Nowcasting the Finnish economy with a large Bayesian vector autoregressive model

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Abstract

Timely and accurate assessment of current macroeconomic activity is crucial for policymakers and other economic agents. Nowcasting aims to forecast the current economic situation ahead of official data releases. We develop and apply a large Bayesian vector autoregressive (BVAR) model to nowcast quarterly GDP growth rate of the Finnish economy. We study the BVAR model's out-of-sample performance at different forecasting horizons, and compare to various bridge models and a dynamic factor model.

1 Introduction

Policymakers and economic agents rely on timely and accurate information on the current condition of the economy. The official statistics, however, are published with a considerable delay and are subject to revisions long after their initial release. European quarterly GDP flash estimates are released with a 45 day delay and the first official statistic with a 60 day delay counting from the end of the quarter. This means that decision makers have to wait 2–5 months for the official GDP statistics of the ongoing quarter, depending on the current date within the quarter.

In economics nowcasting refers to the process of forecasting current state and growth rate of the economy (Banbura et al., 2013). In practice nowcasting is primarily used to forecast of the previous, present and next quarter-on-quarter growth rate of GDP. Other economic variables can be forecast with similar methods as well.

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Nowcasting models typically aim to exploit a large dataset of indicators that are published on a high frequency. For example, consumer and business confidence indicators provide ”soft” information on the state of the economy.[1] Similarly, ”hard” information is provided by indicators of industry and service sector turnouts, industrial production, retail and wholesale sales, and employment. In addition, financial data such as stock market indices and interest rates may be used predict where the economy is headed.

The information set available for nowcasting has several features that complicate matters and set nowcasting apart from other forecasting exercises. First, the number of time series which have the potential to predict economic growth is very large, and indicators are often highly correlated with each other. Second, the information set contains data observed at different frequencies (typically at quarterly, monthly, or daily frequency). Third, different indicators have different publication lags. Soft information (e.g. confidence indicators) becomes available earlier than hard information (e.g. industry turnover). Fourth, indicators might have different starting dates and some have a fairly short history. Fifth, for most indicators, previous observations are revised when new ones are published. Nowcasting models are specially designed to handle such unbalanced and ever-growing information sets. As a result, nowcasting performance tends to improve as more data becomes available.

Currently popular modeling approaches include bridge models, dynamic factor models (DFM) and Bayesian vector autoregressive models (BVAR). Bridge models are simple regression models that employ a single indicator to predict GDP growth rate. A common practice is to use the average forecast of multiple bridge models. In contrast, DFMs aim extract common sources of variation, i.e. factors, from a large dataset in order to produce a more parsimonious model. BVARs employ a large vector autoregressive model with Bayesian priors to mitigate the curse of dimensionality, endemic to models with many parameters and few observations.

Nowcasting models can also be used to assess the importance of new data releases, a practice known as news analysis (Banbura et al., 2013). News is defined as the difference between the observation and model's forecast for that data point. DFMs and BVARs give forecasts for all missing observations in the dataset as a by-product, so these model can be used to analyse the news value of all variables. What matters is not the new data release it self but it's difference to our expectation. Only information that differs from our expectation calls for an adjustment in our view of the current state of the economy. For example, a decrease in unemployment does not necessarily mean that we should revise out GDP forecast

[1] In Finland, the Confederation on Finnish Industries collects data for businesses and the Statistics Finland for consumers. These then are combined in the European Commission's Business and Consumer Surveys.

upward if the decrease in unemployment was anticipated.

The quarterly GDP statistics are relatively noisy in a small open economy like Finland, and this needs to be accounted for when building a picture of current economic condition. First, the quarter-to-quarter growth rate is highly volatile, because even a single business decisions of a large firm might an big impact on GDP.[2] Second, the revision GDP and other data can be significant and revisions occur long after the initial release.

Due to noise, actual observations of quarterly GDP might deviate considerably from the short-run trend. Depending on the purpose for which the nowcasts are used, it is often necessary to build separate forecasting models to track actual GDP and its trend. For example, when nowcasting is used to obtain a better starting point for medium term forecasts, a model that tracks actual GDP might be more useful. On the other had, to convey a wider picture of the general state of the economy and its direction, a model for the short-run trend might be more relevant. Therefore it is important to evaluate the performance of nowcasting models also with respect to a short-run trend, where some of the noise has been filtered out.

Our main contribution in this paper is to develop and apply a large Bayesian vector autoregressive (BVAR) model to nowcast quarterly GDP growth rate of the Finnish economy. A key advantage of a BVAR model is that it can be specified in levels. Stationarizing the data by taking first differences of variables, which is necessary with DMFs, tends to amplify noise, which is already considerable in the case of a small open economy. Also the long-run information contained in levels data might help to produce more consistent forecasts and reduce the persistent upward forecasting error experienced with DFMs. In the practical real time nowcasting it was found during the recent years that the factor model employed at the Bank of Finland gave repeatedly over-optimistic nowcasts and short term forecasts for the GDP growth. Hence using time series tools that work conveniently with non-stationary data might be useful when forecasting volatile economy. In the paper we show the specification of the BVAR model and study its out-of-sample performance at different forecasting horizons, and compare it to various bridge models and a dynamic factor model.

We specify the BVAR model following closely Giannone et al. (2015). The curse of dimensionality is dealt with Bayesian shrinkage. In principle, we use informative priors that push the estimates of parameter rich VAR to more parsimonious processes, namely to unit root processes as originally proposed in Litterman(1979), Doan et al. (1984) and Sims(1993) and known as Minnesota type priors in the literature. Since unit root process is a good approximation to many macroeconomic variables this brings little estimation error but greatly reduces estimation uncer-

[2]For example, one tenth of percentage point quarterly GDP represents only about 50 million Euros.

tainty. Although implementing Bayesian shrinkage using Minnesota type priors dates back to 80's and more sophisticated approaches for Bayesian shrinkage have been developed, has Minnesota type priors gained popularity recently. Giannone et al. (2015) and Bańbura et al. (2015) show that the forecast accuracy of large VAR with Minnesota type Bayesian shrinkage is comparable to forecast accuracy of factor models in US and Euro area data.

Our BVAR model contains 47 variables, of which 9 are observed at quarterly frequency and the rest on monthly frequencies. Data consists of variables that Statistics Finland releases regularly and can be thought be relevant predictors for the state of economy. In addition some foreign variables are included. List of variables for BVAR model is provided in Table 2.

In the literature two distinct ways have been proposed to use mixed frequency data with VAR. Schorfheide and Song (2015) show how to specify the VAR on monthly frequency and the monthly observations of quarterly series are treated as missing observations that can be estimated with the use of Kalman smoother. Alternative approach is given by McCracken et al. (2015) that specify the VAR on quarterly frequency and within a quarter the different monthly observations of a series are treaded as different variables.

In our application different VARs are specified for monthly and quarterly variables and these are merged in Kalman filter/smoother. In the part of the sample where all variables are observed, monthly series are simply time aggregated to quarterly series. When in some quarter (usually the last quarter of the data) there are missing observations of monthly series, these are filled using the monthly VAR and Kalman filter. Then time aggregated quarterly series that consists of partly observed and forecasted monthly variables are treated as noisy signals of the true series. The precision of the signal is obtained from the forecast error variance-covariance matrix of Kalman filter for monthly data.

The paper is organized as follows. In Section 2 we review the most commonly used tools for nowcasting and short term forecasting. Main emphasis is in specifying the large Bayesian model for the Finnish economy. Section 3 compares the forecasting performance of models.

2 Nowcasting models

2.1 Bridge models

Bridge models are simple linear models which forecast GDP quarter-to-quarter growth rate using a single monthly indicator variable, which has been aggregated to the quarterly level (Baffigi et al., 2004). Although recent advances in nowcasting methodology has made more comprehensive and elaborate models available, bridge models are still widely used, and merit their place in the nowcasters tool box. First, they tend to perform better in the beginning of the nowcast period, as will be shown later. Second, bridge models are easy to implement and interpret. Third, practice has show bridge models to be very robust in enduring structural breaks in the economy.

To handle missing monthly observations at the end of the indicator time series, i.e. the ragged edge, we use an ARIMA model to complete the missing values.[3] Let x_t be the aggregated indicator at quarter t, typically calculated as the average of monthly observations (and ARIMA predictions) within the quarter. Let y_t be the GDP quarter-to-quarter growth rate. We use two lags for all models. Hence the model takes the form

$$y_t = \alpha + \beta_1 x_t + \beta_2 x_{t-1} + e_t, \quad t = 1, 2, \ldots,$$

where α, β_1, and β_2 are parameters, and e_t the error term for the quarter t.

For Finland there are several indicators that perform well in a bridge model. The European Commission's Business and consumer surveys, published monthly with a short lag for each EU country, provide many useful indicators. Economic sentiment indicator (ESI), which is a composition of consumer and business confidence indicators, is among the most used. Similarly, consumer confidence indicator, industrial confidence, and industrial production expectations perform well. Also ESI calculated for the Euro area can be used for the Finnish economy.

Euro area Purchasing managers' index (PMI), and other similar foreign indicators, can also be useful (PMI is not published for Finland alone).

Trend indicator of output, produced by Statistics Finland based on the same data as quarterly GDP and published monthly, is very useful in nowcasting, as it is also used to calculate the official GDP flash estimate. Volume index of industrial product another useful indicator, which based on hard information.

2.2 Dynamic factor models

In recent years, dynamic factor models have become one of the main tools for nowcasting at central banks and other institutions that make economic forecasts. The advantage of the model is its capacity to use various sources of information and filter out an up-to-date picture of the economic state and direction. The Bank of Finland uses a dynamic factor model based on the approach by Giannone et al. (2008), a so-called factor-augmented vector autoregressive model (Kostiainen et al., 2013). The latest version of the Bank of Finland indicator model uses information on the economic situation from 76 different statistical series.

[3] We use an an automatic algorithm by Hyndman and Khandakar (2008) to produce the ARIMA forecasts for the indicator.

Dynamic factor models take advantage of the strong covariance among the indicator variables, and extract from the data a small number of common factors that drive the co-movement of the variables.

Let y_t be a vector of n stationary variables observed at time t with mean ν. The dynamic factor model is defined by equations

$$y_t = \nu + \Lambda F_t + e_t \quad \text{and}$$

$$F_t = \Phi_1 F_{t-1} + \cdots + \Phi_2 F_{t-2} + u_t$$

where F_t is a vector of $r \leq n$ common factors, Λ is a $n \times r$ matrix of factor loadings, idiosyncratic component e_t is n-dimensional residual whose covariance matrix Γ is diagonal, and u_t is r-dimensional white noise with covariance matrix Q.

2.3 Large Bayesian vector autoregressive model

The VAR models we consider for both monthly and quarterly series can be represented as:

$$y_t = c + A_1 y_{t-1} + ... + A_p y_{t-p} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma) \tag{1}$$

We assume a conjugate normal-Wishart prior for the coefficients (A's) and for the variance-covariance matrix of the residuals Σ. When a relatively uninformative prior is assumed the estimates are centered on ordinary least squares estimates. Due the properties of conjugate normal-Wishart prior, the distributions of both the coefficients and covariance matrix are obtained through direct sampling.

Our VARs contain a large number of variables which leads to good in-sample-fit but to a poor out-of-sample performance. To reduce the over fit in sample and improve the forecasting performance it has been standard since Litterman (1979) to implement priors that bring the parameter rich VAR towards more parsimonious model. As in the original Minnesota prior by Litterman (1979) we assume on prior that each variable in the VAR follows independent unit root process. Following closely the notation in Bańbura et al. (2015) we set prior means and variance-covariance matrix for VAR coefficients as:

$$E\left[(A_s)_{ij}|\Sigma, \lambda, \Psi(\right] = \begin{cases} 1 & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$cov\left[(A_s)_{ij}(A_r)_{hm}|\Sigma, \lambda, \Psi\right] = \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_i h}{\Psi_{jj}} & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

For each equation in the VAR the coefficient for the first lag of own variable of that equations is assumed to equal unity whereas all other coefficients are assumed to equal zero. The distant the lag, the smaller is the prior variance and hence the prior is more tighter. This is determined by the s^2 term in the denominator. The overall tightness is determined by the λ-parameter. The term $\frac{\Sigma_i h}{\Psi_{jj}}$ accounts for the relative scales of variables and $E[\Sigma] = \Psi$ is the prior mean for the variance-covariance matrix of the residuals. For the intercepts of the VAR, c, a loose, uninformative prior is assumed.

In addition two other priors are implemented. Note that the prior implemented in (2) supports only first order unit root processes. To put prior weight also on unit root processes of higher order, we implement the "sum of coefficients" -prior as suggested originally in Doan et al. (1984). This prior is implemented adding artificial, dummy observations to data the set. Rewriting the VAR model in (1) as

$$y_t = X_t B + \epsilon_t \tag{3}$$

Let $\bar{y}_0$ be an $n \times 1$ vector that contains the averages of first p observations for each variable. We produce dummy observations according to

$$y_\mu = \text{diag}\left(\frac{\bar{y}_0}{\mu}\right) \tag{4}$$

$$x_\mu = \left[\underset{n\times 1}{0}, \bar{y}_0 ... \bar{y}_0\right] \tag{5}$$

To understand the idea of implementing prior beliefs through dummy observations consider following. Equation (4) contains a system of n equations. When stacked to data set, (4) represents one observation. If in an equation i in (4) the sum of coefficients of lags of variable i sum exactly to 1, the size of the error term in that equation is exactly zero. If the coefficients deviate from this an estimation error is resulted to that equation for this observation. μ determines how much weight the prior gets with respect to sample information. If μ is large even a big deviations from the sum-of-coefficients prior do not generate large errors since in practice errors of dummy observations are divided by μ. In contrast, if μ approaches to zero even small deviations from the prior result large errors and hence estimates are pushed close to sum-of-coefficient prior.

Priors in (2) and (4) support only independent unit root processes and are inconsistent with a belief that variables in the VAR share common stochastic trends. To allow for common stochastic trends, Sims' (1993) "dummy-initial-observation" prior is implemented.

$$y_\delta = \left(\frac{\bar{y}_0}{\delta}\right) \tag{6}$$

$$x_\delta = \left[\frac{1}{\delta}, \bar{y}_0 ... \bar{y}_0\right] \tag{7}$$

This prior is consistent with cointegration of any order. The strength of this prior increases as δ decreases.

The strictness/informativeness of our priors is determined solely by the hyperparameters, λ, μ and δ. Sims and Zha (1998) provide "rule of thumb" values 0.2, 1 and 1, respectively. Recently it has gained success to estimate these parameters by maximizing the marginal likelihood of the VAR model as formalized in Giannone et al. (2015). For our data set this was problematic since it seems that the likelihood function has very little curvature for these priors. Alternative approach in the literature has been to choose values that minimize the forecast error in a pre-sample (see e.g. Litterman (1980). We follow this approach and using a grid search choose hyperparameter values that minimize the forecast error of GDP growth in a pre-sample since this criteria is consistent with our forecasting objective. We place our grid around Sims & Zha (1998) values. We have not yet succeeded with this and in the forecasting exercise we use Sims and Zha (1998) values for the hyperparameters.

2.3.1 Ragged edge and time aggregation

When producing real-time forecasts the data has a ragged edge since some variables are observed with longer delays than others. Another feature of our data is that it contains both monthly and quarterly observations. It is common to time aggregate monthly variables by taking quarterly averages or sums. However when data has ragged edge this does not work trivially. Even if time aggregation is used some approach needs to be chosen to fill the missing observations of monthly variables.

In the context of factor models Bańbura and Modugno (2014) show how to specify the model on monthly frequencies and treat the unobserved monthly observations of quarterly variables as missing observations that can be filled with the use of Kalman filter. Schorfheide and Song (2015) show how to implement this in the context of VAR. Alternative approach is given by McCracken et al. (2015) that specify the VAR on quarterly frequency. In their approach each monthly observations within a quarter are treated as different variables. The first approach requires estimation of unobserved variables and a number of iterations between parameter estimates and estimates of unobserved variables. The latter approach almost triples the number of coefficients in the VAR. In order to take into account the time ordering of monthly series, it is required to add restrictions on the VAR, which makes the estimation slightly more complicated.

Our approach relies on time aggregation. The procedure to fill the ragged edge of the data and produce nowcasts (and backcasts and forecasts) is the following. First, we specify a VAR for monthly data only and a VAR for data that consists of time aggregated monthly series and quarterly series. Monthly VAR and Kalman filter are used to fill the missing observations till the end of the last quarter that features any monthly observations. Once the missing observations of monthly series are filled, the series are time aggregate to quarterly series taking the average over the quarter. Time aggregation is done using Kalman filter because this gives us the forecast error variance-covariance matrix for those time aggregated data points that consists partly or fully of forecasts of monthly variables.

Finally forecasts of GDP and other quarterly series are obtained using quarterly VAR. Since the first official GDP statistic is released with a lag of two months there is always more recent releases of monthly variables when doing a real time forecasting exercise. Hence forecast/nowcasts of GDP are obtained conditionally on time aggregated monthly variables. Because some data points of time aggregated series consists of forecasts it is important to take this into account. This is done by assuming that time aggregated monthly series are observed potentially with a measurement error. We obtain variance covariance matrix for measurement errors from the Kalman filter for monthly data. For time aggregated data points that consists only on observed monthly variables the measurement error is zero.

The merit of our approach is that it is much easier to implement in practice than those in Schorfheide and Song (2015) and McCracken et al. (2015). The disadvantage is that the information content of quarterly variables is not used when producing forecasts of monthly variables. However most quarterly variables are observed with a long lag so we don not consider this as a major disadvantage. Time aggregation destroys some information of monthly variables since in principle a variable might be differently related to e.g. quarterly GDP growth depending on whether it is the first, second or the third month of quarter. But taking this into account increases the number of parameters of already parameter rich model and hence the estimation uncertainty of the parameters. Each monthly observation contains also some noise and time aggregation reduces it, which can be useful in practice.

We specify the Kalman filter following closely notation in Bańbura et al. (2015):

Measurement equation

$$Z_t = C_t S_t + v_t \tag{8}$$

Transition equation

$$S_{t+1} = G S_t + w_{t+1} \tag{9}$$

Z_t contains observables variables and S_t potentially unobserved states. We can cast the VAR in (1) a linear state space representation as $Z_t = Y_t$, $C_t = [I_n 0_{n \times np}]$

$$S_t = \begin{pmatrix} Y_t \\ \vdots \\ Y_{t-p+1} \end{pmatrix}, G = \begin{pmatrix} A_1 & A_2 & \dots & A_p & I_n \\ I_n & 0_n & \dots & 0_n & 0_n \\ \vdots & \ddots & \dots & \vdots & \vdots \\ 0_n & \dots & I_n & 0_n & 0_n \\ 0_n & \dots & 0_n & 0_n & I_n \end{pmatrix}, H_t = \begin{pmatrix} \Sigma & \dots & 0_n \\ \vdots & \ddots & \vdots \\ 0_n & \dots & 0_n \end{pmatrix}$$

The sizes of matrices in the transition equation vary depending on which variables are actually observed. Corresponding columns and rows are deleted from C_t and R_t matrixes as some observations are missing. In the context, of a monthly VAR R_t equals only zeros, since observed variables are observed without any noise. When Kalman filter is specified for quarterly VAR corresponding elements in R_t differ from zero when Z_t contains forecast of temporally aggregated monthly variables.

To show concretely how forecast for the time aggregated variables are obtained lets write Kalman filter equations for monthly VAR(3) model.

Transition equation

$$\begin{pmatrix} Y^m_{t+1} \\ Y^m_t \\ Y^m_{t-1} \\ Y^q_{t+1} \end{pmatrix} = \begin{pmatrix} A_1 & A_2 & A_3 & I_n \\ I_n & 0_n & 0_n & 0_n \\ 0_n & I_n & 0_n & 0_n \\ W_n & W_n & W_n & 0_n \end{pmatrix} \begin{pmatrix} Y^m_t \\ Y^m_{t-1} \\ Y^m_{t-2} \\ Y^q_t \end{pmatrix} + w_{t+1} \tag{10}$$

where W_n is $n \times n$ diagonal matrix, diagonal elements equalling 1/3. We take quarterly averages since in the end we are interested on quarterly differences of flow variables for which scaling by 1/3 does not matter and for stock variables and rates quarterly average is of interest. In the equations for Y^q_{t+1} error term is alway zero, since those equations are simply definitions.

Following the Kalman recursion equations in the Appendix we obtain forecasts and forecast error covariance matrix for Y^q_{t+i}. We obtain Y^q_{t+i} for each time period (in months), but naturally we are only interested on values for periods that correspond to the first month of each quarter since this give the time aggregation for the previous quarter. Let $P^q_{t+i|t}$ be the covariance matrix for $E_t[Y^q_{t+i}]$. If on period t all monthly variables on three previous periods are observed, all elements in P^q_t equal zero. In a special case where the first two moths are fully observed and there are no observations from the third month, $P^q_t = W_n \Sigma W_n'$, where Σ variance-covariance matrix of the residual in the monthly VAR.

3 Assessment of the forecasting ability

Assessment of the forecasting ability of models forms an important part of the use and development of forecasting models. Comparison of performed forecasts and actual outcomes is a natural way of assessing the forecasting accuracy of models. The forecasting error is the difference between forecast and actual outcome.

Firstly, a good forecasting model should be unbiased, which means that the model does not systematically generate higher or lower forecasts than the outcomes. Lack of bias can be analyzed by calculating the mean forecast error (MFE) for a certain period. The MFE for an unbiased forecasting model does not significantly deviate from zero.

Lack of bias alone is not enough, as the model should also be accurate. An accurate model generates forecasts that come close to the actual outcomes. The root mean square forecast error (RMSFE) is a frequently used forecast error measure, which is obtained by computing the mean of squared forecast errors and extracting the square root of that. The closer the RMSFE figure is to zero, the more accurate is the forecasting model. In relative terms, the measure gives greater weight to large forecast errors.

When realized forecast errors are assessed and new models developed, it is of vital importance to bear in mind what information was available at the time when the forecast was made. With hindsight, it is easy to build models that explain positive developments, when the variables to be forecasted are already known for a long period. However, in practice, this often gives an overly optimistic picture of the model's forecasting ability. The challenge of the economic forecaster is to assess development in a situation when future observations are not yet known.

To avoid second-guessing, it is always good to use pseudo out-of-sample forecasts in assessment of forecasting ability. Thus the forecast is made only on the basis of the part of statistical data that was available prior to the period to be forecasted. In that case, the forecasting models are compared in the same situation as the one when the forecaster applied the model.

3.1 GDP revisions

The information on GDP development provided by national accounts is updated in connection with new statistical releases. The statistical information becomes more detailed as the statistical authority gets access to more information on the development of different sectors of the economy. A more accurate picture of GDP is obtained through personal tax information, for example, but this information is not final before the tax forms have been filed and the taxation decisions have been made.

Thus the first information on GDP is not final. In this respect, GDP is a moving target, which complicates the forecaster's task. Even if the forecast were to exactly hit the growth rate in the statistical release, it is very possible that the forecast will be off when the statistics get updated. From a practical point of view, this means that perfect accuracy cannot be expected from nowcasting forecasts.

The uncertainty connected with the actual statistics can be assessed by studying the difference between data in the first releases and the latest information. At times, the adjustment of GDP growth rates has been considerable. In particular, the exceptionally large drop in the first quarter of 2009 was not yet revealed in the first statistical release. The official statistic has been revised for the initial growth rate of -2.7% to -6.9% in the latest release.

The adjustment of statistics can be assessed by using the same measures as in the study of forecast errors. In 2008–2015, the average statistical revision of quarterly GDP growth was 0.2%. The figure is comparable with the MFE figure presented above. Thus the growth rates in the first statistical releases have been slightly higher than the latest growth rates, i.e. the picture of GDP growth has slightly deteriorated as the data have been adjusted.

The deviation of statistical revisions in growth rates has been fairly wide. In half of the cases, the revision was between -0.3% and 0.5%. Correspondingly, 75% of the revisions fitted in between -0.5% and 0.8%. The standard deviation of statistical revisions was 0.99. The figure is comparable with the RMSFE figure measuring the forecast error of the forecasting models.

The standard deviation of statistical revisions can also be considered as a sort of lower limit of forecast errors of forecasting models, and better accuracy cannot be expected. Even if the forecasting model were always to hit exactly the figure of the first statistical release, as the statistics are updated the RMSFE figure of the forecasting model in question would increase to close to one in a comparison with the latest statistical GDP release.

3.2 Out-of-sample forecasting

Results for our out-of-sample forecasting exercise are shown in Table 1. Our target variable is quarter on quarter GDP growth rate in percentages. Forecasting horizon varies from nowcasting the current quarter at the end of the last month of that quarter (0) to forecasting five months before the end of a quarter (5). Consistent with findings in the literature, dynamic factor model and BVAR are able to outperform the simpler models on the shorter horizons, but on the longer horizons the ranking is less clear. In terms of root of mean squared forecasting error, BVAR slightly outperforms factor model on the short horizons. As can be seen from Figure 1 the forecasts of BVAR and factor model are highly correlated. However, the forecasts of BVAR suffer form a smaller bias (mean error in Table 1) especially on longer horizons.

4 News analysis

Nowcasting models can also be used to assess the importance of new data releases, a practice known as news analysis (Banbura et al., 2013). The model gives forecasts for each missing observations in the data set, so we can define news as as the difference between the observation and model's forecast for that data point. What matters is not the new data release it self but it's difference to our expectation. For example, a decrease in unemployment does not necessarily mean that we should revise out GDP forecast upward if the decrease in unemployment was anticipated. Only information that differs from our expectation is regarded as news, in the sense that it calls for an adjustment in our view of the current state of the economy.

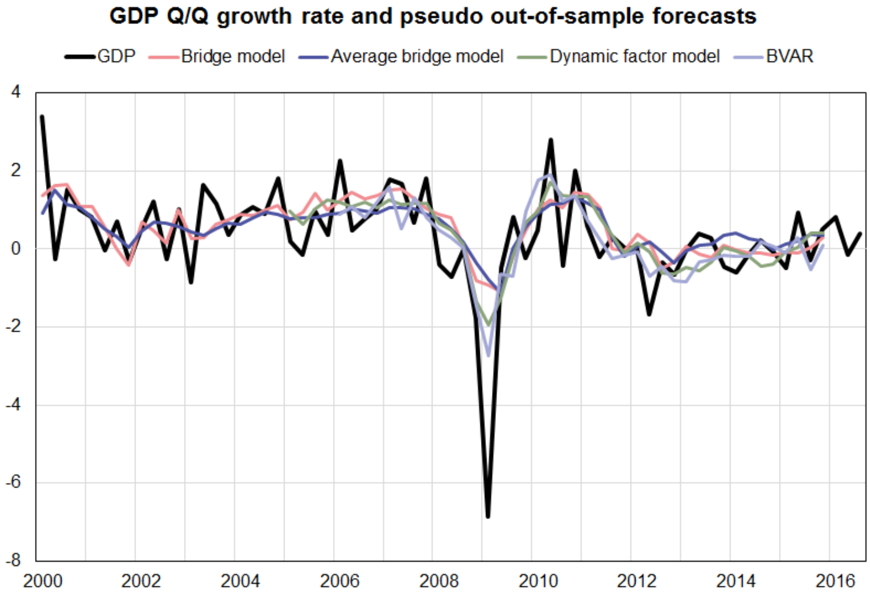
Figure 2 illustrates the news analysis in practice.

Table 1: Forecasting performance

		Root squared mean error			Mean absolute error			Mean error		
	Horizon	2000-2015	2006-2015	2006-2015 exl. 2009	2000-2015	2006-2015	2006-2015 exl. 2009	2000-2015	2006-2015	2006-2015 exl. 2009
Random Walk	4	1.69	1.93	1.08	1.08	1.16	0.84	0.02	0.03	0.10
	1	1.62	1.75	1.23	1.16	1.20	0.95	0.01	0.00	0.04
AR	4	1.35	1.55	0.96	0.84	0.94	0.73	0.12	0.29	0.17
	1	1.36	1.50	1.00	0.93	0.97	0.76	0.09	0.19	0.13
ARIMA	4	1.49	1.74	1.23	0.99	1.12	0.88	0.02	-0.03	-0.05
	1	1.40	1.59	1.02	0.96	1.06	0.78	0.01	-0.03	0.02
Bridge model										
	5	1.25	1.40	0.90	0.83	0.89	0.72	0.22	0.35	0.26
	4	1.20	1.33	0.89	0.81	0.85	0.70	0.22	0.36	0.27
	3	1.19	1.32	0.89	0.81	0.85	0.70	0.22	0.35	0.27
	2	1.13	1.27	0.85	0.72	0.78	0.64	0.23	0.33	0.24
	1	1.10	1.24	0.80	0.70	0.77	0.62	0.22	0.32	0.22
	0	1.08	1.22	0.79	0.70	0.77	0.63	0.22	0.32	0.21
Average bridge model										
	5	1.24	1.38	0.90	0.81	0.88	0.72	0.23	0.38	0.27
	4	1.23	1.37	0.90	0.81	0.88	0.72	0.22	0.37	0.27
	3	1.22	1.36	0.90	0.80	0.87	0.71	0.22	0.37	0.27
	2	1.14	1.29	0.85	0.74	0.80	0.66	0.21	0.34	0.22
	1	1.12	1.26	0.82	0.72	0.77	0.63	0.20	0.33	0.21
	0	1.12	1.25	0.81	0.72	0.77	0.63	0.19	0.32	0.21
Dynamic factor model										
	5		1.53	0.93		0.95	0.74		0.43	0.31
	4		1.42	0.97		0.92	0.75		0.35	0.27
	3		1.22	0.92		0.83	0.69		0.30	0.24
	2		1.17	0.86		0.80	0.69		0.32	0.21
	1		1.02	0.75		0.74	0.63		0.22	0.13
	0		1.07	0.73		0.72	0.59		0.19	0.10
	-1		1.08	0.71		0.71	0.58		0.20	0.11
BVAR										
	5		1.43	0.97		0.90	0.77		0.21	0.05
	4		1.37	0.96		0.91	0.79		0.19	0.07
	3		1.34	0.92		0.88	0.76		0.19	0.06
	2		1.17	0.78		0.77	0.64		0.17	0.05
	1		1.05	0.68		0.68	0.57		0.11	0.01
	0		0.97	0.68		0.66	0.54		0.08	-0.01
	-1		0.93	0.70		0.64	0.54		0.05	-0.04

In Table 1, the bridge model is based on the Economic sentiment indicator for Finland. The average bridge model is based on 17 bridge models and indicator variables[4] whose forecasts have been weighted the inverse of out-of-sample RMSEs.

Figure 1:



5 Conclusions

In this paper we have a specified a large Bayesian VAR for the Finnish economy. According to our out-of-sample forecasting exercise BVAR's forecasting accuracy is comparable or better to forecasting accuracy of bridge models and dynamic factor model. Most importantly BVAR does not seem to suffer from as large positive mean error as other models do. Hence BVAR seems as a reliable forecasting tool. Since BVAR uses a large dataset we are able to use it for news analysis, to asses the importance of new data releases, which we have illustrated in this paper.

[4]Economic sentiment indicator, Consumer confidence indicator, Consumer confidence on general economic situation over next 12 months, Consumer unemployment expectations over next 12 months, Construction confidence indicator, Construction employment expectations, Industrial confidence indicator, Industrial order books, Industrial production expectations, Services confidence indicator, Services confidence: evolution of employment in recent months, Retail trade confidence indicator, Retail trade employment expectations, Economic sentiment indicator for the euro area, IFO index ISM Manufacturing PMI, and Markit Eurozone Composite PMI.

Table 2: Indicator variables in BVAR

	Logs	Frequency	Lag
Bruttokansantuote	x	Q	2
Yksityiset kulutusmenot	x	Q	2
Julkiset kulutusmenot	x	Q	2
Investoinnit pl. asuinrakennukset	x	Q	2
Investoinnit asuinrakennuksiin	x	Q	2
Vienti	x	Q	2
Tuonti	x	Q	2
Ansiotasoindeksi	x	Q	1
Asuntojen hintaindeksi	x	Q	2
Teollisuustuotannon volyymi-indeksi	x	M	1
Kapasiteetin käyttöaste Myönnetyt rakennusluvat	x	M	2
Vähittäiskaupan liikevaihto, määräindeksi	x	M	1
Teollisuuden liikevaihtokuvaajan uudet tilaukset	x	M	2
Tavaraviennin määrä	x	M	1
Tavaratuonnin määrä	x	M	1
Työlliset, 15-74-vuotiaat	x	M	1
Työttömyysaste, 15-74-vuotiaat	o	M	1
Avoimet työpaikat	x	M	1
Työttömyysaste (TEM)	o	M	1
Työttömät työnhakijat	x	M	1
Vireille pantujen konkurssien määrä	x	M	1
NASDAQ OMX Helsinki PI -yleisindeksi	x	M	0
Kuluttajien luottamus: oma talous	o	M	0
Kuluttajien luottamus: yleinen taloudellinen tilanne	o	M	0
Teollisuuden luottamusindikaattori	o	M	0
Rakentamisen luottamusindikaattori	o	M	0
Teollisuuden luottamus, tuotanto-odotukset	o	M	0
Kuluttajahintaindeksi	x	M	1
Rakennuskustannusindeksi	x	M	2
Rakentamisen liikevaihto, määräindeksi	x	M	3
Teollisuuden tuottajahintaindeksi	x	M	1
Vientihintaindeksi	x	M	1
Tuontihintaindeksi	x	M	1
Teollisuuden uudet tilaukset	x	M	1
Yhdysvaltain ostopäällikköindeksi (ISM), teollisuus	o	M	0
Saksan IFO-indeksi	o	M	0
Palkkasummakuvaaja	x	M	1
Uudisrakentamisen volyymi-indeksi	x	M	2
Koko talouden luottamusindikaattori, euroalue	o	M	0
Teollisuuden liikevaihtokuvaaja	x	M	3
Aloitetut rakennukset	x	M	3
Valmistuneet rakennukset	x	M	3
Yöpymiset majoitusliikkeissä, suomalaiset	x	M	2
Yöpymiset majoitusliikkeissä, ulkomaalaiset	x	M	2
Maailmankauppa	x	M	3
Palvelualojen liikevaihtokuvaaja	x	M	2

Figure 2: News analysis

Viikko 50

	Muuttuja			Toteutunut havainto	Edellinen havainto	Muuttujan ennuste	Uutinen	BKT:n ennusteen muutokset 2016Q3	2016Q4	2017Q1
1	Teollisuuden liikevaihtokuvaajan uudet tilaukset	M9	lnΔ M/M	2,66	0,31	0,52	2,13	0,00	0,06	-0,01
2	Rakentamisen liikevaihto, määräindeksi	M9	lnΔ M/M	0,17	1,71	-0,83	1,00	0,00	0,04	0,00
3	Teollisuuden liikevaihtokuvaaja	M9	lnΔ M/M	14,43	9,64	0,71	13,72	0,00	0,09	-0,04
4	Kapasiteetin käyttöaste %, teollisuus	M10	-	81,26	82,07	81,72	-0,46	0,00	0,02	0,00
5	Vähittäiskaupan liikevaihto, määräindeksi	M10	lnΔ M/M	0,67	0,48	0,10	0,57	0,00	0,03	0,04
6	Tukkukaupan liikevaihto, määräindeksi	M10	lnΔ M/M	0,94	-0,21	0,57	0,36	0,00	0,02	0,02
7	Moottoriajoneuvojen kaupan liikevaihto, määräindel	M10	lnΔ M/M	-1,25	1,06	0,96	-2,21	0,00	-0,02	0,00
8	Palkkasummakuvaaja	M10	lnΔ M/M	0,18	0,70	0,01	0,16	0,00	0,05	0,00
9	Yöpymiset majoitusliikkeissä, suomalaiset	M10	lnΔ M/M	-0,82	1,18	0,27	-1,08	0,00	0,01	-0,03
10	Yöpymiset majoitusliikkeissä, ulkomaalaiset	M10	lnΔ M/M	-1,07	1,46	0,74	-1,80	0,00	-0,01	-0,01
11	Vireille pantujen konkurssien määrä	M11	lnΔ M/M	-49,53	16,99	-10,60	-38,93	0,00	0,05	0,05
12	Kuluttajahintaindeksi	M11	lnΔ M/M	0,02	0,21	0,21	-0,19	0,00	0,01	0,01
13	Rakennuskustannusindeksi	M11	lnΔ M/M	0,00	0,51	0,16	-0,16	0,00	-0,03	0,00
	Revisioiden vaikutus								0,06	-0,01

	BKT:n ennusteet 2016Q3	2016Q4	2017Q1
Ennen päivityksiä		0,56	0,59
Päivitysten jälkeen		**0,83**	**0,60**
TK:n havainto	0,39	-	-

Viikko 49

	Muuttuja			Toteutunut havainto	Edellinen havainto	Muuttujan ennuste	Uutinen	BKT:n ennusteen muutokset 2016Q3	2016Q4	2017Q1
1	Aloitetut rakennukset	M9	lnΔ M/M	16,47	-16,08	0,76	15,72	0,00	0,03	0,05
2	Valmistuneet rakennukset	M9	lnΔ M/M	5,23	-2,48	5,13	0,09	0,00	0,00	0,00
3	Teollisuustuotannon volyymi-indeksi	M10	lnΔ M/M	-0,21	2,73	-0,28	0,07	0,00	0,02	0,00
4	Tavaraviennin määrä	M10	lnΔ M/M	2,21	2,01	3,73	-1,52	0,00	0,02	0,01
5	Tavaratuonnin määrä	M10	lnΔ M/M	-0,66	-0,99	0,89	-1,55	0,00	0,05	0,04
6	Teollisuuden uudet tilaukset	M10	lnΔ M/M	4,88	-12,55	5,19	-0,31	0,00	0,00	0,00
7	NASDAQ OMX Helsinki PI -yleisindeksi	M11	lnΔ M/M	-2,82	0,91	-1,29	-1,53	0,00	0,02	0,01
	Koodin muutokset								0,06	0,00
	Revisioiden vaikutus								0,00	0,01

	BKT:n ennusteet 2016Q3	2016Q4	2017Q1
Ennen päivityksiä		0,60	0,62
Päivitysten jälkeen		**0,56**	**0,59**
TK:n havainto	0,39	-	-

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6 Appendix A

Kalman filtering equations

$$
\begin{aligned}
E_t &= Z_t - C_t S_t \\
K_t &= P_{t|t-1} C_t' F_t^{-1} \\
S_{t|t} &= S_{t|t-1} \\
S_{t+1|t} &= G S_{t|t} \\
F_t &= C_t P_{t|t+1} C_t + R_t \\
L_t &= I - K_t C_t \\
P_{t|t} &= P_{t|t-1} L_t' \\
P_{t+1|t} &= G P_{t|t} G' + H_t \\
r_{t-1} &= C_t' F_t^{-1} E_t + L_t' r_t \\
S_{t|T} &= S_{t|t-1} + P_{t|t-1} r_{t-1}
\end{aligned}
$$