Mixed Frequency Models with MA components by Foroni, Marcellino and Stevanovic

ANA BEATRIZ GALVAO

UNIVERSITY OF WARWICK

Mixed Frequency Models

Data are available at different frequencies.

Two options:

- aggregate all data to the lower frequency
- use mixed frequency models.

Two different classes of mixed frequency models:

- models that assume a process for the underlying unobserved high frequency data
- “partial” models that directly link low to high frequency data. MIDAS models.

MIDAS vs State Space Models

Bai, Ghysels and Wright (2013) show that state-space models imply a direct projection of the low frequency to the high frequency variable. The reason is that updating (or Kalman gain) occurs when there are observables.

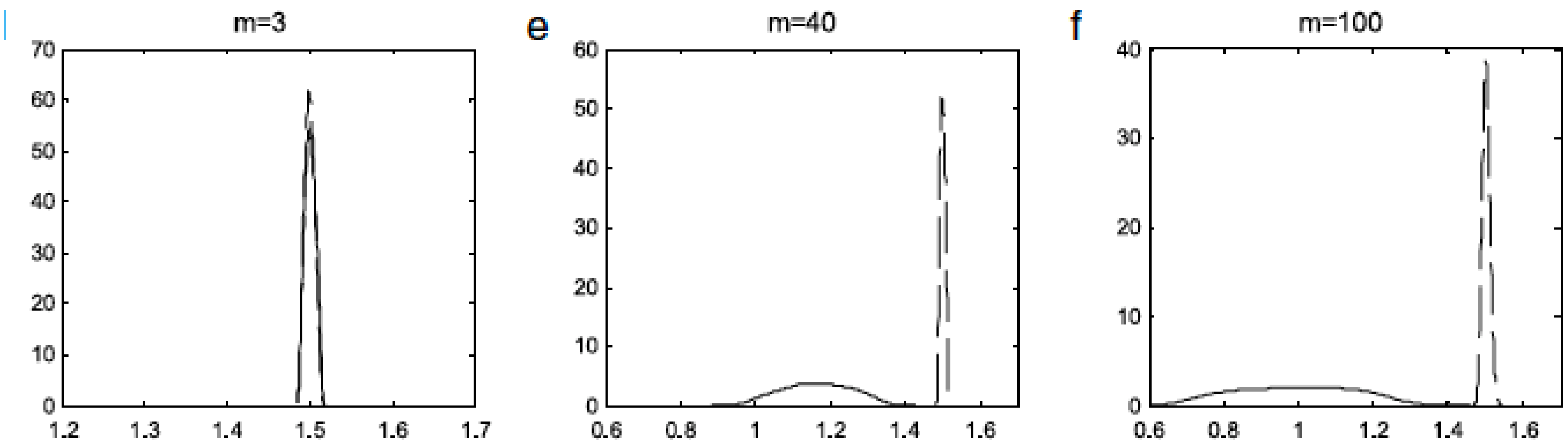
The projection for quarterly/monthly data is:

$$y_{t+h} = \beta_y \sum_{j=0}^{\overline{K}} w_j(\theta_y) y_{t-j} + \beta_x \sum_{j=0}^{3\overline{K}} w_j(\theta_x) x_{t-j/m} + \varepsilon_{t+h},$$

UMIDAS specifications remove the nonlinearity caused by the multiplication between weights and slopes.

MIDAS vs Low Frequency Regression

Andreou, Ghysels and Kourtellos (2009) assume that the true model is a mixed frequency regression. If the high frequency predictor is persistent and the predictor is aggregated by averaging in a low frequency regression, the slope of the low frequency regression is biased and estimates are inefficient. Gains are mainly for ***m*** (difference in frequency) large.



Forecasting with ADL-MIDAS vs Low Frequency ADL model

Clements and Galvao (2008): we can improve the accuracy of nowcasts using MIDAS models instead of the usual ADL model, but just because we are able to use the most recent information (or we are able to use leads as in Andreou et al (2013)).

There is very little empirical evidence that mixed frequency models are better in forecasting than low frequency models if we give both exactly the same information set.

Even if *m* is large (that is, daily to predict quarterly data).

Possible example: use of daily SP500 returns to predict GDP data revisions (Clements and Galvao, 2017).

MIDAS models are mispecified

Foroni, Marcellino and Stevanovic (2017) exploit the issue that partial aggregation (of the y variable) in MIDAS regressions lead to errors with MA terms.

The argument starts from a unobserved high frequency bivariate VAR. This is as in Ghysels, Hill and Motegui (2016).

But Ghysels et al (2016) looked at mixed frequency and low frequency VARMA representations of HF VAR models. Only able to set the highest AR and MA orders.

But Ghysels et al (2016) mixed frequency VAR approach only works when m is small.

MIDAS regressions work with large m.

MIDAS models and MA terms

The regression representation for the first variable of the HF VAR(1) aggregated by average sampling is:

$$\begin{aligned}\left(1-L^{3}a^{3}\right)\widetilde{y}_{t_m} &= \left(1+aL+a^{2}L^{2}\right)bL\left(1+L+L^{2}\right)x_{t_m}+\\ &\left(1+\left(a+1\right)L+\left(a^{2}+a+1\right)L^{2}+\left(a^{2}+a\right)L^{3}+a^{2}L^{4}\right)e_{yt_m};\end{aligned}$$

And one can see the MA(1) in the errors because the residuals are sampled quarterly.

Foroni et al (2016) show how one can figure out the order of the MA based on the DGP!

MA in MIDAS models

The results of the monte carlo exercise suggest that the MA terms (that should be there because the DGP is a HF VAR)

contribute very little to improve the forecast accuracy of MIDAS and UMIDAS models.

But is the MIDAS model with no MA term the correct benchmark?

Why not follow the previous literature and compare with the low frequency regression?

Efficiency gains as in Andreou et al (2009)? What about a comparison of the predictive variances? What about regressions with large m?

MIDAS + MA empirical application

The empirical application provides stronger evidence that MA terms improve the forecasting performance of MIDAS models.

The evidence is stronger for forecasting inflation.

But MIDAS models are not really very popular forecasting models of inflation (because of the availability of monthly inflation; mixed frequency models are not part of the models evaluated by Faust and Wright (2013)).

Is because we have been ignoring the MA terms from aggregation?

Or because the MIDAS model is in general mispecified?

MIDAS + MA empirical application

Can MIDAS models improve over low frequency models?

And popular models of inflation?

What is the impact of data revisions? (GDP growth and deflator are the target variables).

And about interval/density forecasts?

Summary

Foroni, Marcellino and Stevanovic (2017) contribute to the literature on macroeconomic forecasting with mixed frequency models by reminding us of the impact of partial aggregation on the disturbances of a MIDAS regression.

We should be estimating MIDAS-MA models! (and in the paper they consider different estimation methods for direct forecasting).