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PREDICTIVE PERFORMANCE OF DSGE MODEL FOR SMALL OPEN ECONOMY – THE CASE STUDY OF CZECH REPUBLIC

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Multivariate time series forecasting is applied in a wide range of economic activities related to regional competitiveness and is the basis of almost all macroeconomic analysis. From the point of view of political practice is appropriate to seek a model that reached a quality prediction performance for all the variables. As monitored variables were used GDP growth, inflation and interest rates. The paper focuses on performance prediction evaluation of the small open economy New Keynesian DSGE model for the Czech republic, where Bayesian method are used for their parameters estimation, against different types of Bayesian and naive random walk model. The performance of models is identified using historical dates including domestic economy and foreign economy, which is represented by countries of the Eurozone. The results indicate that the DSGE model generates estimates that are competitive with other models used in this paper.

GDP growth, inflation, interest rates, DSGE, DSGE-VAR, Log predictive density score, Bayesian averaging model

Focus on the production of various models for the analysis of macroeconomic data is related to the commencement of the publication of national statistics in the 40th years of the twentieth century. The first significant progress in this area is associated with Cowles Commission for Economic Research, whose members during the 50th years suggested techniques for identification and estimation of simultaneous equations being used for modeling economic data, for example see Hildreth (1986). These models are composed of a large number of equations linking specific explanatory variables, however, while these variables were determined on the basis of economic theory, the parameters were estimated on the basis of purely empiric based on historical data. During the seventies, especially during the oil crisis and the subsequent price shocks, this approach has been subjected to considerable criticism. From an empirical point of view, these models are confronted with the appearance of stagflation, which is incompatible with the traditional Phillips curve included in these models. The main criticism of simultaneous equations model focuses on theoretical models and is referred to the Lucas critique. Lucas (1976) noted that agents adapt their behavior dynamic optimizer access and rational use of available information, thus adapting their current and future behavior to the expected changes in the economic environment. These agents then changes to economic policy respond by changing their behavior. At the same time Sims (1980) proposes vector autoregression (VAR) model, which has gained great popularity. A disadvantage of this model could be seen in the problem of the need to estimate a large number of parameters, whereupon Doan (1984) have proposed the application of Bayes approach to VAR – BVAR model. Cooley and Leroy (1985) drew attention to the fact that the vector autoregression models may apply the above Lucas critique. The problem is in the fact that these approaches are primarily focused on the statistical point of economic model and do not consider features such as preferences, technology, etc. The first time integration of these features in to the model did Kydland and Prescott (1982), whose paper has stimulated the development of a DSGE

(Dynamic Stochastic General Equilibrium) models. First DSGE models (RBC – Real Business Cycles) are based on the neoclassical approach, where households and firms optimize their behavior through flexible pricing, economic fluctuations are caused by the reaction of agents to random technological shocks and the business cycle can simply be explained by rationally optimizing agents reactions to these shocks. More can be found e.g. in Gali (2008). This approach has become very popular among macroeconomists and represented a significant advance in modern macroeconomic modeling. But in the second half of the eighties RBC models have been the subject of considerable criticism. The main problem was that in the case of perfectly flexible prices any change in the nominal interest rate will always result in the same change in inflation, and thus real interest rate remains unchanged. This would mean that monetary policy has no effect on real variables, which is contrary to the popular notion.

The above weaknesses of RBC models have led to the early nineties in the New Keynesian Macroeconomics (NKM). This new approach is based on microeconomic foundations as well as RBC models, but without the assumption of perfect competition and perfectly flexible prices. Instead, there is considered monopolistic competition and various kinds of nominal and real rigidities. With these assumptions, the important role play an economic stabilization policy, and it is possible to capture some of the interesting features of macroeconomic time series that RBC models elusive. One of the first models based on this approach comes from Rotemberg and Woodford (1997).

The core work dealing with the predictive performance of DSGE models came from Smets and Wouters (2004, 2007), who showed that the DSGE model applied to the U.S. economy gives comparable predictive power of non-structural econometric models VAR and BVAR. Similar results occur for example in Adolfson *et al.* (2007), who used for comparison DSGE model used in the Sveriges Riksbank applied to Euro zone data. Other relevant research was published by Lees *et al.* (2007) who compared the official forecasts of the New Zealand central bank (Reserve Bank of New Zealand), along with predictions derived applications DSGE-VAR model proposed in Del Negro and Schorfheide (2004). Warne *et al.* (2012) focus on the forecasting performance of DSGE and DSGE-VAR model. They use NAWM model (New Area-Wide Model) developed and used by the ECB as a DSGE model.

The vast majority of the above results concludes that the forecasting performance of individual models is influenced by multiple factors and therefore cannot be found among any universal model that gives the best results in every situation. With these instability issues dealt Timmermann (2006) who propose a solution of this problem. He used the averaging model with the finding that the weighted average of the forecasts obtained from several non-structural model outperforms the predictions of these models. Combining the predictions of structural and non-structural models used for example Gerard & Nimark (2008) on DSGE Bayesian VAR FAVAR model. Wolters (2012) extended their work considering the addition of another three DSGE models.

From the point of view of political practice is appropriate to seek a model that reached a quality prediction performance for all the variables. The aim of this paper is to extend the work of Gerard & Nimark (2008) and Wolters (2012) by comparison of forecasting performance of DSGE, DSGE-VAR, two types of BVAR models and naive random walk model with a combination created by Bayesian averaging. As monitored variables were used GDP growth, inflation and interest rates.

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MATERIALS AND MODELS

This part of the paper present models, which are then used for determining the macroeconomic forecast. Like Wieland and Wolters (2012) we divide these tools for structural and non-structural. As we consider the structural New Keynesian DSGE model of open economy and the second group will consist of two variants of BVAR model with Litterman prior density and naive random walk model. In addition to these models, we will also consider some kind of combination of structural and non-structural model, namely DSGE-VAR model.

DSGE Model

The planned DSGE model was described by Seneca (2010) and is based primarily on work of Adolfson *et al.* (2007, 2008). The model consists of domestic and foreign economies. The domestic economy has a continuum of households and firms and the monetary authority. Fiscal policy is considered as passive in the sense that the government uses lump-sum taxes to meet their budgetary constraints. Government expenditures are considered as exogenous. Market goods and services and the labor market is monopolistic competitive. Each of the companies through leased capital and different types of jobs to households produce different intermediates. Setting the prices of goods and services is done on the basis of Calvo mechanism, individual goods and services are valued in the currency of the country in which they are sold. Each firm chooses specific factors of production in order to minimize their costs and because of the pay and expenses resulting from the lease of capital. Each household consumes in each period domestic and foreign intermediates. They further continue to invest in both domestic (in domestic currency) and foreign (foreign currency) bonds, due to the costs of international financial intermediation. Households also in every other period decide how much money they should invest in new capital to investment adjustment costs and selects the utilization rate of their current capital. Wage-setting is also based on the Calvo mechanism. The central bank conducts monetary policy based on the Taylor rule, monetary regime based on inflation targeting. Foreign economy is considered as a closed version of the domestic economy, while the domestic economy has almost no effect to foreign economy. For this reason, we could consider foreign economy as exogenous to the domestic small open economy and thus the model can be simplified by replacing the vector autoregressive model – as well as Seneca (2010) or Adolfson *et al.* (2007) who use a VAR (4) model.

The model is estimated using 13 observed variables covering the period 2000Q1 through 2012Q2. We include the following variables: consumption, harmonized consumer price index, exports, government spending, investments, imports, the real exchange rate, interest rate (three-month PRIBOR), gross domestic product, real wages, foreign GDP, foreign harmonized consumer price index and foreign interest rate. Foreign economy is represented by countries of Euro area. All the variables are seasonally adjusted and transformed by logarithmic difference.

Let θ as a vector parameter log-linearized model. The model can now be solved in the following state space form

$$x_t = Fx_{t-1} + u_t$$

$$y_t = \mu + Hx_t + e_t,$$

where x_t is r – dimensional vector model variables and represents n – dimensional vector of observed variables, further $u_t \sim N(0, I_r)$, $e_t \sim N(0, R)$ and μ represents vector of steady state variables y_t contingent on θ. Given that many theoretical unobserved variables, e.g. r > n, we assume that an unknown are for different periods normally distributed and are estimated using a Kalman filter. Matrix F (r × r), H (n × r) and R (n × n)are functions of the parameters log – linearized model.

The model is parameterized using the calibration and the formal estimate. Specifically, it was calibrated by 14 parameters, for the values commonly used in published works see Table 1. Furthermore, the parameters of the structural VAR model for the three foreign variables were estimated separately and government spending are specified as AR (1) process. The values of other parameters were estimated.

The model is estimated by Bayesian methods. The posterior distribution of the estimated parameters is simulated using 1 000 000 selections from Random-Walk Metropolis algorithm, where the first 600 000 were discarded.

BVAR Model

As a non-structural uses Bayesian VAR model with a lag order p.

$$y_t = B_0 + \sum\nolimits_{i=1}^{p} B_i y_{t-i} + \varepsilon_t \,, \tag{1}$$

where y_t, t = 1, …, T is vector m × 1 consisting of data m endogenous variables, B_i are matrices m × m consisting of the search parameters of the model, B_0 is m × 1 constant vector, further ε_t is vector of residuals for which we may apply $\varepsilon_t \sim$ i.i.d. $N(0, \Sigma_\varepsilon)$. $B = (B_0, B_1, \ldots, B_p)'$ $Y = (y_1, \ldots, y_T)'$. In our case p = 4. We use Litterman prior density. Hence prior distribution of all 21 parameters has normal distribution with mean equal to one for the parameters of the variables with its own lag of order 1, for details see, e.g. Koop and Korobilis (2010) and the standard deviation in the shape of γ, and other parameters with the zero mean and variance $^{\gamma}/_{l}$ parameter for the variable with its own de and $^{\gamma}/_{l}\, \theta\, ^{s_i}/_{s_j}$ in other cases. The ratio $^{s_i}/_{s_j}$ is used to capture differences in the variability of the variables. Hyperparameters γ and θ together with lag l have the task of ensuring that the standard deviation decreased with increasing delay. In our case, we put γ = 0,5, θ = 1 (BVAR1) and γ = 10^2, θ = 1 (BVAR2). In the case of BVAR2 options, due to the high value of γ and neutral θ, we can consider unlimited prior standard deviation, i.e. BVAR2 can be compared to an unrestricted VAR model, see Mao (2010).

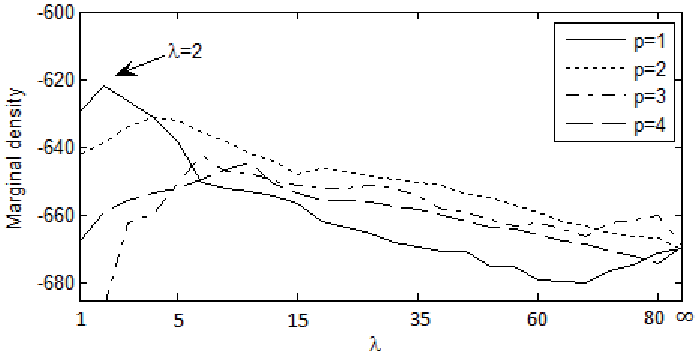
The likelihood function $p(Y|B, \Sigma_\varepsilon)$ and aposterior density p(B|Y) is determined by Koop and Korobilis (2010). As variables we used quarterly time series covering Q1 of 2000 to Q2 of 2012. Specifically, we monitor real GDP, HCPI and interest rate (three-month PRIBOR) for the domestic economy, as well as foreign variables are used – the same as in the DSGE model. All the variables are seasonally adjusted and transformed by logarithmic difference. External variables are considered as exogenous to domestic variables.

DSGE-VAR Model

In addition, we will consider Bayesian VAR model with prior density derived from the above DSGE model, i.e. DSGE-VAR model. Prior distribution parameters of DSGE-VAR model has the following hierarchical structure:

$$p(B,\Sigma_\varepsilon, \theta|\lambda) = p(B,\Sigma_\varepsilon|\theta,\lambda)p(\theta), \tag{2}$$

where $B = (B_0, B_1, \ldots, B_p)$, θ is the vector of parameters of log-linearized DSGE model and hyperparametr λ expresses the degree of deviation DSGE and VAR model to DSGE-VAR model. In extreme cases λ = 0 is an unrestricted VAR model, for λ = ∞ is VAR model whose parameters are fully identified by DSGE model – represents a reasonable approximation of the DSGE model. Denote β = vec (B), then $\Sigma_\varepsilon|\theta,\lambda$ has invers Wishart prior distribution and $\beta|\Sigma_\varepsilon, \theta,\lambda$ becomes normal prior distribution. Further details



1: *Selection of the optimal* λ
Source: authors

about prior and posterior distribution could be find in Del Negro & Schorfheide (2004). A key issue in the estimation of DSGE-VAR model is the choice of λ, in our case we solve this problem like Del Negro & Schorfheide (2004), using the criteria of maximum marginal data density. So all the combinations of pairs (λ, p), for $\lambda \in R^*_+$ and p = 1, 2, 3, 4. Based on the graph in Figure 1 we have chosen for further analysis DSGE-VAR model with the order of the lag 1 and λ = 2.

METHODS

For the formulation of conclusions and recommendations from the methodological point of view use the following methods.

Comparing Forecast Accuracy

To determine the quality of the predictions of each model we evaluate point predictions, both in univariate and multivariate perspective. For one-point forecast we use RMSFE (Root Mean Squared Forecast Errors), which is subject to

$$RMSFE=\sqrt{\frac{1}{N_h}\sum_{t=T}^{T+N_h-1}(A_{t+h}-F_{t+h})^2}\,, \qquad (3)$$

where A_{t+h} denotes the actual value of the monitored variable in period t + h, F_{t+h} is the forecasted value in period t + h, and N_h is the number of h – steps forecasts.

From the point of view of a multidimensional point prediction we use two statistics that were suggested by Adolfson *et al.* (2007). This is the trace and the logarithm of the determinant MSE matrix $\Sigma_M(h)$, for which

$$\sum\nolimits_M(h)=\frac{1}{N_h}\sum_{t=T}^{T+N_h-1}\tilde{\epsilon}_{t+h|t}\tilde{\epsilon}'_{t+h|t}\,, \qquad (4)$$

where $\tilde{\epsilon}_{t+h|t} = M^{-1/2}\,\epsilon_{t+h|t}$, where $\epsilon_{t+h|t}$ stand for the error h – step predictions made during the t and M is a positive definite matrix – in our case we consider M as a unit matrix

In addition we evaluate predictive density of each model. For this purpose we used Adolfson *et al.* (2007) and Christoffel *et al.* (2011) LPD score (Log Predictive Density), which is the h – step prediction density shape

$$S_h(m)=\sum_{t=T}^{T+N_h-1}\log p(y_{t+h}|Y_t,m)\,, \qquad (5)$$

where $p(y_{t+h}|Y_t, m)$ is the marginal predictive likelihood function for y_{t+h} depending on observed data $Y_t = \{y_1, \dots, y_T\}$ and model m.

Given that the evaluation of predictive capabilities is focused on three variables, namely GDP growth, inflation and interest rates, it is necessary in the case of monitored models considered marginal predictive likelihood function in the form $p(z_{t+h}|Y_t, m)$, i.e. equation (5) written in the form

$$S_h(m)=\sum_{t=T}^{T+N_h-1}\log p(z_{t+h}|Y_t,m)\,, \qquad (6)$$

where $z_t = K'y_t$, wherein K is matrix of type $n \times n^*$, where n is dimension y_t and n^* then z_t. In our case $n^* = 3$ will K contain three columns of the unit matrix I_n corresponding to positions searched variables in the vector y_t.

The problem in the above approach is to determine in $p(z_{t+h}|Y_t,m)$ (6). According to Adolfson *et al.* (2007) we could name likelihood for h = 1 a $z_i = y_i$, i =1, …, T determine analytically, for other cases it is suggested marginal predictive likelihood approximate by density of a normal distribution $p_N(z_{t+h}|Y_t, m)$ with mean and covariance matrix of the marginal predictive distribution for z_{t+h} given the model m. The marginal predictive likelihood is then obtained by averaging S of random samples from, $p_N(z_{t+h}|Y_t, m)$, i.e.

$$p(z_{t+h}|Y_t,m)=\frac{1}{S}\sum_{j=1}^{S}p_N(z^j_{t+h}|Yt,m)\,. \qquad (7)$$

Averaging Models

Based on the results of the methods mentioned above we cannot say that there are models that served consistently better prediction performance than other models. It seems that the models are only suitable for certain variables and, furthermore, only for a certain period – see Figure 2. The problem of instability in the forecasting performance of various models was discussed by Rossi (2012), who concluded that one solution is to combine predictions from different models.

Now suppose Ω_t^m is the set consisting of all the information about the model m in period t, that this set includes a model m equation, parameter estimation, the observed variable, etc. As the combined point prediction for model for horizon h we consider a weighted sum of the prediction densities $p(z_{t+h}|\Omega_t^m)$, with weights $\omega_{m.h}$ and divided by the number of selections S, i.e.

$$E(z_{t+h}\left|\Omega_t^1,\ldots,\Omega_t^M,\omega_{1.h},\ldots,\omega_{M.h}\right.)=\frac{1}{S}\sum_{m=1}^{M}\omega_{m.h}p(z_{t+h}\left|\Omega_t^M\right.), \tag{8}$$

where z_t as in the previous section includes our predicted variables. While constructing $p(z_{t+h}|\Omega_t^m)$ we use procedure referred to in Gerard & Nimark (2008).

To determine the weights several approaches were proposed which in the context of Bayesian analysis is the most popular Bayesian model averaging (BMA) – details see for example Koop (2005). This approach is based on the application of marginal likelihood of the functions of the model, i.e. the weight belonging to the true model m is

$$\omega_{m.h}=\frac{p(Y_t.m)}{\sum_{i=1}^{M}p(Y_t.i)}, \tag{9}$$

where $p(Y_t, m)$ is the marginal likelihood function of the model m. As is shown for example by Andersson & Karlson (2007), these scales cannot be used in the case of models with different number of time series. Another problem is that Gerard & Nimark (2008) that models with many parameters, which are excellent for in-sample modeling, but poor accuracy in out-of-sample predictions, are rated high weights. To overcome this problem the authors above replaced the marginal likelihood function by prediction likelihood functions $p(Z_{t.h}|Y_t, m)$, where $Z_{t.h}(z_{t+h}, \ldots, z_T)'$, for the calculation applies

$$p(Z_{t.h}\left|Y_t,m\right.)=\Pi_{t=T}^{T+N_h-1}p(z_{t+h}\left|Y_t,m\right.). \tag{10}$$

Thus $p(Z_{t.h}|Y_t, m)$ actually represents LPD score "without logarithms", i.e. using equation (5) we can put

$$p(Z_{t.h}|Y_t, m) = \exp(S_h(m)) \tag{11}$$

and now we get to determine the weights

$$\omega_{m.h}=\frac{\exp(S_h(m))}{\sum_{i=1}^{M}\exp(S_h(i))}. \tag{12}$$

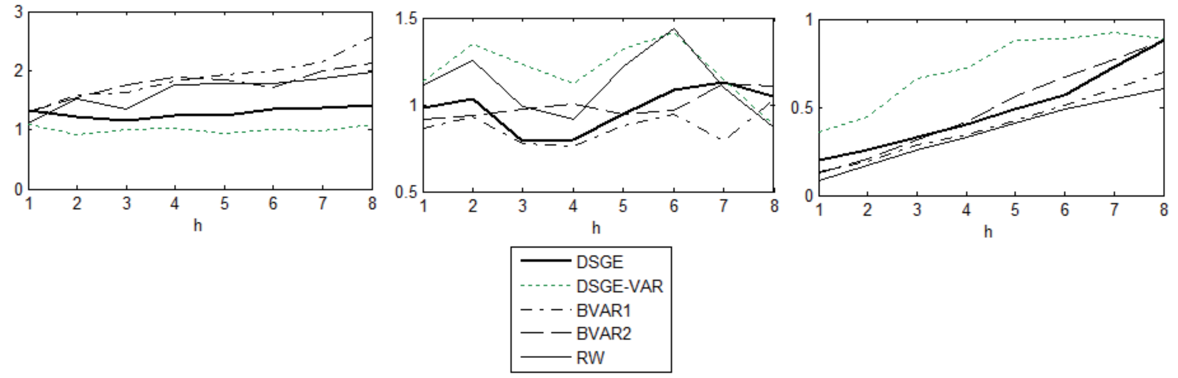
RESULTS

A comparison of the forecasting performance of the above models is performed for the h – step forecasts, h = 1, …, 8 variables GDP, harmonized CPI, interest rate from 2007:Q1 to 2012:Q2. Thus, the shortest predictive horizon (one quarter) gives 22 observations and longest horizon (8 quarters) gives 15 observations.

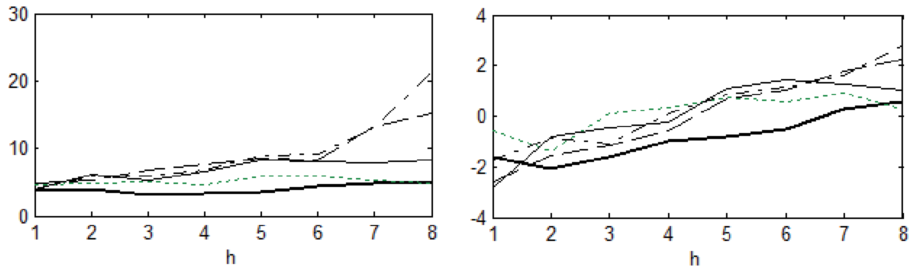
Values of RMSFE for reference variables are shown in the graphs in Fig. 2. On the basis of this one-dimensional analysis we cannot any of the monitored model consider as a universal predictions for all the variables. For example, the DSGE-VAR model gives the best performance in predicting GDP growth, but the remaining two variables fails. If we focus on the prediction of inflation, the most credible results provide BVAR1 model, despite all the forecasting horizons.

Traces of MSE matrix for individual values of h are shown in Fig. 3 on the left. Besides are logarithms of MSE matrix determinants – see legend for Fig. 2. Both statistics evaluated as the most powerful DSGE model.

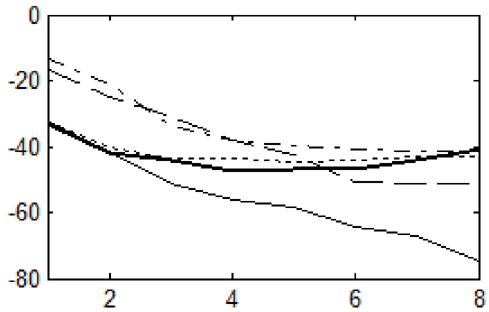
Fig. 4 shows the development of LPD score for each model – marking corresponds to the legend in Fig. 2. If the we first focus on the comparison DSGE and DSGE-VAR, then LPD score of DSGE-



2: *RMSFE: GDP growth (left), inflation (middle), interest rate (right)*
Source: authors



3: *Trace of MSE matrix (left) and log determinant of individual models*
Source: authors



4: *LPD score of individual models*
Source: authors

I: *Weights used for the LPD score*

h	DSGE	DSGE-VAR	BVAR1	BVAR2	nRW
1	0,00	0,00	0,96	0,04	0,00
2	0,00	0,00	0,99	0,01	0,00
3	0,00	0,00	0,07	0,93	0,00
4	0,00	0,00	0,45	0,55	0,00
5	0,00	0,01	0,94	0,05	0,00
6	0,00	0,04	0,96	0,00	0,00
7	0,08	0,15	0,76	0,00	0,00
8	0,50	0,09	0,41	0,00	0,00

Source: authors

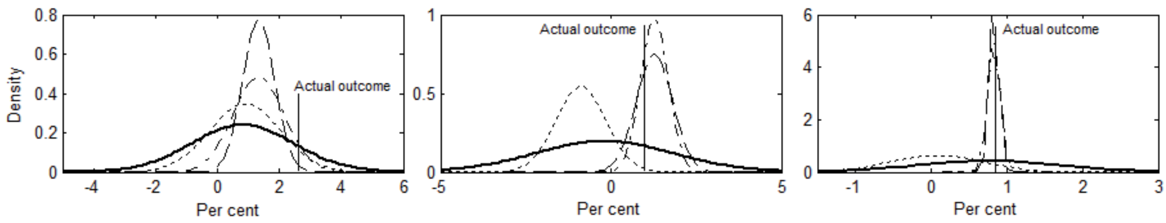
VAR shows a horizon predictor 1–7 slightly higher values – only about 3 to 5 units, while the last term, the situation is reversed. The greatest score reaches BVAR1 model and thus overcomes other non-structural models used in all forecasting horizons, DSGE and DSGE-VAR model are overcome BVAR1 model in the first seven periods. The lowest score achieved LPD naive random walk model (RW).

The prediction of the likelihood function could be also used to calculate weights for Bayesian model averaging. At this point we only mention that in the case of our DSGE and DSGE-VAR model we use equality (11) and other models, due to their variables, will be considered $p(z_{t,h}|Z_t,m)$, we can use score S_h (m) defined previously. Tab. I shows the weight determined in accordance with (12) and it is clear that the shorter forecasting horizons preferred BVAR models, namely, the first two BVAR1 and the other two BVAR2 model. In the fifth to seventh run again significantly BVAR1 model prevails in longest final term with a predominance of lighter preferred DSGE model.

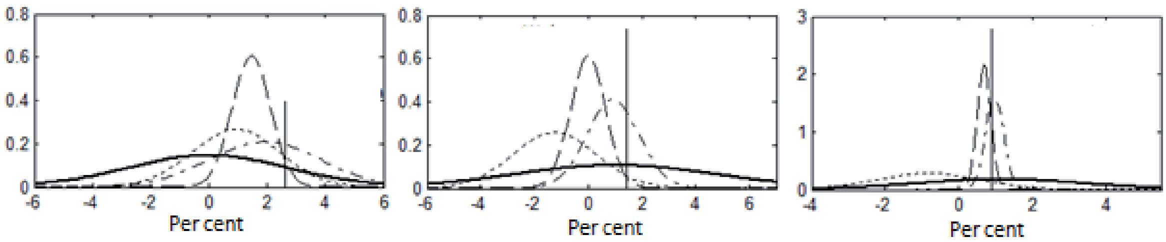
In Figs. 5 and 6 we can see clarity predictive density for individual one-step and four-step predictions for each variable in the period Q4 of 2006. DSGE models, DSGE-VAR, and BVAR BVAR1 are labeled as in Fig. 2. The graphs in figures show that in both prediction horizons shows DSGE model uncertainty highest compared to other models. Furthermore, there is very high uncertainty in the case BVAR1 model at higher forecasting horizons, especially for h > 5 the first two variables – GDP growth and inflation.

Results of Combined Forecasts

To determine the quality of the predictions obtained by the above models, we use a combination of unvaried RMSE and multivariate MSE statistics.



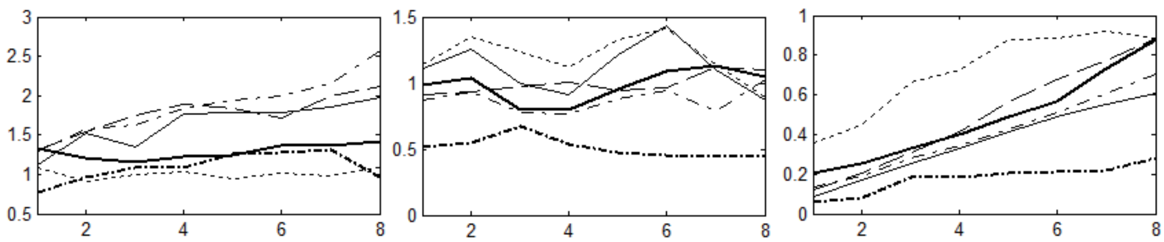
5: *One-quarter-ahead density forecasts made in 2006: Q4*
Source: authors



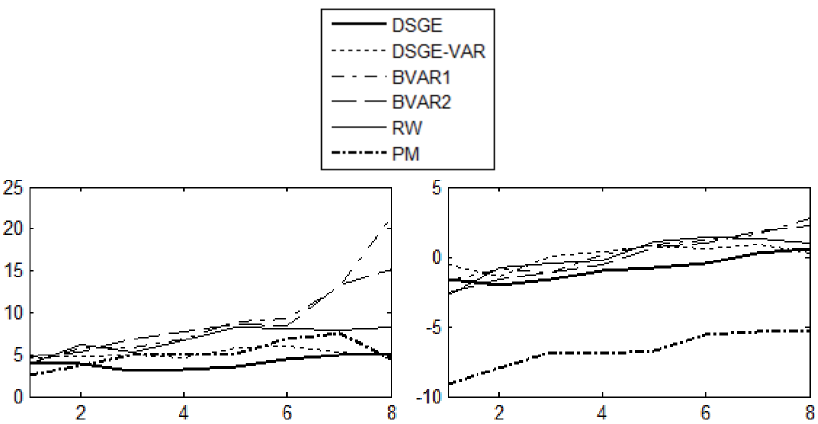
6: *Four-quarter-ahead density forecasts made in 2006: Q4*
Source: authors

Fig. 7 shows the evolution of RMSFE statistics for each variable in the h – step predictions. The graphs show that the model obtained by combining predictive densities of other models (PM) provides a very good performance, especially in forecasts of inflation and interest rates. In the case of GDP outperforms other models in the first and last term predictor. Fig. 8 shows that in the case of traces of MSE matrix achieve best performance DSGE-VAR and PM. Logarithm of the determinant of the MSE matrix is then the smallest in the case of PM.

Thus, the above graphs show that PM provides better prediction performance than other models. But for example, when forecasting GDP is slightly below the DSGE-VAR. The source of the above problem may be a choice of types of scales – in this



7: *RMSFE for GDP growth, inflation and interest rate*
Source: authors



8: *MSE for GDP growth, inflation and interest rate (trace of matrix in the left)*
Source: authors

text are calculated by weight LPD score, but Wolters (2012) works with several different types of scales and shows that the scales set by LPD score does not always lead to the best forecast performance. This problem can be solved as the introduction of time-varying weights, see, e.g. Stock & Watson (2004), Jore *et al.* (2010). Another possible solution is the calculation of the LPD score instead of the normal approximation prediction of the likelihood function used an estimate of its analytical expression provided by Warne *et al.* (2012a, b), which show that the prediction of the likelihood function in (5), for h > 1.

$$p(y_{t+h}|Y_t,m)=\frac{p(y_{t+h},Y_t,m)}{p(y_t,Y_t)} \quad (13)$$

Problem with missing h – 1 variables in the numerator on the right side (13) addresses in the case of a linear state space model by the Kalman filter. Specific estimate of the predictive likelihood function then performs through Laplace transform (Warne 2012a) or by Importance Sampling estimator (Warne 2012b).

DISCUSSIONS

Over the last decade, DSGE models have become the cornerstone of modern macroeconomic analysis. The aim of this paper was to evaluate the predictive power of New Keynesian DSGE model of a small open economy. As a model economy has been selected the economy of the Czech Republic.

For comparison, there were used Bayesian VAR model with both Litteramann's priori density and the prior density derived from DSGE model, so called DSGE-VAR model. In addition, we used a naive random walk model as a benchmark model. In the DSGE and DSGE-VAR model have been used fourteen variables, where eleven ones of the domestic economy represented by the Czech Republic and three based on the foreign economy, represented EU15 countries. Other models have been estimated for six variables, of which, as in the case of DSGE and DSGE-VAR three variables from abroad, which were considered as exogenous. Foreign economy is represented by countries of Euro area. The predictive ability of models was tested through three common variables, namely GDP growth, inflation and interest rate.

Evaluation prediction performance of the above mentioned models was based on two methods, namely the point forecast and forecast densities evaluation. The point forecasts were monitored as one-dimensional root mean square errors (RMSFE) and Mean square errors (MSE) as a multivariate measure of point forecast accuracy. Forecast densities were evaluated on the basis of the log predictive score.

RMSFE statistics show that the best predictive performance of GDP growth is achieved using DSGE and DSGE-VAR. On the other hand, DSGE-VAR model fails to forecast inflation and interest rates. For the prediction of inflation gives the best performance Bayesian VAR model with Littermann's prior density (specifically BVAR1 model). This model also shows good results in predicting interest rate.

In addition we used some multidimensional statistics for a more comprehensive evaluation of forecasts. Specifically, when the statistics calculation based traces MSE matrix were used, there was found that the best prediction performance is achieved when using DSGE and DSGE-VAR. This result can be explained mainly for their very small RMSFE in predicting of GDP growth.

Evaluation point forecast is very inaccurate, primarily due to the fact that it is not taken into account the density, from which the resulting predictions. Therefore, in addition to point forecasts also evaluated the predictive density through the log predictive score. The results show, from this point of view achieves the best performance of Bayesian VAR models with Litermann's priori density. The reason is found in the fact, the predictive distribution of DSGE models have a much larger variance than the distribution of Bayesian VAR models.

From the point of view of political practice is appropriate to seek a model that reached a quality prediction performance for all the variables. The above results show that for example, in predicting GDP growth is the best prediction performance DSGE model, however, in predicting inflation gives the best performance Bayesian VAR model Littermann's priori density. From the point of view of multivariate statistics is best assessed DSGE model, which is probably due to the high uncertainty of the predictive density. On the basis of these results we are not able to find a model suitable for all variables; we propose the use of model based on combining forecasts, as evidenced by the results obtained.

SUMMARY

Multivariate time series forecasting is used in a wide range of economic activities and is the basis for almost all macroeconomic analysis. Such methods of using common variables derived from the analysis of socio-economic factors (e.g. foreign direct investment, unemployment, GDP, inflation, interest rates, etc.) are often used practically and published (eg Trojan *et al.* 2012). From the point of view of political practice is appropriate to seek a model that reached a quality prediction performance for all the variables. The aim of this paper is to extend the work of Gerard & Nimark (2008) and Wolters (2012) by comparison of forecasting performance of DSGE, DSGE-VAR, two types of BVAR

models and naive random walk model with a combination created by Bayesian averaging and evaluate the predictive power of the New Keynesian DSGE model of a small open economy. As monitored variables were used GDP growth, inflation and interest rates in a small open economy of the Czech Republic.
The result implies that DSGE model with the DSGE-VAR model provides good performance in predicting GDP growth in the other two variables enforcement is weaker. There is also evident, none of the models cannot be used as a versatile tool for the most predictive macro variables. One of the ways to approach this ideal situation is to combine predictions from different models, as evidenced by the results.

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