Comments on

"Weekly Hedonic House Price Indices and the Rolling Time Dummy Method: An Application to Sydney and Tokyo"

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Summary

- Two questions: (1) What is the approximate window length for the Rolling Regression? (2) Based on the estimates of the time varying rolling regression models, how should we build a price index?

- Using weekly transaction data of Sydney and Tokyo, this paper concludes (1) the optimal window length is 21 week for Sydney, (2) the conventional linking method is hard to be improved.

Impressions

- If you are using rolling regression to control for the effects of possible structure changes, the choice of the window length is crucial.
- When constructing price index, the choice of the linking method can be also important.
- This paper gives us a simple and intuitive answer.
- The logic is easy to understand. The results are clear for the case of Sydney (but not for Tokyo). The suggested methods are also very easy to conduct.
- A very good paper for practitioners who are using rolling regression to construct price index. I have learned a lot!!!

Comments and Questions: Three Points

(1) Are there other ways to obtain the optimal window length?

(2) Is rolling regression so good for the objective?

(3) Other Possible Estimation Methods.

Comments (1)

Are there other ways to obtain the optimal window length?

Selection of the window length for rolling regression

- It has been long recognized that when choosing the window length for rolling regression, we are facing the bias-variance tradeoff.
- There are many papers on the selection of window length, Foster and Nelson (1996 EMA), Pesaran and Timmermann (2007, JOE), Clark and McCracken (2009 IER), Pesaran, Pick, and Pranovich (2012 JOE), and Inoue, Jin, and Rossi (2017 JOE).
- Most of them use the minimum Mean Squared Forecast Error (MSFE) estimators to derive the "optimal" window length and weights for past observations.
- Many papers proposes decreasing weights for past observations.

Selection of the window length for rolling regression

- This paper is unique because it uses (1) “the asymptotically linear dissimilarity index” by Diewert (2002)” and (2) quarterly price index as the reference.
- The estimators based on the asymptotically linear dissimilarity index belongs to a class of M-Estimators. So, the estimators will satisfy the consistency and asymptotic normality.
- But the speed of convergence might be faster than that of OLS. There might be some other unique characteristics. Formal investigation of statistical properties of the estimator might be an interesting topic.
- I think more discussion is needed to justify using the quarterly price index (the geometric average of the weekly price index) as the reference. If quarterly index is regarded as the true index, there must be some reasons. If the reasons can be quantified, we can use the reasons to construct the objective function.

Selection of the window length for rolling regression

- I think the MSFE is a more natural candidate as the selection criteria than the minimum dissimilarity from the quarterly index.

- At least, the paper can use the MSFE as the benchmark to be compared.

- Then, the paper can derive the optimal weight structures among lagged variables within a window. Putting the largest weight on the most recent information makes sense to me.

Comments (2)

Is Rolling Regression the best to capture structural changes when estimating weekly hedonic house price model?

Rolling Regression is good because

(1) It is easy to implement (linear regression)

(2) Standard errors can be obtained easily (regression)

(3) Compared to regression based on cross-sectional data, the sample size is larger, which will give us sharper estimation results (smaller standard errors).

(4) Compared to regression based on cross-sectional data, or hedonic imputation methods, the estimation results will be smoother (assuming fixed coefficients for window length).

(5) It is easy to be applied to large scale data (linearity)

However..

- Rolling regression is sometimes called "poor man's" time varying regression model (Zivot and Wang (2006)p.300).

- There are several major problems in rolling regression.

Rolling Regression is not good because

- To get meaningful results from the rolling regression, time varying coefficients, the specification of the model **MUST** be incorrect.

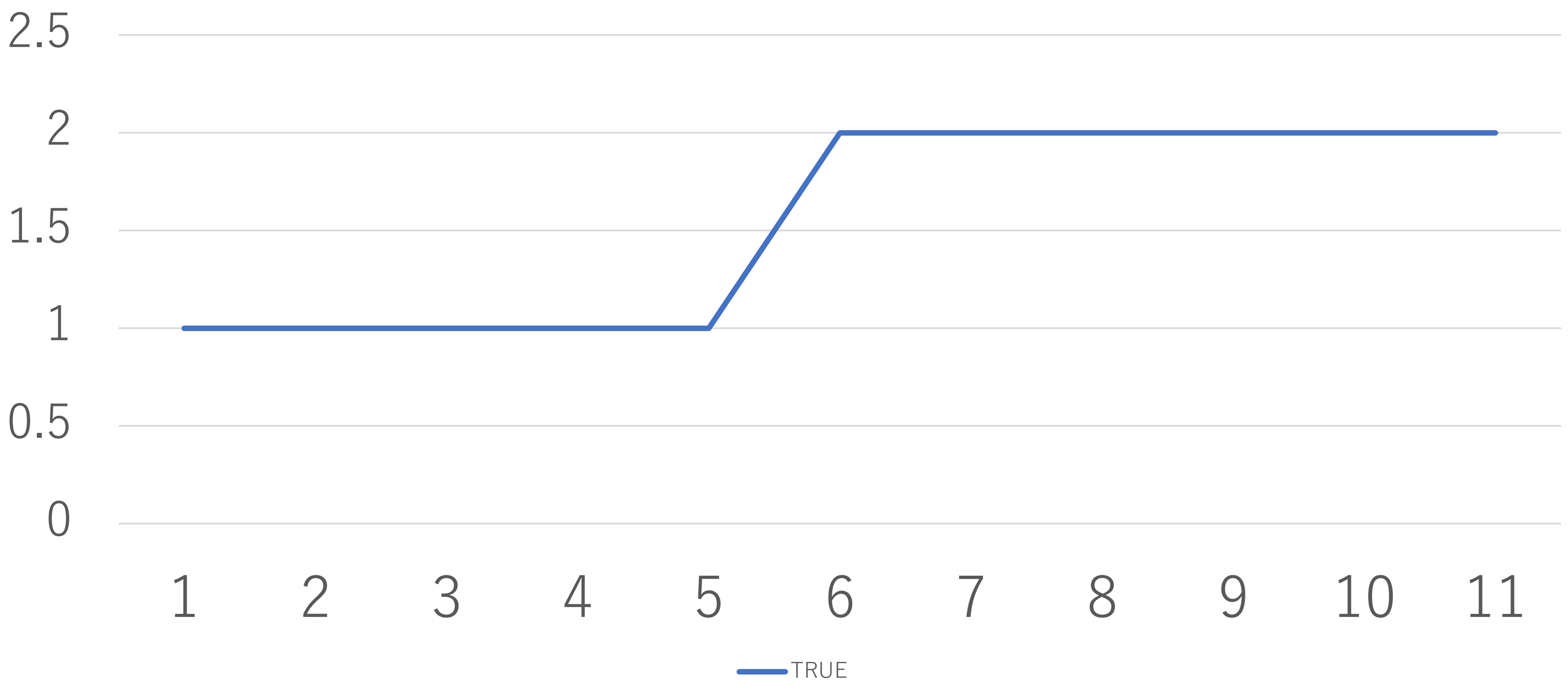
Rolling Regression is not good because

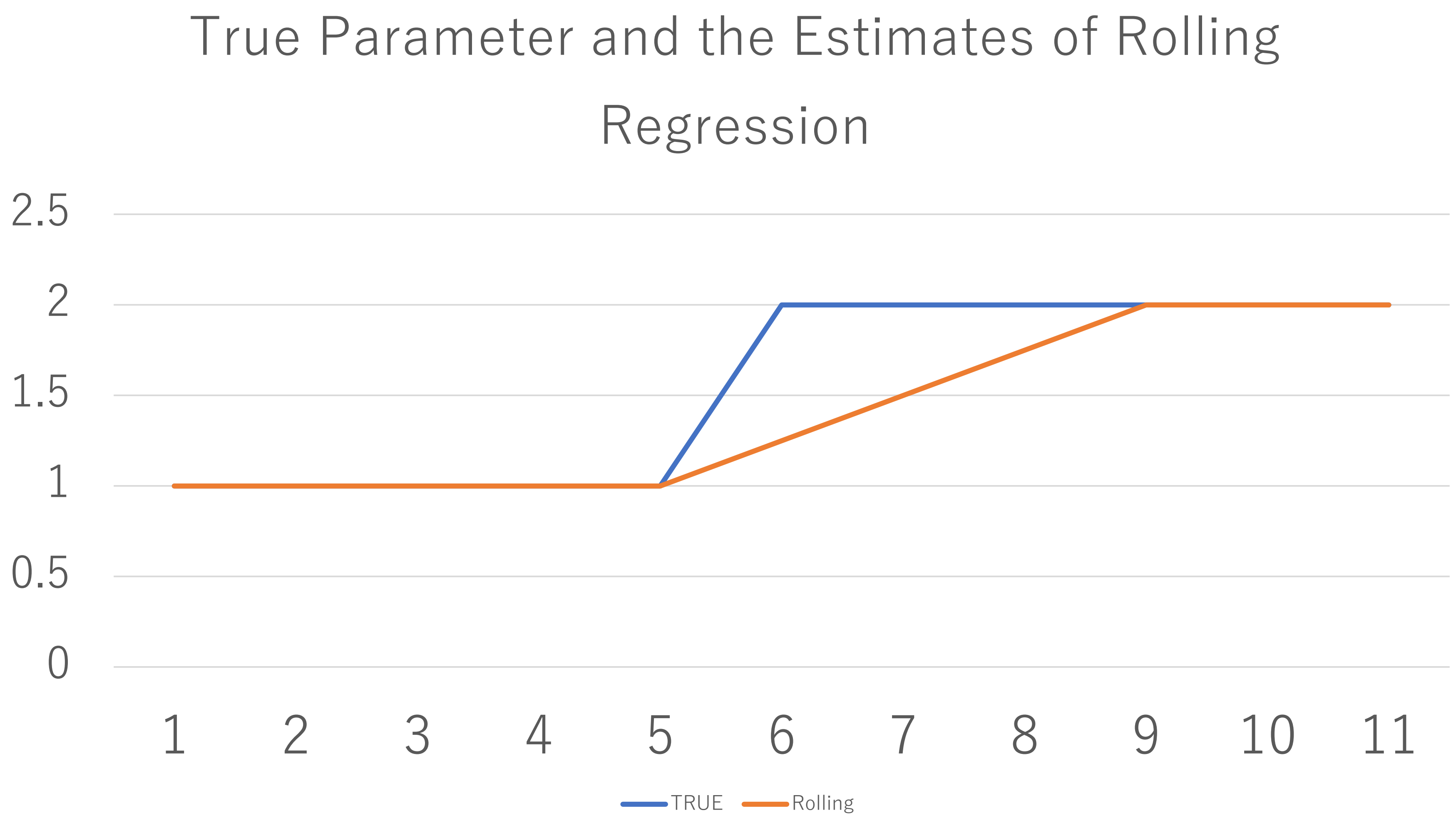
- Suppose we use four periods for one window, (t, t+1, t+2, t+3). Then, the next window will be (t+1, t+2, t+3, t+4).
- In the first regression, we assume the parameters for t and t+1 are the same.
- In the next regression, we assume the parameters for t+1 and t+2 are the same.
- Therefore, when we conduct rolling regressions, we assume the parameters for t and t+2 are the same. That is, all the parameters for all the rolling windows must be the same.
- To avoid the above problem, two windows should not have common periods. This is not a rolling regression.

Rolling Regression is not good because

- It is slow to capture the effects of structural changes.

True Parameter and the Estimates of Rolling Regression




True Parameter and the Estimates of Rolling Regression
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
TRUE
Rolling

Problems in rolling regression (3)

- If the true parameter jumps permanently, the estimates of rolling regression cannot capture the changes immediately.
- This is because the rolling regression treats the current and lagged regressors equally.
- Probably, we need to put more weight for current regressors. Weighted Rolling Regression seems better than the equal weight rolling regression when the change is persistent and discrete.

Rolling Regression is not good because

- It might be smaller prediction powers than the standard time varying model, the Kalman filter.

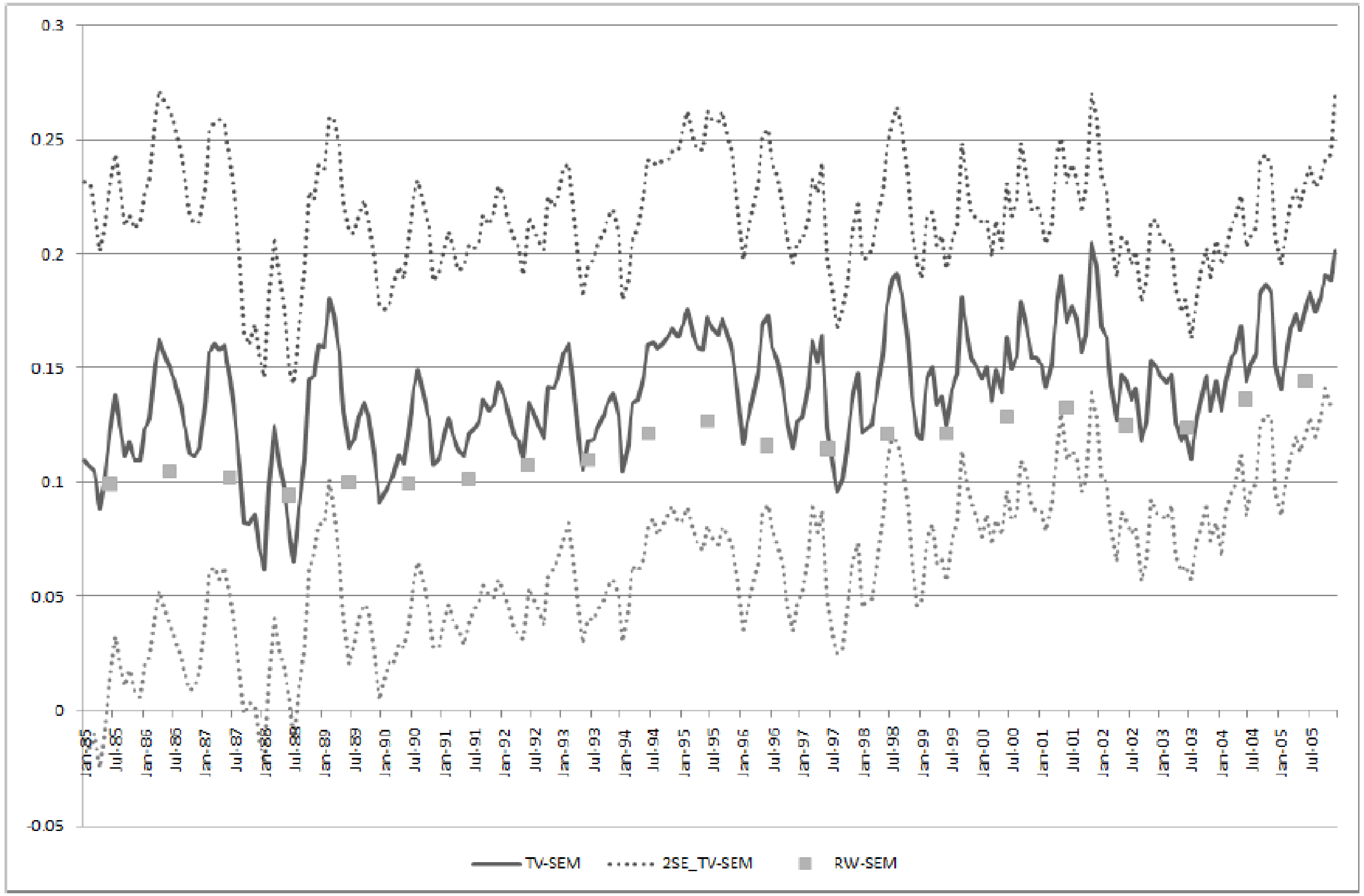


Figure 3: TV_SEM. BATH Coefficient

From Rambaldi and Rao (2011)

Rolling Regression is not good because

Rambaldi and Rao (2011) compared the estimates based on the Kalman filter and rolling regression.

They found that sometimes, estimates based on the Kalman filter and rolling regressions differ, which created major differences in their predictions.

Compared several time varying models, Rambaldi and Rao wrote “(rolling regression) produces predictions with the highest root mean square prediction errors.”

Rolling Regression is not good because

Since the presenter also uses the Kalman filter to estimate time varying hedonic house price model in a different paper, (Hill, Rambaldi, and Scholz (2017)), I am wondering why models with the Kalman filter do not appear in the paper.

Although the calculation of the Kalman filter is more difficult than rolling regression, with this size of the observations and the number of regressors, I don’t think it is so difficult.

Comments (3)

Other Possible Estimation Methods

If we need smoother estimates…

- I guess estimates based on the weekly hedonic imputation method or the Kalman are too volatile for the authors.
- If we use an econometric model of the data generating process, the process of the true parameter might be written as

$$\beta_t = x_t + \varepsilon_t,\ x_t = \rho x_{t-1} + \omega_t, \qquad \rho > 0,\ \ \varepsilon_t \text{ and } \omega_t\text{: i.i.d.}$$

- Under the standard asset pricing model with a complete market, ρ must be unity.
- Suppose we are interested in the persistent component, x_t, only.

If we need smoother estimates…

$\beta_t = x_t + \varepsilon_t$, $x_t = \rho x_{t-1} + \omega_t$, $\quad \rho > 0$, ε_t and ω_t: i.i.d.

However, identification of ε_t and ω_t is very difficult.

We need information on future values, $\beta_{t+1}, \beta_{t+2}, \beta_{t+3}, \beta_{t+4},..$ to know how the changes in β_t is decomposed into ε_t and ω_t.

What kinds of methods can be used to obtain the estimates of x_t at time t?

What I think worth trying is…

(1) Estimate a full structural model by MLE. Obtain the estimates of x_t and the distribution functions of ε_t , ω_t.

(2) With the estimate of the distribution functions of ε_t and ω_t, we can add the standard deviations for the estimates like a track forecast of hurricane.

Much Easier Methods

(1) Estimate weekly hedonic imputation model.

(2) Draw a periodogram and check whether any peaks in high frequency range exist or not.

(3) Use a band pass filter to eliminate the peaks.

(4) Or use the HP filter with the conventional value of smoothing parameter, λ, for weekly data, $\lambda = 100 \times 52^4$.