Assessing Macro Uncertainty in Real Time When Data Are Subject to Revision

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Assessing Macro Uncertainty In Real-Time
When Data Are Subject To Revision

Michael P. Clements

ICMA Centre, Henley Business School, University of Reading
1 Introduction

- Large literature on modelling and forecasting data subject to revision.

- Just using latest available vintage at the time the forecast is to be made in principle can be bettered, e.g.,
  
  - Model the revisions process (see, e.g., Cunningham, Eklund, Jeffery, Kapetanios and Labhard (2009), Jacobs and van Norden (2011), Kishor and Koenig (2012));
  
  - Use single-equation models with ‘real-time-vintages’ (as in Koenig, Dolmas and Piger (2003), Clements and Galvão (2013b));
– Model multiple vintages of data, as with vintage-based vector autoregressive models (see, e.g., Patterson (1995, 2003), Clements and Galvão (2013a)).
• All concerned with first-moment prediction.

• We investigate the implications of data revisions for assessments of forecast uncertainty (here, Box-Jenkins prediction intervals).

• Effects of data revisions more marked than for first-moment prediction.

• The ‘traditional’ approach to calculating prediction intervals will tend to be either too wide, when data revisions ‘add news’, or too narrow, when the revisions process ‘removes noise’.

• RTV provides correctly-sized intervals.
2 Simple case; generalizes to multiple revisions processes and AR\((p)\) models

- Suppose the true (i.e., fully-revised) values \(y_t\) follow an AR(1):

\[
y_t = \alpha y_{t-1} + \eta_t + \nu_t
\]

and the estimates of \(y_t\) are given by:

\[
\begin{align*}
y_{t+1} & = y_t - \nu_t + \varepsilon_t \\
y_{t+n} & = y_t
\end{align*}
\]

for \(n = 2, 3, \ldots\).
Traditional approach: an AR(1) is estimated on the EOS data:

\[ y_t^T = \beta y_{t-1}^T + e_{t,EOS}, \quad \text{for } t = \ldots, T - 2, T - 1 \]  

(2)

and the forecast of \( y_T \) is given by:

\[ \hat{y}_{T,EOS} = \beta y_{T-1}^T. \]  

(3)
2.1 News revisions

- As the number of observations gets large, the estimated standard error \( \hat{\sigma}_{T-1,EOS} \) from (2) will approach \( \sqrt{\sigma^2_\eta + \sigma^2_v} \).

- The expected squared error of the out-of-sample forecast is given by:

\[
E \left( y_{T+1}^T - \hat{y}_{T,EOS} \right)^2 = E \left( y_T - v_T - \alpha (y_{T-1} - v_{T-1}) \right)^2 \\
= \sigma^2_\eta + \alpha^2 \sigma^2_v. \tag{4}
\]

In-sample estimate of uncertainty exceeds oos uncertainty surrounding the forecast of \( y_{T+1}^T \).

- For the fully-revised actual, the BJ interval under-estimates oos uncertainty.
2.2 Noise revisions

- In-sample fit of the model under-estimates oos uncertainty.

- If instead we target the fully-revised value, the in-sample estimate under-estimates oos uncertainty but to a lesser extent.
3 RTV-estimation

- Assume forecasts will be conditioned on data estimates from the latest- available vintage at the time the forecasts are made: for an AR($p$), this will be $y_{T-1}^{T} = [y_{T-1}^{T}, y_{T-2}^{T}, \ldots y_{T-p}^{T}]$.  

- RTV estimates the AR($p$) on matching early-release data:
  \[
  y_{t-1}^{t} = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-1-i}^{t-1} + e_{t,RTV}, \quad \text{for } t = \ldots, T-1, T, \tag{5}
  \]

- Forecast of $y_{T}$ is $\hat{y}_{T,RTV} = \beta_0 + \beta_1 y_{T-1}^{T} + \ldots + \beta_p y_{T-p}^{T}$.  

• Clements and Galvão (2013b) show that the solution \((\phi_0^*, \phi^*)\) of:

\[
\arg \min_{\phi_0, \phi} E \left[ \left( y_{T+1}^T - \phi_0 - \phi' y_{T-1}^T \right)^2 \right]
\]

(6)

is satisfied by the RTV-population values: \(\beta_0 = \phi_0^*\), and \(\beta = \phi^*\).

• RTV delivers (in population) the values of the intercept and autoregressive parameters which minimize the expected squared error.

• Follows that RTV-estimation will provide correct assessments of out-of-sample uncertainty. Expected squared errors of (6) and (7) are the same:

\[
(\beta_0^*, \beta^*) = \arg \min_{\beta_0, \beta} E \left[ \left( y_{t+1}^t - \beta_0 - \beta' y_{t-1}^t \right)^2 \right].
\]

(7)
4 Empirical results

- 25 US macro variables subject to data revisions.

- Data vintages are taken from the Real-Time Data Set for Macroeconomists (RTDSM) of Croushore and Stark (2001).

- First ‘vintage-origin’ is 1996:Q2, and the last is 2011:Q1, so that we have 15 years of quarterly forecast origins.

- Rolling-window forecasting scheme, where for the first vintage origin of 1996:Q2, we use data from 1984 onwards.
• For RTV, we need data vintages going back to 1984 to have data over the same historical period. That is, we require an additional 12 years of data-vintages for RTV estimation.

• We use AR(2) models (i.e., two autoregressive lags).
Table 1: RTV and EOS BJ Intervals Coverage Rates

<table>
<thead>
<tr>
<th></th>
<th>Ratio RTV to EOS sd.</th>
<th>$t$- stat for ‘news’</th>
<th>$t$- stat for ‘noise’</th>
<th>50% interval RTV EOS</th>
<th>75% interval RTV EOS</th>
<th>90% interval RTV EOS</th>
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</table>
5 Summary: In-sample

• 9 of the 25 variables have data revisions which are news.

• All 9 variables’ in-sample s.d. estimated by EOS exceeds the RTV estimate.

• 7 of the 25 variables have noise revisions.

• For all 7 the EOS standard deviation is smaller than the RTV estimate.

• Hence relative magnitudes of the in-sample s.d.’s are as expected.
6 Summary: oos

- For around 80% of the variables the RTV intervals are more accurate than the EOS intervals: actual coverage closer to nominal.

- Analysis suggests EOS-interval coverage should exceed that of RTV for variables with news revisions, with the opposite holding for noise.

- Of the 9 variables categorized as having news revisions, EOS-interval coverage is greater for either all, or all but one, of these variables.

- Of the 7 variables with noise revisions, the RTV coverage rate is greater for all 7 variables for the 50% and 75% intervals.
Table 2: RTV and EOS forecasts with AR models and ADL

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<th>ADL\textsubscript{med}</th>
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</table>
7 First-moment performance

- RTV improves accuracy by 5% on RMSE for forecasting output growth.

- But this is at the top end of the gains to RTV, and a number of the entries exceed one, suggesting EOS is more accurate for those variables.

- This suggests that the RTV-intervals chiefly benefit from more accurate estimates of scale rather than location.

- The general point is that RTV estimation in practical forecasting may matter more for second-moment type forecasts (such as prediction intervals) than for point forecasting.
8 Conclusions

- Assessments of future macroeconomic uncertainty based on the in-sample fit of a model are likely to be misleading when the variable being modelled is subject to revision.

- Especially for predicting early-vintage estimates of future observations.

- A simple solution is to use real-time-vintage (RTV) data.

- Based on the evidence for the 25 macro variables we consider in this paper, RTV-estimation is more beneficial for second-moment forecasting than first-moment forecasting.
References


