Forecasting with large Bayesian Vectorautoregressions

Luis Gruber[1] and Gregor Kastner[2]

[1]Department of Statistics, University of Klagenfurt
[2]Department of Statistics, University of Klagenfurt

Abstract Vectorautogressions (VARs) are widely applied when it comes to modeling and forecasting macroeconomic variables. Increasing availability of data and technical developments have led to a trend working with large datasets. One characteristic feature of VARs is their large number of parameters, which is quadratic in the number of employed variables. Hence, VARs are prone to overfitting. Bayesian methods have shown to be successful in overcoming this problem. Many different shrinkage priors have been proposed in the Bayesian VAR literature in order to cure the curse of dimensionality. Among them the popular Minnesota (MP) and Stochastic Search Variable Selection (SSVS) priors. In the present paper we compare hierarchical refinements of the MP and SSVS priors, as well as the Dirichlet-Laplace (DL) prior. We shed more light on the ongoing *Illusion of Sparsity* (IoS) debate by evaluating several sparseness measures on both, simulated and empirical data. In a simulation study we show that the DL and the SSVS prior show superior performances in sparse scenarios, whereas the MP prior performs best in dense scenarios. All our models feature Stochastic Volatility (SV) in the variance-covariance matrix since there is general consent in financial and economic applications, that volatility is varying over time. In an empirical forecasting exercise with data from the US economy, we find no clear answer whether sparse or dense models perform better. This varies across evaluated metrics, evaluated economic variables and across time frames. Since the financial crisis in 2007/2008, it seems that priors favoring sparse scenarios outperform 'dense' priors. The highly competitive results of 'dense' priors before that crisis indicate a structural break in the economy.