputed prices can be inserted into standard price index formulas**.

2. Hedonic Imputation and Index Quality

- Scholz et al. refer to a formula that focuses on the **houses that sold in the earlier period t** as **Laspeyres-type**, and formula that focuses on the **houses that sold in the later period $t+1$** as **Paasche-type**.
- The **double imputation** Paasche index (DIP), Laspeyres index (DIL), and Fisher index (DIF) are defined as follows:

$$\bullet (4) P_{t,t+1}^{DIP} = \sqrt{H_{t+1} \frac{\prod_{h=1}^{H_{t+1}} \hat{p}_{t+1,h}(z_{t+1,h}, \hat{g}_{t+1,h})}{\hat{p}_{t,h}(z_{t+1,h}, \hat{g}_{t+1,h})}}$$

$$\bullet (5) P_{t,t+1}^{DIL} = \sqrt{H_t \frac{\prod_{h=1}^{H_t} \hat{p}_{t+1,h}(z_{t,h}, \hat{g}_{t,h})}{\hat{p}_{t,h}(z_{t,h}, \hat{g}_{t,h})}}$$

$$\bullet (6) P_{t,t+1}^{DIF} = \sqrt{P_{t,t+1}^{DIP} \times P_{t,t+1}^{DIL}}$$

2. Hedonic Imputation and Index Quality

– Guo et al. (2014) propose the use of the following three **signal-to-noise measures for index returns** $r_t = \ln(P_{t+1} / P_t)$, where P_t is the level of the price index in period t :

- (i) The volatility (VOL) measure is the **standard deviation** of r_t .
- (ii) The **first-order autocorrelation** (AC1) measure is $\bar{\beta}$ from the following OLS regression: $r_{t+1} = \beta r_t + \varepsilon_{t+1}$.
- (iii) The **deviation from a smoothed Hodrick-Prescott (HP) filter representation**. This deviation is calculated as follows:

$$HP = \sum_{t=1}^{T-1} \left(\ln \frac{P_{t+1}}{P_t} - \ln \frac{HP_{t+1}}{HP_t} \right)^2$$
, where HP_t is the smoothed price index calculated using the HP filter.

2. Hedonic Imputation and Index Quality

- A **smaller value of VOL and HP**, and a **higher value of AC1** indicate a smoother and hence **better performing index**.
- A **fourth measure uses repeat sales as a benchmark** against which to measure index performance.
- Define V_h as the **ratio of the actual to imputed price relative** for house h :
 - (7)
$$V_h = \frac{p_{t+k,h}}{p_{t,h}} / \frac{\hat{p}_{t+k,h}}{\hat{p}_{t,h}}.$$
- The **quality measure** is then the average squared error of the log price relatives of each hedonic method:
 - (8)
$$D = \frac{1}{H} \sum_{h=1}^H (\ln V_h)^2,$$
 - where **Scholz et al. prefer whichever model has the smaller value of D.**

3. Empirical Application

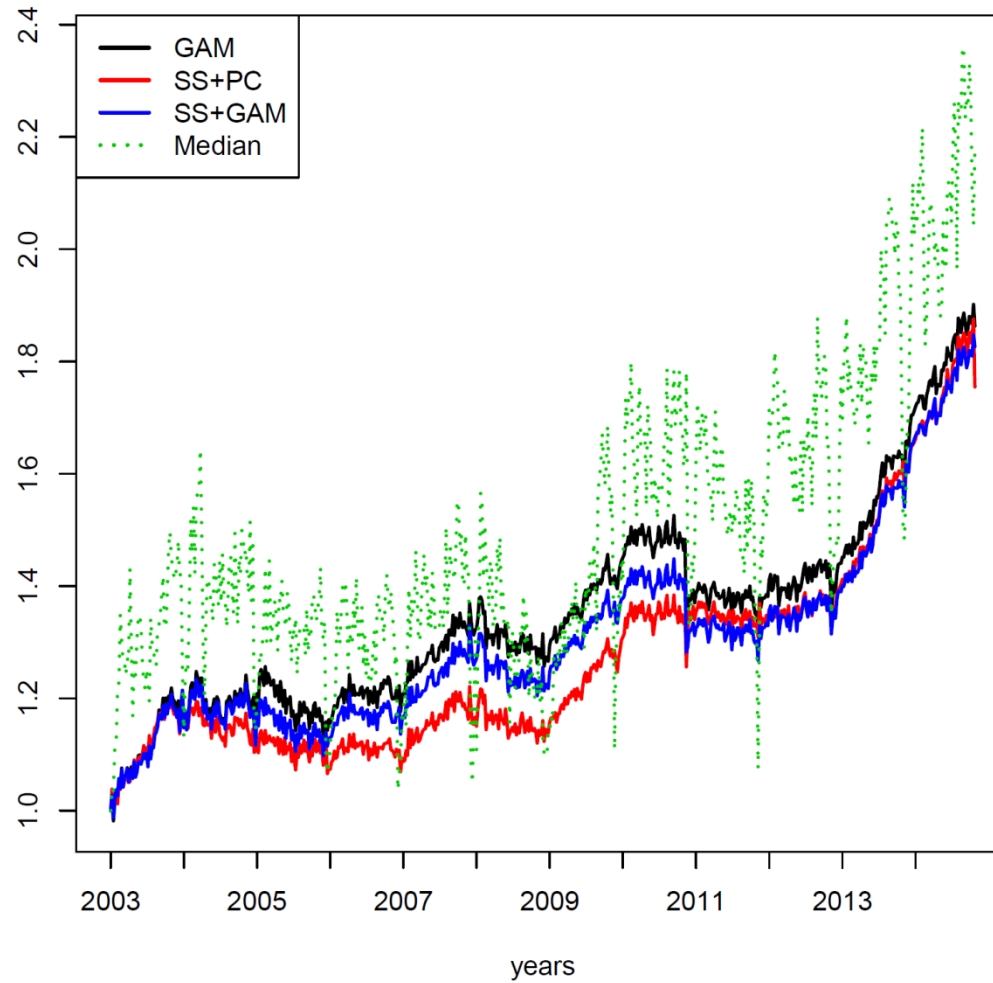
- Scholz et al. use a data set obtained from Australian Property Monitors that consists of **prices and characteristics of houses sold in Sydney (Australia) for the years 2001 – 2014.**
- For each house they have the following **characteristics**:
 - the actual sale price,
 - time of sale,
 - postcode,
 - property type (i.e., detached or semi),
 - number of bedrooms,
 - number of bathrooms,
 - land area,
 - exact address,
 - longitude and latitude.
- For a robust analysis it was necessary to **remove some outliers.**

3. Empirical Application

- Complete data on all hedonic characteristics are available for **433 202 observations**.
- **House price indexes for Sydney** are generated using
 - (1) the **GAM** method (i.e., hedonic imputation with a spline but no state space model),
 - (2) **SS+PC** (i.e., hedonic imputation with postcodes and a state space model), and
 - (3) **SS+GAM** (i.e., hedonic imputation with a spline and state space model).
- The three hedonic indexes while **broadly comparable**, exhibit significant differences particularly in the middle part of the data set.

3. Empirical Application

Figure 1: Weekly House Price Indexes from 2003 to 2014



3. Empirical Application

- The **performance** of the three hedonic methods, a median index, and a repeat-sales (RS) index are compared in the table below.
 - **SS+PC** performs best according to **VOL** followed by SS+GAM.
 - Surprisingly the **median index** performs best according to **AC1**.
 - The **HP results** are **similar** to the **VOL results**.
 - The **GAM method without a state space model** performs best according to the **D criterion**.

Method	VOL	AC1	HP	D
GAM	0.0161	−0.4312	0.1415	0.1008
SS+PC	0.0148	−0.4673	0.1203	<i>0.1068</i>
SS+GAM	0.0156	−0.4376	0.1339	0.1020
Median	<i>0.0567</i>	−0.1819	<i>1.5845</i>	—
RS	0.0170	−0.5182	0.1631	—

4. Conclusion

- The results are still **very preliminary**. The performance criteria are still being fine tuned, and Scholz et al. may still also include more criteria.
- The extent of the **short-term volatility in the weekly hedonic indexes** though is surprising. It remains to be seen how much of this volatility is genuine and **how much reflects measurement problems**.
- It is also perhaps surprising that the **use of state space models does little to reduce the volatility** of the price indexes, and it remains to be seen whether it can really be argued that the **use of state space models improves the quality of the weekly indexes**.
- Scholz et al. **intend to increase the flexibility of the state space model** by including 16 Residex region dummies for Sydney. Another issue they are considering is **to try extend the analysis to daily indexes**.

Discussion

$$-(3) y = Z \beta_t + \bar{g}_t \gamma_t + \varepsilon$$

- The estimated locational component \bar{g}_t is based on **periodwise estimation** of model (1), i.e. it is **not interconnected over time**. While this is certainly not at all an easy task, **Scholz et al. are working on this** what is highly recognised!
- Ceteris paribus the very **same location** defined on the geospatial data (latitudes and longitudes) **should have the same estimated location component**; this can actually be tested with their data **using repeat sales as a benchmark**: $\bar{g}_{t,h} = \bar{g}_{t+k,h}$.
- More generally, any attempt to give an **interpretation to the nonparametric part** would be very much welcomed, e.g. can certain parts of Sydney be singled out based on the data that are particularly high or low in (land) prices and can this be **attributed to some economic factors** (such as income or the like)?

Discussion

$$- (4), (5) P_{t,t+1}^{DIP} = \sqrt[{}^{H_{t+1}}]{\prod_{h=1}^{H_{t+1}} \frac{\hat{p}_{t+1,h}(z_{t+1,h}, \hat{g}_{t+1,h})}{\hat{p}_{t,h}(z_{t+1,h}, \hat{g}_{t+1,h})}}, P_{t,t+1}^{DIL} = \sqrt[{}^{H_t}]{\prod_{h=1}^{H_t} \frac{\hat{p}_{t+1,h}(z_{t,h}, \hat{g}_{t,h})}{\hat{p}_{t,h}(z_{t,h}, \hat{g}_{t,h})}}$$

- The notion of **Paasche and Laspeyres price indices** usually is via the **quantities used in the arithmetic aggregation**; the later period $t+1$ and the earlier period t , respectively.
- Here, however, price indices are constructed by taking the **geometric mean** of the price relatives, giving **equal weight to each house**.
- While this is perfectly fine from an index theory point of view and the need to make a **distinction for the period to which the z s and \bar{g} s refer** is understandable, “Paasche-type” and “Laspeyres-type” might not be the best labels for the two indices (and neither would thus “Fisher-type” be).

Discussion

- (VOL) Standard deviation of index returns $r_t = \ln(P_{t+1} / P_t)$.
 - Why should a **smaller value of VOL** indicate a **better performing index**?
 - **Smoothness is no quality criterion!** If it was, **zero VOL** could be achieved by a formula that gives a **horizontal line** for the index returns, i.e. a constant.
 - The **benchmark** might be the **repeat-sales index** and the performance measure the mean square error of index returns.
- Having said that, however, a question remains on the **repeat-sales index**: How has **depreciation** be dealt with?
 - Comparing the value of the same house over time is **not comparing apples with apples**, or it is **but a fresh apple with a rotten apple**.
 - While **values might have decreased** due to depreciation, **quality-adjusted prices would have remained the same**.

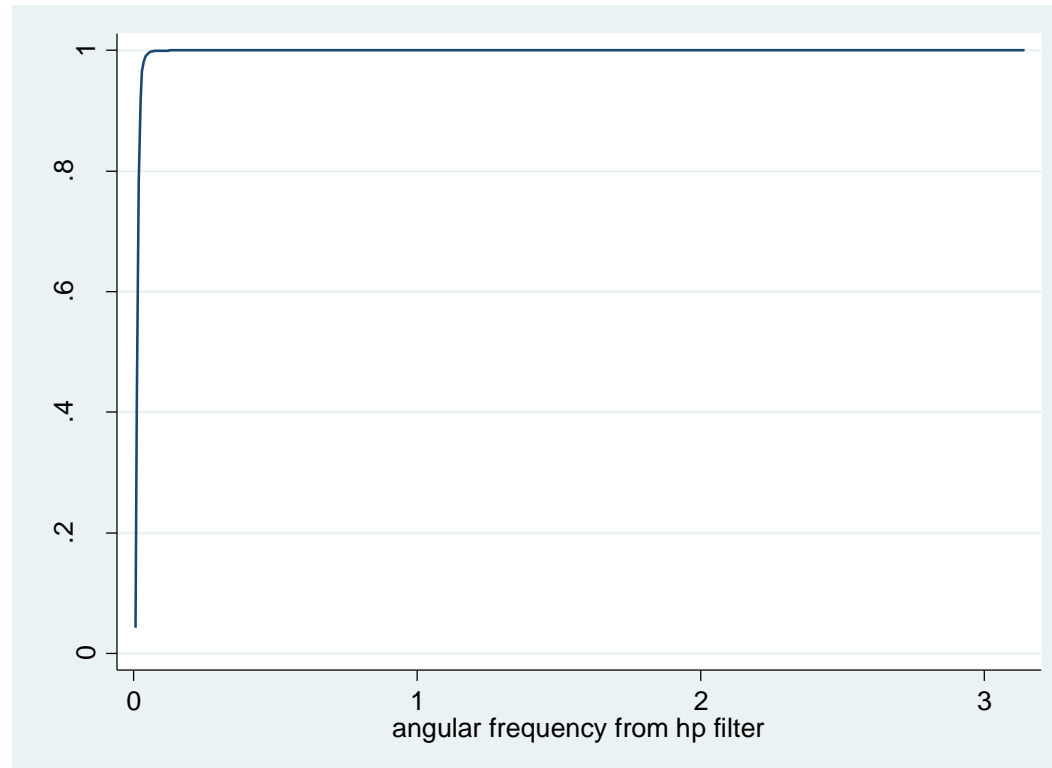
Discussion

- (AC1) First-order autocorrelation measure
 - First of all, AC1 does **not measure smoothness** of index returns **but persistence**. So, why does a **higher value of AC1** indicate a **better performing index**?
 - Secondly, the **estimator $\bar{\beta}$ is biased** should the underlying **data generating process be different from the postulated zero-mean AR(1)**, which appears very likely.
 - Last but not least, from the **theory of temporal aggregation** we know that if the **high-frequency data are IMA(1,0)**, the **averaged low-frequency data are IMA(1,1)** with the limiting case having a **first-order autocorrelation of 0.25** (Tiao, 1972). Also, end-of-month data, say, show **weaker (no?) ARCH effects** than weekly or even daily data.

Discussion

- (HP) Deviation from a smoothed Hodrick-Prescott (HP) filter representation
 - To reiterate, **smoothness of the index is no quality criterion**. Hence, why should a smaller value of HP be better?
 - Next, the HP filter makes an **implicit assumption about the cyclical component** that is it tends to cut out frequencies corresponding to **periods close to ten years**. This number would be rather on the short end of what is usually suggested for a **housing cycle of eight to thirty years**.
 - In the **frequency domain** $f = 2 \pi / 52 = 0.1208$ denotes the first seasonal frequency while lower frequencies are associated with the trend component.
 - Letting λ equal 1600×12^4 for **weekly data** (Ravn and Uhlig, 2002), the gain from the HP filter at the first seasonal frequency is 0.9999. The **filter gain exceeds 0.5 for frequencies $f > 0.0132$** corresponding to a **period of 9.2 years**.

Discussion



Discussion

- (D) Using repeat sales as a benchmark
 - This is an exceptional measure given that there is **no(?) sample selection issue!**
 - As Klein (1960) already wrote in *Econometrica*: “I look towards **improvements in precision of econometric judgments of the order of magnitude of fifty per cent ... through the use of more accurate data.** In contrast, I would expect marginal improvements of **five or ten per cent through the use of more powerful methods** of statistical inference.”
- Might **weekly be the continuity limit** with roughly 600 observations per week?
- How robust is the **price index performance in relation to official ABS data?**
- The **excellent performance of the simple SS+PC model** is noteworthy!