Real-Time Nowcasting with a Bayesian Mixed Frequency Model with Stochastic Volatility

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Introduction

- Work on economic forecasting with large datasets (hundreds of variables) started about 15 years ago with Stock and Watson and Forni, Lippi, Hallin and Reichlin. Main challenge to provide proper theory for serially correlated variables
- Stock and Watson also proposed a method to handle large unbalanced datasets, but not so used till recently
- More recently (Reichlin et al.), focus on now-casting, in particular of GDP, using large unbalanced datasets

Introduction

- Nowcasting important because timely forecasts of GDP growth and inflation are useful summaries of recent news on the economy and commonly used as inputs to structural forecasting models
- A lot of work on nowcasting, see e.g. Banbura et al (2011, 2012), Foroni and Marcellino (2013) and section 2 of the paper
- Our apporach motivated by previous studies and three other key findings in the broader forecasting literature.

- First, estimation with Bayesian shrinkage is a viable alternative to factor model methods (e.g. De Mol, Giannone, and Reichlin (2008), Banbura, Giannone, and Reichlin (2010) and Carriero, Kapetanios, and Marcellino (2011))
- Second, useful for forecasting purposes to incorporate stochastic volatility into VAR models, for both point and density forecasts (e.g., Clark (2011), Carriero, Clark, and Marcellino (2012), and D'Agostino, Gambetti, and Giannone (2012)). Role of TVP less clear cut, but potentially relevant.
- Third, in practice direct multi-step methods of forecasting can be at least as accurate as iterated methods (e.g., Marcellino, Stock and Watson (2006))

- We develop a new Bayesian Mixed Frequency (BMF) model with Stochastic Volatility (SV) for point and density nowcasting.
- Our formulation also readily allows the regression coefficients to be time-varying.
- We produce current-quarter forecasts of GDP growth with a (possibly large) range of available within-the-quarter monthly observations of economic indicators, such as employment and industrial production, and financial indicators, such as stock prices and interest rates.. Each time series of monthly indicators is transformed into three quarterly time series, each containing observations for, respectively, the first, second or third month of the quarter. Higher frequency info can be also handled.

- We use Bayesian methods to estimate the resulting model, which expands in size as more monthly data on the quarter become available.
- Bayesian estimation facilitates providing shrinkage on estimates of a model that can be quite large, conveniently generates predictive densities, and readily allows for stochastic volatility and time-varying parameters.
- Assess accuracy of the resulting nowcasts of real-time GDP growth in the U.S. from 1985 through 2011.
- Most prior nowcasting research has focused on point forecasts (except Aastveit, et al. (2011) and Marcellino, et al. (2012)), we consider both point and density forecasts.

- For point forecasts, our proposal is comparable to alternative mixed frequency econometric methods and survey forecasts.
- In addition, it provides reliable density forecasts, for which the stochastic volatility specification is quite useful, while parameter time-variation does not seem to matter.
- Compared to other partial model approaches or studies, the key innovations of our analysis include the use of Bayesian shrinkage to consider a possibly large set of indicators; the allowance for time variation in coefficients; the inclusion of stochastic volatility; and the analysis of density nowcasts.

The Bayesian Mixed Frequency Model

- We consider nowcasting the quarterly growth rate of GDP in month m of the current quarter based on the regression:

$$y_t = X'_{m,t}\beta_m + v_{m,t}, \quad v_{m,t} \sim i.i.d.N(0, \sigma^2_m), \tag{1}$$

where the vector $X_{m,t}$ contains the available predictors at the time the forecast is formed, t is measured in quarters, and m indicates a month (as detailed below).

- $X_{m,t}$: transformed to achieve stationarity. At the quarterly frequency, for each monthly variable, we then define three different variables, by sampling the monthly series separately for each month of the quarter.
- Similar approach can be used to incorporate higher frequency info. The largest model we consider includes over 50 explanatory variables in $X_{m,t}$

The BMF with stochastic volatility (BMF-SV) and time-varying parameters (BMF-TVP-SV)

- In the stochastic volatility (SV) case, model becomes:

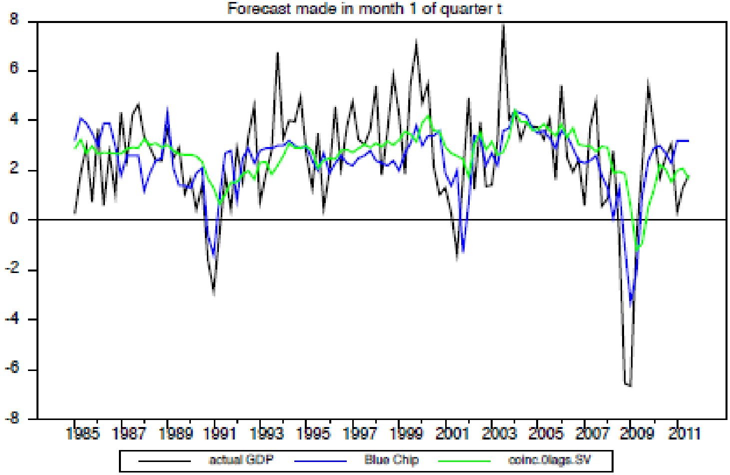
$$\begin{aligned} y_t &= X'_{m,t}\beta_m + v_{m,t} \\ v_{m,t} &= \lambda_{m,t}^{0.5}\epsilon_{m,t},\ \epsilon_{m,t} \sim i.i.d.N(0,1) \\ \log(\lambda_{m,t}) &= \log(\lambda_{m,t-1}) + \nu_{m,t},\ \nu_{m,t} \sim\ i.i.d.N(0,\phi_m), \end{aligned} \quad (2)$$

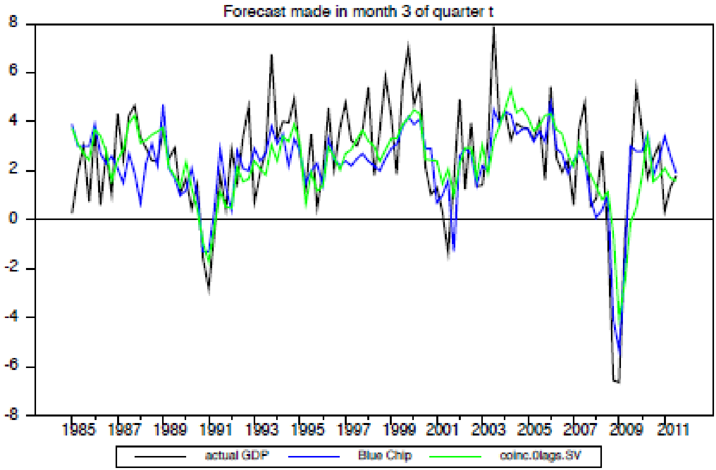
- For TVP, the coefficient vector becomes $\beta_{m,t}$, with

$$\beta_{m,t} = \beta_{m,t-1} + n_{m,t}, \quad n_{m,t} \sim\ i.i.d.N(0, Q_m).$$

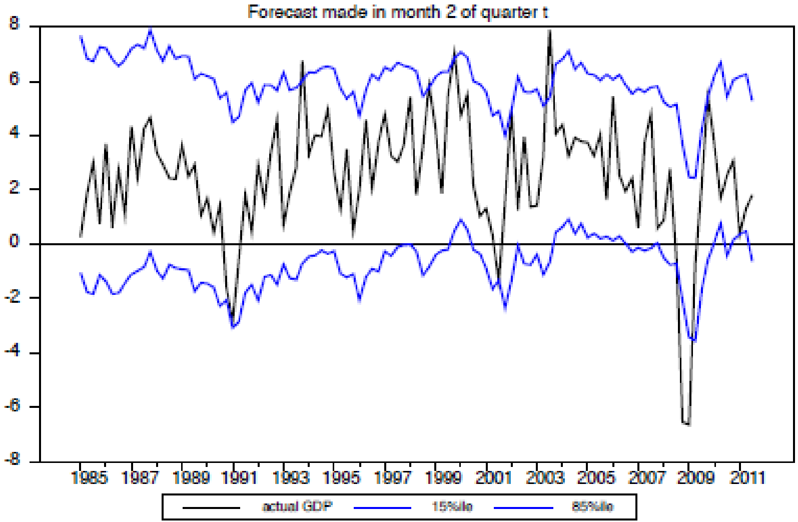
- Estimation with Bayesian methods.

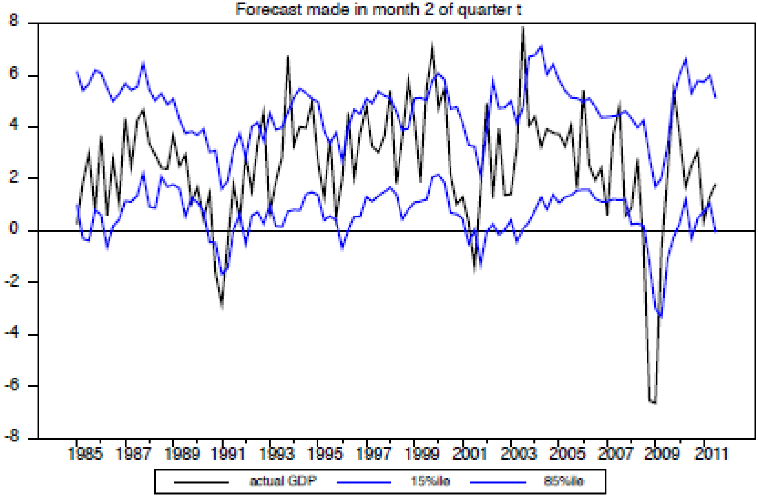
Point forecasts, comparison of Blue Chip and BMFSV




Forecast made in month 3 of quarter t
8
6
4
2
0
-2
-4
-6
-8
1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011
actual GDP
Blue Chip
coinc.0lags.SV

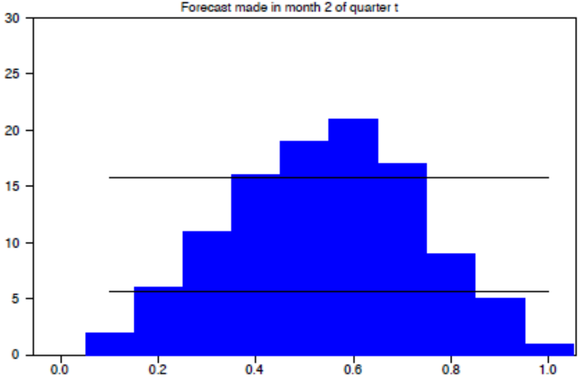
Effects of SV on interval forecasts

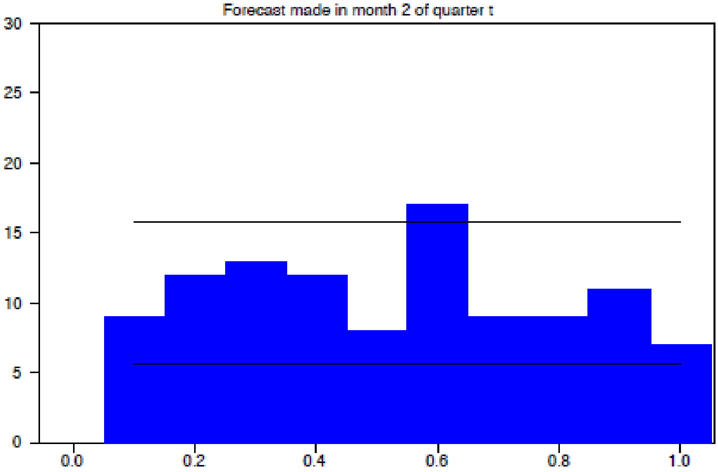



Forecast made in month 2 of quarter t
8
6
4
2
0
-2
-4
-6
-8
1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011
actual GDP
15%ile
85%ile

Effects of SV on probability integral transforms (PITs)

- If the forecasting models were properly specified, the PITs would be uniformly distributed, yielding a completely flat histogram.




Forecast made in month 2 of quarter t
30
25
20
15
10
5
0
0.0
0.2
0.4
0.6
0.8
1.0

Conclusions

- We have developed a Bayesian Mixed Frequency method for producing current-quarter forecasts of GDP growth with a (possibly large) range of available within-the-quarter monthly (or higher frequency) observations of economic indicators, such as employment and industrial production, and financial indicators, such as stock prices and interest rates.
- We also consider versions of the model with stochastic volatility, while most of the existing approaches assumed that the variance is constant. Similarly, we introduce models with time-varying regression coefficients (with or without stochastic volatility), while the latter are treated as constant in most of the literature on mixed frequency models.
- We use Bayesian methods to estimate the model, in order to facilitate providing shrinkage on the (possibly large set of) model estimates and conveniently generate predictive densities. We use it to produce point, interval and density forecasts, that turn out to be rather good.