Discussion of "Exploiting the monthly data-flow in structural forecasting" by Giannone, Monti, Reichlin

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Introduction

- A lot of interest in now-casting recently, in particular during and after the crisis, due to low frequency and release delays in some key economic indicators, such as GDP.
- To exploit higher frequency data and implement now-casting in real time -> mixed frequency (MF) models
- Various types: MF-VARs, MF-Factor models, MIDAS regressions
- MF handled either by state space form + Kalman filter or by nonlinear modeling + NLS

Introduction

- Mostly reduced form MF models
- Recently some attention also to MF structural models:
    - Giannone, Monti, Reichlin (2010): use of higher frequency info for estimation of DSGE models
    - Kim (2010), Foroni and Marcellino (2013): effects of temporal aggregation and MF in DSGE models
    - Ghysels (2012), Foroni and Marcellino (2014): effects of temporal aggregation and MF in structural VAR models
    - Marcellino and Sivec (2014): structural MF factor models

Aim of this paper

- This paper proposes a method to exploit higher frequency (*monthly*) information when now-casting / short-term forecasting with a standard DSGE model developed at the quarterly frequency.
- It shows:
  - How to map the quarterly DSGE model into its monthly counterpart
  - How to augment the latter with additional timely (monthly) information
  - How to implement the procedure in practice, using an augmented version of the Gali, Smets, Wouters (2011) model for producing point nowcasts of the quarterly growth rate of GDP, the monthly unemployment rate and a measure of the output gap.

The empirical application

1. It would be useful to also consider longer forecast horizons h, and see what is the maximum h for which the higher frequency information is relevant. Is h very short as typically for reduced form forecasting or does the DSGE structure help?
2. Results for GDP deflator inflation, consumption and investment could be also briefly discussed.
3. The density forecasting performance of M+panel for GDP growth is a bit disappointing.
4. Even though you are interested in structural models, it might be interesting to compare the forecasting results with those from time series mixed frequency models, such as MIDAS regressions or a mixed frequency factor model based on your full information set.

Adding the monthly information

- This is by now rather standard in a state space set-up
- Perhaps I would reverse the equation that links the auxiliary monthly variables (X) to the (quarterly/monthly) model variables (Y). Now X depends on Y, while Y depending on X seems more standard (in practice, you want to use X to get a monthly version of Y, when not available).

Mapping the quarterly DSGE into a monthly DSGE

- In general, the solution of a log-linearized DSGE model is of the form:

$$y_t = A_1(\theta) s_t + A_2(\theta) s_{t-1} + u_t, \quad (1)$$

$$s_t = B(\theta) s_{t-1} + C(\theta) \varepsilon_t, \quad (2)$$

where s_t is the $k \times 1$ state vector, y_t is the $N \times 1$ vector of observables, θ is the vector of the structural parameters, ε_t is the $p \times 1$ vector of shocks, and u_t is the $N \times 1$ vector of possible measurement errors.

- The key element for mapping the quarterly DSGE into a monthly DSGE is to find the cube root of $B(\theta)$, $B_m(\theta)$, such that

$$B(\theta) = B_m(\theta)^3$$

Mapping the quarterly DSGE into a monthly DSGE

- As a simple example, suppose that

$$B(\theta) = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

Then, clearly, $B_m(\theta) = I_2$.

- However

$$B_m(\theta) = \begin{bmatrix} -d-1 & -\frac{1}{f}\left(d^2+d+1\right) \\ f & d \end{bmatrix}, \quad d, f \in \mathbf{R}, \quad f \neq 0, \tag{3}$$

is also a cube root of $B(\theta)$: $B_m(\theta)^3 = I_2 = B(\theta)$.

Mapping the quarterly DSGE into a monthly DSGE

- The paper provides conditions to select one $B_m(\theta)$.

1. It would be interesting to provide an economic interpretation for these conditions. For example, would it be enough that each endogenous variable in the high frequency DSGE depends only on its own past (and on the contemporaneous values of a few endogenous variables)?
2. With an even aggregation frequency (e.g. quarterly to yearly, or weekly to quarterly), things should be more difficult.
3. Can we really take the quarterly DSGE model as given if we believe the economy behaves in higher frequency?

Time aggregation issues in DSGE models

Let us imagine the true frequency is monthly, but we build a quarterly DSGE. Time aggregation generates two different problems:

- Since it confounds parameters across equations, it is not always possible to identify the parameters of the high frequency model, once it has been aggregated at a lower frequency.
- Even when the identification is not an issue, considering the same structural model at a different frequency leads to different interpretations of the parameters values.

A simple New Keynesian model

- The equations which describe the monthly model are:

$$\pi_t = \beta E_t \pi_{t+1} + k y_t^* + \varepsilon_{st}, \tag{4}$$
$$y_t^* = E_t y_{t+1}^* - \tau \left(R_t - E_t \pi_{t+1} \right) + p y_{t-1}^* + \varepsilon_{dt}, \tag{5}$$
$$R_t = \rho_r R_{t-1} + (1 - \rho_r) \left(\phi_\pi \pi_t + \phi_y y_t^* \right) + \varepsilon_{rt}. \tag{6}$$

- The model can be rewritten as:

$$A_0 X_t^* = A_1 X_{t-1}^* + \epsilon_t, \tag{7}$$

we normalize σ_d to 1 (or calibrate its value) to obtain identification.

Aggregation and loss of identification

- Since y_t^* is not observable at monthly frequency, we aggregate the model at the quarterly frequency (i.e., we use $t, t-3, t-6, \ldots$):

$$A_0^Q X_\tau = A_1^Q X_{\tau-1} + \epsilon_\tau^Q, \tag{8}$$

with $\epsilon_\tau^Q \sim N\left(0, \Sigma^Q\right)$.

- Not all the parameters which describe the monthly structural model can be uniquely identified from A_0^Q, A_1^Q and Σ^Q (only σ_s and σ_r are easily identifiable), see Foroni and Marcellino (2013).

Naif vs quarterly aggregated model

- zero restrictions:
  - naif model

$$A_0^N = \begin{bmatrix} X & X & X \\ 0 & X & X \\ X & X & X \end{bmatrix}, A_1^N = \begin{bmatrix} 0 & 0 & 0 \\ 0 & X & 0 \\ 0 & 0 & X \end{bmatrix}, \Sigma^N = \begin{bmatrix} X & 0 & 0 \\ 0 & X & 0 \\ 0 & 0 & X \end{bmatrix}$$

  - quarterly aggregated model:

$$A_0^Q = \begin{bmatrix} X & X & X \\ 0 & X & X \\ X & X & X \end{bmatrix}, A_1^Q = \begin{bmatrix} 0 & 0 & 0 \\ 0 & X & X \\ 0 & X & X \end{bmatrix}, \Sigma^Q = \begin{bmatrix} X & 0 & 0 \\ 0 & X & X \\ 0 & X & X \end{bmatrix}$$

- The naif econometrician imposes zero restrictions even where in the proper aggregated model there are not.

Exploiting mixed-frequency data to deal with identification issues

$$
\begin{aligned}
\frac{1}{\sigma_s}\pi_t + Fy_t^* + GR_t &= \epsilon_{st} && (9)\\
Hy_t^* + LR_t &= \frac{p}{\sigma_d} y_{t-1}^* + \epsilon_{dt} && (10)\\
\frac{\phi_\pi}{\sigma_r}\left(\rho_r - 1\right)\pi_t + \frac{\phi_y}{\sigma_r}\left(\rho_r - 1\right) y_t^* + \frac{1}{\sigma_r} R_t &= \frac{1}{\sigma_r}\rho_r R_{t-1} + \epsilon_{rt}. && (11)
\end{aligned}
$$

- No problems in estimating eq. (9) and (11) at $t = 3, 6, 9...$
- Need to modify eq. (10) such that it contains only variables which are available at the time of estimation:

$$
y_t^* = \left(\frac{p}{H}\right)^3 y_{t-3}^* - \frac{L}{H} R_t - \frac{L}{H}\left(\frac{p}{H}\right) R_{t-1} - \frac{L}{H}\left(\frac{p}{H}\right)^2 R_{t-2} + \xi_t. \quad (12)
$$

- From eq. (9), (12) and (11), we can now identify all the parameters (Foroni and Marcellino (2013)).

Conclusions

- A very interesting and useful paper
- Mixed frequency information relevant also in a structural context
- Perhaps better develop directly mixed frequency DSGE models