"Short-Term Inflation Projections: a Bayesian Vector Autoregressive approach"

by

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  - interpreting the short-term inflation fluctuations within the components of HICP: unprocessed food, processed food, non-energy industrial goods, energy and services sectors.
  - allowing for all possible interactions among determinants and spillovers between HICP components.
- These kind of questions are very interesting to policy makers.
- The authors study the effects of an oil shock and the evolution of inflation during the global financial crisis.

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- Using Bayesian shrinkage.

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- The Philips curve appears to be relevant in the Euro area in the post-August 2007 period.
- They assess the uncertainty around the median BVAR projection and the possibility of deflation during the heart of financial crisis (i.e. from the third quarter of 2008 to the third quarter of 2009).

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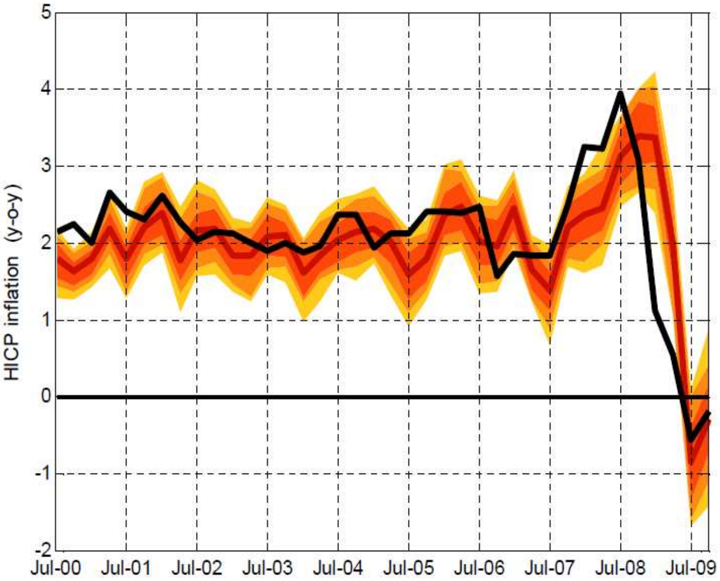
- They assess the uncertainty around the median BVAR projection and the possibility of deflation during the heart of financial crisis (i.e. from the third quarter of 2008 to the third quarter of 2009).
- The conditional BVAR lies closer to the quarterly Eurosystem/ECB macroeconomic projections than the unconditional BVAR.

General Comments

- Very interesting.
- Stimulating and policy relevant.
- Can be extended in many interesting directions.
- Nicely done but needs a bit more work to make a convincing case.

Six months ahead BVAR forecasts



Can we do better?

Specific Comments

- Model Uncertainty
- High Frequency Information

Model Uncertainty

- The authors condition on a particular specification (choice of variables, lag structure, priors, volatility structure).
- Suppose the researcher includes variables suggested by Theory 1 (e.g. gdp). Then, the inclusion of one set of theories says nothing about whether other possible theories (e.g. yield curve) should be included (or not) in the model.
- This implies that researchers face substantial model uncertainty in their work: the fear is that the inclusion or exclusion of variables may significantly alter the conclusions one had previously arrived at for, say, the relevance of the Philips curve is based on a particular model in the model space.
- the policy analysis should not be done conditional on a specific model but rather should reflect model uncertainty
- This leads to model averaging methods that treat model specification as unobservable.

Model Uncertainty

- A policymaker will want more information than simply a summary statistic of the effects of a policy on outcomes where model dependence has been averaged out.

- Forecast combinations or model averaging can provide more accurate forecasts by using evidence from all the models considered rather than relying on a specific model. This is important for policy makers!

- In many cases we view models as approximations because of the model uncertainty that forecasters face due to the the different set of predictors, the various lag structures, and generally the different modeling approaches.

- Furthermore, forecast combinations can deal with model instability and structural breaks under certain conditions.

Model Uncertainty

- In a more relevant context to this paper, Anderson and Karlsson (2007) propose Bayesian forecast combination for VAR model. They consider the marginal predictive likelihood for the variable of interest rather than the joint predictive likelihood.
- In terms of evaluation it would be nice if the authors also used the predictive likelihood in addition to the MSFE.

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- How do the results differ when we use alternative priors?

- A notable alternative is the prior that combines the Minessota prior with the Stochastic Search Variable Selection (SSVS).
  - SSVS specifies a hierarchical prior which is a mixture of two Normal distributions; see George, Sun, and Ni (2008).

$$\alpha_j | \delta_j \sim (1 - \delta_j) N(0, \theta_{0j}^2) + \delta_j N(0, \theta_{1j}^2),$$

where δ_j is a dummy variable and $\theta_{ij} = c_i \sqrt{\widehat{Var}(\alpha_j)}$, $i = 1, 2$ and $\widehat{Var}(\alpha_j)$ is based on a posterior or LS.

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- A prior that combines the Minessota prior with SSVS prior. That is, $\widehat{Var}(\alpha_j)$ is set to be the prior variance of α_j from the Minessota prior.

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Model Uncertainty

Alternative priors

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  This can be useful for model selection or model averaging.

- Koop and Korobilis (2010) find that the prior that combines the Minessota with SSVS works the best.

Model Uncertainty

Stochastic Volatility

- Another problem with the framework of the paper is that it does not take into account changes in volatility.
- While the Great Moderation sharply lowered variability recent events have raised it: bigger shocks to food and energy prices, sharp recession.
- The monetary transmission mechanism and the variance of the exogenous shocks may have changed over time; see for example e.g. Primiceri (2005).
- Failing to take account of these changes produces unreliable inference.
- One solution is TVP-VARs with Stochastic Volatility
- S&W propose a UC-SV model for inflation, which has two components: a stochastic permanent component and a serially uncorrelated temporary component. The variance of the disturbance terms is allowed to change over time. Also see Cogley et al (2007).

High Frequency Information

- Exchange rates, oil prices, and other commodity prices are available at higher frequency.
- In fact there is a huge number of financial times series available on a daily or even an intra-daily basis.
- There is a large literature in Finance and Macroeconomics according to which financial variables are forward looking and thereby good predictors of economic activity.

High Frequency Information

- How can we use the daily financial information to improve traditional monthly or quarterly forecasts?
- One difficulty is that of mixed frequencies.
- Since macroeconomic data are typically sampled at monthly or quarterly frequency, the conventional approach “throws away” the high frequency data and temporally aggregates them to the same (low) frequency by using an equal weighting scheme (flat aggregation).

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- Since macroeconomic data are typically sampled at monthly or quarterly frequency, the conventional approach “throws away” the high frequency data and temporally aggregates them to the same (low) frequency by using an equal weighting scheme (flat aggregation).
- Loss of information through temporal aggregation.
- Forego the possibility of providing forecasts using real-time daily information especially from financial markets.
    - Structural approach: State space models $\rightsquigarrow$ many assumptions + lose parsimony
    - Reduced form approach: MIDAS models $\rightsquigarrow$ flexible + parsimonious

High Frequency Information

- Andreou, Ghysels, and Kourtellos (2010) provide evidence that using daily financial information can help us improve traditional forecasts using aggregated data.
- Eraker and et al (2008) propose a Bayesian mixed frequency VAR.
- MIDAS models with leads provide real-time forecast updates of the current quarter but can also be extended beyond nowcasting the current quarter to forecast multiple quarters ahead; see Andreou, Ghysels, and Kourtellos (2010).

High Frequency Information

MIDAS in a nutshell

- Let π_{t+1}^{L} be monthly or quarterly inflation
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- Let π^L_{t+1} be monthly or quarterly inflation
- X^L_t predictor, e.g. monthly or quarterly oil price returns. Also available, $X^H_{j,t}$ as predictor (day j of quarter t).

- Conventional ADL(1,1)

$$\pi^L_{t+1} = \mu + \alpha \pi^L_t + \beta X^L_t + u_{t+1}$$

High Frequency Information

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- Conventional ADL(1,1)

$$\pi_{t+1}^{L} = \mu + \alpha \pi_{t}^{L} + \beta \left[\sum_{j=1}^{N_H} \frac{1}{N_H} X_{j,t}^{H} \right] + u_{t+1}$$

High Frequency Information

MIDAS in a nutshell

- ~~Conventional ADL(1,1)~~ $\rightsquigarrow$ Model with daily data

$$\pi^L_{t+1} = \mu + \alpha\pi^L_t + \beta[\textstyle\sum_{j=1}^{N_H} \frac{1}{N_H} X^H_{j,t}] + u_{t+1}$$

$$\Downarrow$$

$$\pi^L_{t+1} = \mu + \alpha\pi^L_t + \beta \textstyle\sum_{j=1}^{N_H} w_j X^H_{j,t} + u_{t+1}$$

- Parameter proliferation problem. In the case of monthly data N_H = 22, then we have to estimate 24 slope coefficients! This number grows to 68 in the case of quarterly data.

High Frequency Information

MIDAS in a nutshell

- ~~Conventional ADL(1,1)~~ $\rightsquigarrow$ ADL-MIDAS(1,1)

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$$\pi^L_{t+1} = \mu + \alpha\pi^L_t + \beta\sum_{j=1}^{N_H} w_j(\theta^H) X^H_{j,t} + u_{t+1}$$

- Hyper-parameterized weighting scheme solves parameter proliferation. In the above example it yields only 4 unknown parameters.

- ~~Conventional ADL(1,1)~~ $\rightsquigarrow$ ADL-MIDAS(1,1)

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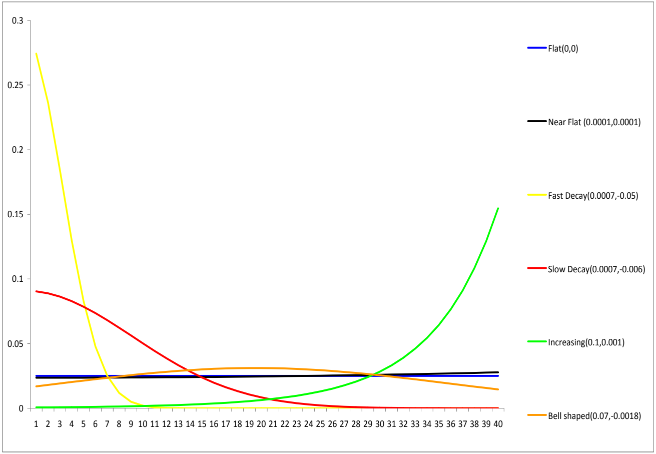
- Exponential Almon (see e.g. Judge et al. 1985) with **two** parameters:

$$w_j(\theta^H) \sim \exp\left[\theta^H_1 j + \theta^H_2 j^2\right]$$

- Various other parameterizations are possible.

Exponential Almon lag polynomial



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- MIDAS regression models with *leads* mimics this process by incorporating real-time information available mainly on the daily financial variables.

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- Suppose our objective is to forecast quarterly inflation and we stand on the first day of the last month.

- This means that if we wish to make a forecast for the current quarter we could use up to 44 leads of daily data for financial markets that trade on weekdays.

HIGH FREQUENCY INFORMATION

MIDAS REGRESSION MODELS WITH LEADS (CONT'D)

- Consider the simplest $ADL - MIDAS$ with one quarterly lag and daily leads for the daily predictor.

High Frequency Information

MIDAS Regression Models with Leads (cont'd)

- Consider the simplest $ADL-MIDAS$ with one quarterly lag and daily leads for the daily predictor.

$$
\begin{aligned}
\pi^L_{t+1} &= \mu + \alpha \pi^L_t + \\
& \beta[\underbrace{\sum_{i=0}^{J_X^H-1} w_i(\theta^H_X) X^H_{J^H_X-i,t+1}}_{\overset{\shortparallel}{\text{leads}}} + \underbrace{\sum_{i=0}^{N_H-1} w_i(\theta^H_X) X^H_{N_H-i,t}}_{\overset{\shortparallel}{\text{no-leads}}}] \\
& + u_{t+1},
\end{aligned}
$$