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MEDIUM-TERM FORECASTING OF EURO-AREA MACROECONOMICVARIABLES WITH DSGE AND BVARX MODELS

by Lorenzo Burlon†, Simone Emiliozzi†, Alessandro Notarpietro† and Massimiliano Pisani†

Abstract

The paper assesses the performance of medium-term forecasts of euro-area GDP and inflation obtained with a DSGE model and a BVARX model currently in use at the Bank of Italy. The performance is compared with that of simple univariate models and with the Eurosystem projections; the same real time assumptions underlying the latter are used to condition the DSGE and the BVARX forecasts. We find that the performance of both forecasts is similar to that of Eurosystem forecasts and overall more accurate than that of simple autoregressive models. The DSGE model shows a relatively better performance in forecasting inflation, while the BVARX model fares better in forecasting GDP.

JEL Classification: C53, E32, E37.
Keywords: forecasting, DSGE, BVARX, euro area.

Contents

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1 Introduction[1]

This paper considers medium-term forecasts of euro-area GDP and inflation produced by two models currently in use at the Bank of Italy. The first is a dynamic stochastic general equilibrium (DSGE) model of the euro area and the rest of the world; the second is a small Bayesian vector autoregression with exogenous regressors (BVARX). Both models are estimated using quarterly data for the euro area. Forecasts are then obtained by conditioning each model to a set of assumptions on a number of variables; the conditioning assumptions correspond to those used in the Eurosystem projections. Hence, our forecasts are subject to the same information set underlying the Eurosystem projections. The DSGE and BVARX forecasts are compared with the Eurosystem projections and those of simple univariate models.

Both DSGE and BVAR models are increasingly used to provide - either alone or together with more traditional semi-structural models - the forecasts in national central banks and other policy institutions.[2] Hence, the analysis of the forecasting ability of these models is of crucial relevance in the current policy debate. Del Negro and Schorfheide (2013) and Gürkaynak, Kısacıkoğlu, and Rossi (2013) for example look at the out-of-sample forecasts of DSGE models, reduced-form models, Blue Chip, and the Board of Governors' Greenbook. They find that there is no single best forecasting method, and that DSGE models tend to provide better predictions of GDP at longer horizons and of inflation at shorter horizons. Moreover, they stress the importance of additional sources of information such as nowcasts and surveys to improve the forecasting performance and to account for the better performance of Blue Chip and official forecasts over DSGE and reduced-form models in the shorter horizons. Edge and Gürkaynak (2010), Edge, Gürkaynak, and Kısacıkoğlu (2013), and Gürkaynak, Kısacıkoğlu, and Rossi (2013) adopt a real-time, vintage-based perspective: this forecasting set-up allows comparing DSGE and BVAR forecasts with the official time-stamped forecast records of the different policy institutions. Previous studies such as Adolfson, Andersson, Lindé, Villani, and Vredin (2007) for Sweden's Riksbank, Edge, Kiley, and Laforte (2010) for the Federal Reserve Board, and Lees, Matheson, and Smith (2011) for the Reserve Bank of New Zealand find that both DSGE and BVAR models are competitive with respect to official

[1]The views expressed do not necessarily reflect those of the Bank of Italy. We would like to thank Fabio Busetti, Michele Caivano, Andrea Gerali, Alberto Locarno, and Stefano Siviero for their comments and suggestions. All remaining errors are ours.

[2]See Christoffel, Coenen, and Warne (2010), Del Negro and Schorfheide (2013), and Wieland and Wolters (2013) for extensive reviews on the forecasting performance of DGSE and BVAR models.

forecasts.

In this paper we focus on quarterly forecasts of euro-area GDP and inflation for each quarter from 2002Q3 to 2014Q1 over the same three full-years horizon adopted in Eurosystem projections.[3] The exogenous variables on which we condition our exercises involve the short-term interest rate, the nominal effective exchange rate, the oil prices expressed in US dollars, and the euro-area foreign demand.[4] Moreover, we also use high-frequency information and nowcasts on GDP and the inflation rate to align the projections for the first quarter with the whole available information set. For the DSGE model, we also investigate how different degrees of anticipation of the structural shocks alter the response of the agents; for the BVARX model, we follow Litterman (1986) and use Minnesota priors.

Our main results are the following:

1. Using the RMSFE metric, the DSGE-based forecasts are relatively more accurate for inflation, whereas the BVARX provides a better performance for GDP. In particular, the BVARX appears to have a systematic advantage from 4 to 8 quarters ahead. Interestingly, DSGE-based projections tend to be more accurate when the path of the conditioning variables is not immediately anticipated by the agents.

2. The DSGE model tends to overestimate GDP dynamics, except for two and three quarters ahead with unanticipated shocks; inflation is on average underestimated by most of the considered model specifications. Overall, the mean bias is smaller in BVARX-based forecasts.

3. Overall, the forecasting performance of both models (as measured by the Root Mean Squared Forecast Error) is comparable to the historical performance of the Eurosystem projections.

The paper is organized as follows. Section 2 describes the main features of the DGSE and the BVARX models. Section 3 presents the results of a forecast comparison between our models and simple univariate regressions as well as Eurosystem projections. Section 4 summarizes the results and suggests possible lines of future research.

[3] The forecast horizon varies in length over the year. Namely, in the first, second, third, and fourth quarter of each year the forecast horizon spans 12, 11, 10, and 9 quarters, respectively. See Alessi, Ghysels, Onorante, Peach, and Potter (2014) for a recent evaluation of ECB's and Federal Reserve Bank of New York's forecasting performance during the financial crisis using the same full-years horizon.

[4] The BVARX model includes also an index of prices set by Euro-area foreign competitors.

2 The models

2.1 The DSGE model

The DSGE is a two-country New Keynesian model estimated using euro-area and rest-of-the-world data.[5] The model features nominal and real rigidities. In addition, it differentiates between oil and non-oil goods. As such, aggregate demand shocks in the rest of the world affect the euro-area economy through two channels: a traditional direct trade channel and an oil-price channel. We produce conditional model-based projections, where the conditioning set corresponds to the main assumptions of Eurosystem projections. This set includes the following variables: the Euribor 3-month interest rate, a measure of euro-area foreign demand, the nominal effective exchange rate vis-à-vis 20 countries, and the Brent oil price quoted in US dollars.

In order to perform a pseudo-real time forecasting exercise, we estimate the model recursively, thus progressively increasing the sample size. We employ Bayesian methods over a time period that spans from 1995Q1 to 2013Q4. The time series we use for the EA are GDP, private and public consumptions, investment, exports, imports, total employment (heads), wages (nominal compensation per employee), the Euribor 3-month interest rate, the nominal effective exchange rate of the euro vis-à-vis 20 countries, the consumption and investment deflators, and the energy and non-energy components of the Harmonized Index of Consumer Prices (HICP). Information about the rest of the world is captured through the US 3-month interest rate, the world GDP deflator, an index of euro-area foreign demand, and the spot oil price in US dollars (Brent).

In the DSGE model, household and firms are forward-looking, as their decisions depend in every period on expectations over the economy's future developments. Hence, it is possible to condition the model-based forecasts over Eurosystem projections' assumptions in various ways, which differ in terms of the economic agents' information set. We consider two polar cases. In the first one, households and firms ignore the future path of the conditioning variables and are therefore surprised in each and every period by a combination of structural shocks that reproduces the assumed realization of the conditioning variables in that quarter. We call this case "unanticipated conditional forecasts." In the alternative setup (labeled "anticipated conditional forecasts"), households and firms are surprised only in the first quarter of the forecast horizon, when they learn the whole future development of Eurosystem projections' conditioning set. The different assumptions about the

[5]See Forni, Gerali, Notarpietro, and Pisani (2012) for a thorough description of the model structure.

information set of the agents result in markedly different responses of the main macroeconomic variables to the external shocks. In particular, in the anticipated conditional forecasts setup the impact responses (at the beginning of the forecast horizon) are larger compared to those observed in the unanticipated conditional forecasts case. The difference is due to an anticipation effect, which reflects the forward-looking behaviour of the agents.

Eurosystem projections are typically conditional on all up-to-date information, making use of high-frequency information coming from sample surveys and nowcasts, i.e., flash estimates on economic activity indicators and the inflation rate in the current period (quarter or month, respectively). In order to control for such informational advantage and to provide a level playing field across competing models in our forecasting race, we augment the DSGE-based forecasts with Eurosystem projections for the initial quarter of the forecasting sample. Hence, the forecasting performance of Eurosystem projections and the DSGE model is identical, by construction, in the first quarter.

2.2 The BVARX model

The BVARX model contains six endogenous euro-area variables: GDP, imports, exports, private consumption deflator, unit labor cost, and the euro-area long-term interest rate.[6] In addition, the model includes five exogenous variables: the Euribor 3-month interest rate, a measure of euro-area foreign demand, an index of prices set by euro-area foreign competitors, the nominal effective exchange rate of the euro vis-à-vis 20 countries, and the Brent oil price quoted in US dollars. We therefore adopt the denomination BVARX to denote the model with exogenous variables. The latter are used to provide the conditioning set under which the model-based forecasts are produced. As in the case of DSGE-based forecasts, for the first quarter of the forecasting horizon we use the historical Eurosystem projections. Hence, the performance of the BVARX and the DSGE-based forecasts is the same in the first quarter.

The model is specified in levels with 2 lags ($p_y = 2$) for the endogenous variables and one ($p_x = 1$) for the exogenous ones (for the latter, contemporaneous values are also included). The model is estimated recursively, using quarterly data for the period ranging from 1985Q1 to 2013Q4.

[6]The BVARX contains less variables than the DSGE. However, as observed in Adolfson, Andersson, Lindé, Villani, and Vredin (2007), this does not necessarily imply a disadvantage in terms of the forecasting performance, since the more parsimonious specification adopted for the BVARX significantly reduces the number of parameters to be estimated.

Denoting with y_t the 6×1 vector of endogenous variables and with x_t the 5×1 vector of exogenous variables, the BVARX takes the form

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + B_0 x_t + B_1 x_{t-1} + \varepsilon_t \quad \text{with} \quad \varepsilon_t \sim \mathscr{N}(0, \Sigma).$$

More compactly, the model can be rewritten as

$$y_t = \beta X_t + \varepsilon_t,$$

where $X_t \equiv I_6 \otimes W_t$, $W_t \equiv [\mathbf{1}', y'_{t-1}, y'_{t-2}, x'_t, x'_{t-1}]'$ and $\beta \equiv \mathrm{vec}\,(c, A_1, A_2, B_0, B_1)$. The model is estimated by means of Bayesian techniques. Regarding prior distributions, the coefficients of the i-th equation, denoted β_i, are assumed to follow a Gaussian distribution with prior mean $\bar{\beta}_i$ and prior variance Ω_i: $p(\beta_i \mid \Omega_i) = \mathscr{N}(\bar{\beta}_i, \Omega_i)$. The Minnesota prior is used for the coefficients of the endogenous variables in A_1 and A_2.[7] The hypothesis underlying this prior is that, in order to forecast the future path of a variable, there is a greater amount of information in recent own lags compared with both distant ones and those of other variables: the time series is seen a priori as a *random walk* process. Regarding the coefficients capturing the contemporaneous effect of exogenous variables (the block B_0), prior means are chosen in such a way that the model replicates the impact responses of endogenous variables to a standardized shock to the exogenous variables, as implicit in the euro-area National Central Banks' forecasting models. Such responses are denoted as Projection Update Elasticities (PUE).[8] Formally, the expected value of the prior distribution of these coefficients can then be written as

$$\mathbb{E}\left(\beta_{i,j,l_y(l_x)} \mid \Sigma, \Omega_i\right) = \begin{cases} 1 & \text{if } i = j \text{ and } l_x = 1, \\ \mathrm{PUE}_{ij} & \text{if } i \neq j, j \text{ exogenous, and } l_x = 0, \\ 0 & \text{otherwise,} \end{cases}$$

where $l_y = 1, \ldots, p_y$ ($l_x = 1, \ldots, p_x$) denotes the j-th endogenous (exogenous) variable lag order of the coefficient $\beta_{i,j,l_y(l_x)}$. The a priori variance-covariance matrix Ω_i of the coefficients is assumed to be diagonal and each of its elements is assumed to be a function of a vector of hyperparameters $\Lambda \equiv [\tau, \Gamma, \Phi]$, where τ defines the overall tightness and regulates the variance dispersion common to all coefficients, the vectors in $\Gamma = [\gamma_1, \gamma_2]$ control for the variance dispersion of the endogenous variable coefficients while the vector

[7] See Litterman (1979).

[8] See ECB (2001). PUE may be thought of as consolidated reduced-form versions of the forecast models in use in euro-area National Central Banks.

$\Phi = [\phi_1, \phi_2, \phi_3, \phi_4, \phi_5]$ collects the hyperparameters defining the prior variance dispersion of the exogenous variable coefficients. The larger the values of the hyperparameters, the lower is the weight attached to the prior in the computation of the posterior estimates: in the limiting case of flat prior, the posterior estimates converge to those that would be obtained using maximum likelihood. When really small values are assigned to the hyperparameters, the posterior estimates tend to be close to the prior values. Denoting with Ω_{ij} the a priori variance of the coefficient referring to the j-th variable in the i-th equation, we parametrize it according to

$$\Omega_{ij} = \mathbb{V}\left[\beta_{i,j,l_y(l_x)} \mid \Sigma, \Lambda\right] = \begin{cases} \tau \dfrac{\gamma_1}{{l_y}^2} & \text{if } i = j, \\ \tau \dfrac{\gamma_2}{{l_y}^2} \dfrac{\sigma_i}{\sigma_j} & \text{if } i \neq j \text{ and } j \text{ endogenous}, \\ \tau \phi_j \dfrac{\sigma_i}{\sigma_j} & \text{if } i \neq j \text{ and } j \text{ exogenous}. \end{cases}$$

We follow the BVAR literature in the calibration of the overall-tightness τ and the hyperparameters in the endogenous block γ_1 and γ_2; for those in the exogenous block we calibrate them in order to obtain a tight prior on the contemporaneous coefficients of the predetermined variables. The scale factors σ_i are proportional to the standard deviation of the residuals coming from a univariate autoregressive model with 8 lags run on each of the variables included in the BVARX.

In the forecasting exercise we also consider a BVAR model without exogenous variables. The specification of the model is kept unchanged in terms of endogenous variables and lags.

3 The forecast comparison exercise

Table 1 reports the Root Mean Squared Forecast Errors (RMSFE) for real GDP at different horizons (4, 8, and 12 quarters ahead), obtained using the DSGE model (both *unanticipated* and *anticipated* conditional forecasts) and the BVAR model (with and without exogenous variables), together with the RMSFE obtained using a simple univariate model (an autoregression model with four lags).[9] The BVAR, both with and without exogenous variables, systematically yields a better forecasting performance, at all the considered projection horizons. The DSGE model provides a comparable performance

[9]The lag-length of the AR models for GDP and inflation is (1) estimated using the Bayesian Information Criterion (BIC) on the whole sample ranging from 1985Q1 to 2013Q4 and (2) kept constant during the forecast exercise.

4 quarters ahead (unanticipated case), and its accuracy worsens gradually over time. The AR model always results in the largest RMSFE, suggesting that the information embedded in past realizations of GDP is insufficient to produce accurate predictions on future output developments.

Table 1: RMFSE 4, 8, and 12 quarters ahead (GDP).

	4 Q ahead	**8 Q ahead**	**12 Q ahead**
AR(4)	0.7706	0.8028	0.8398
DSGE anticipated	0.7153	0.7323	0.8339
DSGE unanticipated	0.6778	0.7426	0.8678
BVAR	0.6618	0.7279	0.8229
BVARX	0.6702	0.7179	0.7750

Table 2 provides RMSFEs for inflation, defined as the year-on-year percentage change of the private consumption deflator. In this case the DSGE-based projections (both anticipated and unanticipated) are uniformly the most accurate. The gain with respect to the BVARX and the AR is particularly large for 4 and 12 quarters ahead forecasts, while it slightly falls at the intermediate horizon.

Table 2: RMFSE 4, 8, and 12 quarters ahead (Consumption deflator).

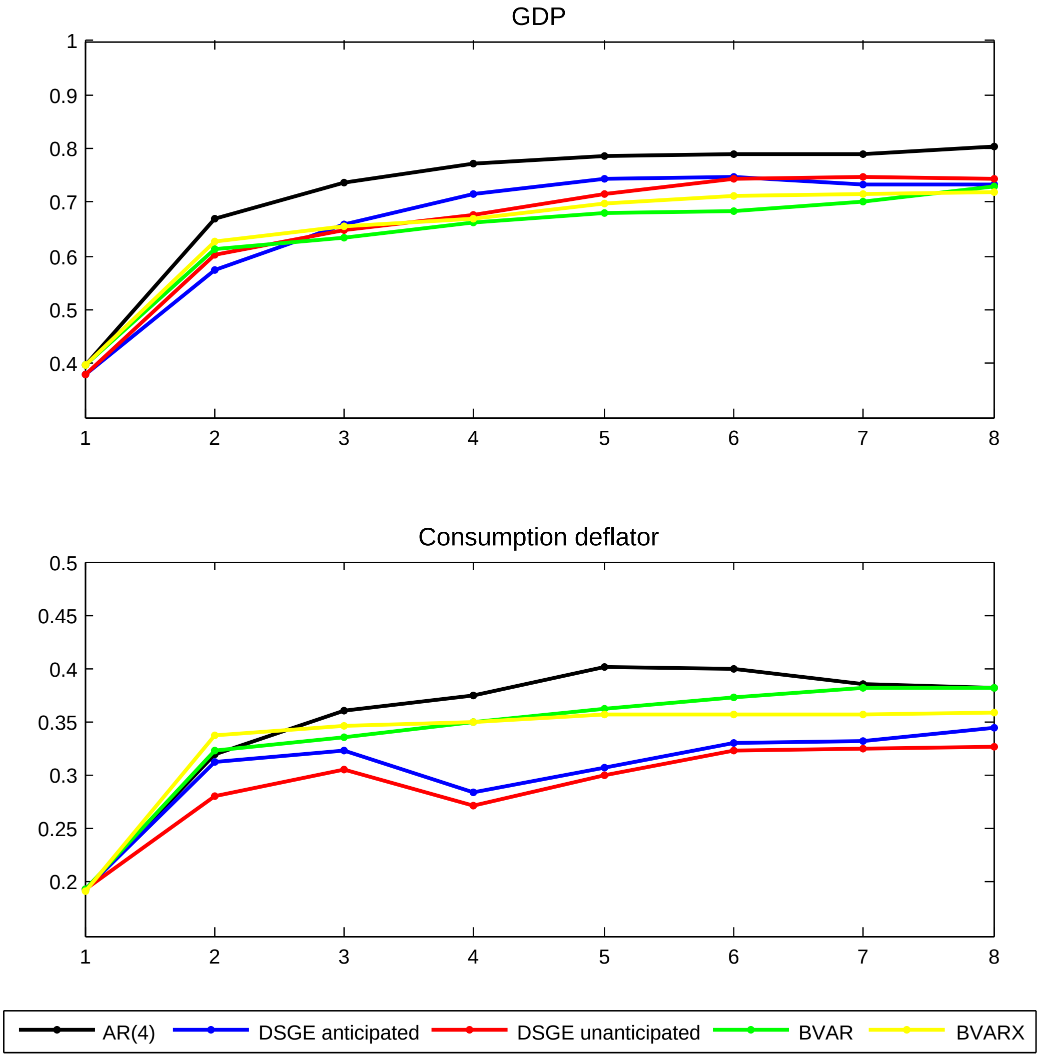
	4 Q ahead	**8 Q ahead**	**12 Q ahead**
AR(4)	0.3751	0.3819	0.4348
DSGE anticipated	0.2833	0.3446	0.3971
DSGE unanticipated	0.2721	0.3276	0.3927
BVAR	0.3494	0.3822	0.4667
BVARX	0.3502	0.3584	0.4423

In order to complement the information contained in Tables 1 and 2, Figure 1 reports the evolution of the RMSFEs as the forecasting horizon varies from 1 to 8 quarters.[10]

A few patterns emerge. Concerning GDP, the DSGE-based forecasts (both anticipated and unanticipated) are broadly similar to the BVARX-based ones, especially up to four quarters ahead. The BVARX starts performing better from 4 quarters ahead and provides the smallest RMSFE two

[10]As already noted, the use of high-frequency information in the first quarter implies that all models have the same forecasting performance one quarter ahead. Hence, the RMSFE is the same across models in the first period.

Figure 1: RMSFE at different horizons.



years ahead, when the performance of the two models (in all their specifications) becomes similar. The AR model consistently provides the least accurate forecast for GDP over all forecast horizons.

With regard to inflation, the DSGE-based projections display on average a smaller forecast error compared to the alternative models. In particular, the unanticipated (conditional) forecasts tend to perform better than the anticipated: the large initial reaction of endogenous variables to the fully anticipated future developments of exogenous variables generates too large fluctuations in inflation compared to the dynamics observed in the data. Importantly, the DSGE-based forecasts (especially in the unanticipated case) are more accurate than the BVARX-based ones also in the first four quarters of the forecast horizon. Once more, the AR model provides the worst forecasting performance, especially between four and eight quarters ahead.

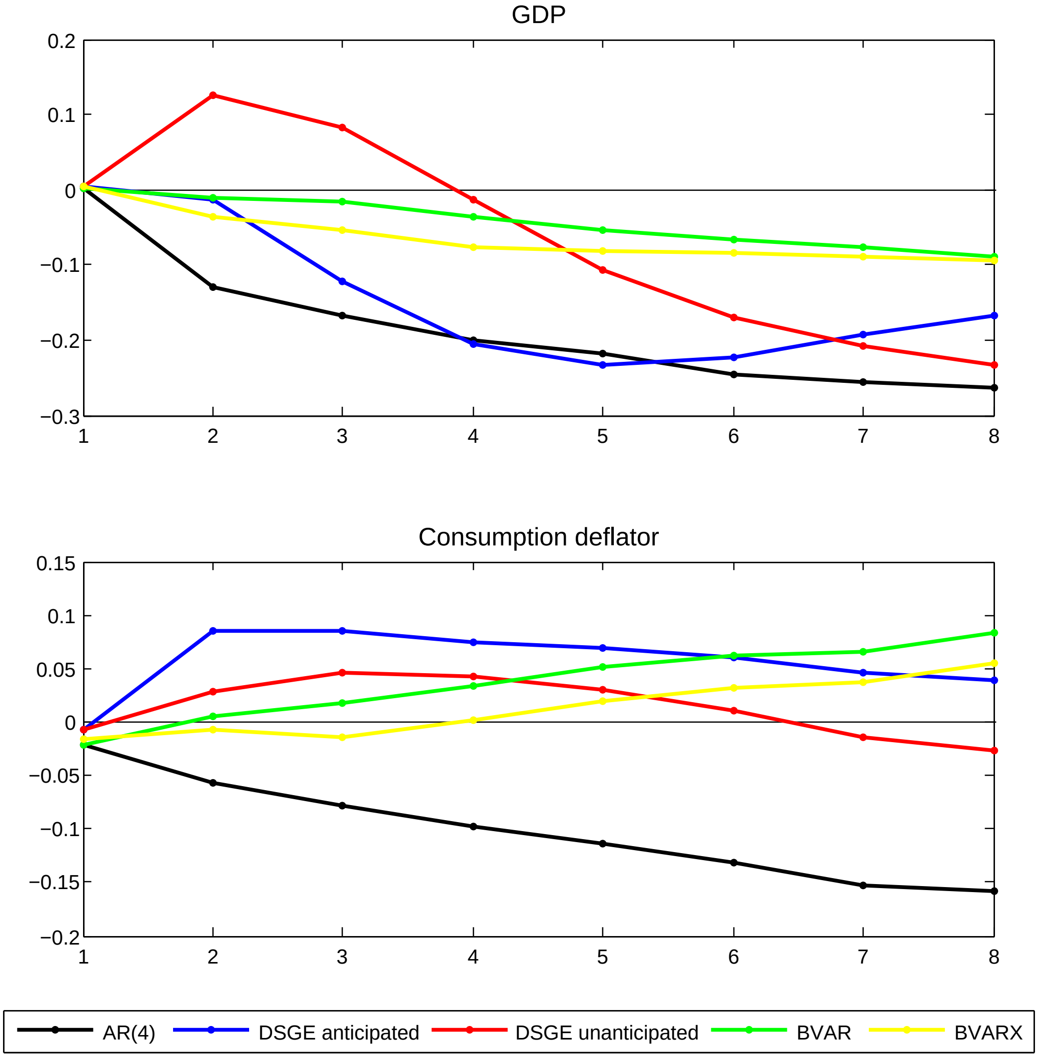
Figure 2 provides additional insights on the properties of the alternative models, by showing how the forecast bias implied by the different models changes along the forecast horizon. The bias is computed as the difference between the data and the corresponding forecast; hence, negative values signal overestimation, while positive ones indicate underestimation. The figure reports the *mean* forecast bias, computed over all the considered vintages in the 2002Q3-2014Q1 period.

Regarding the DSGE-based GDP forecasts, two features are worth emphasizing. First, the anticipated forecasts on average overestimate GDP growth at all horizons. The unanticipated DSGE forecasts show an initial tendency to underestimation (up to four quarters ahead), that subsequently reverts to overestimation. The BVAR and BVARX tend to predict GDP quite accurately at all horizons, with a small negative bias that remains broadly constant as the forecast horizon lengthens. The AR model features a systematic and increasing negative bias.

Concerning inflation, its dynamics is on average underestimated; such result is common to both the DSGE and the BVARX specifications. In particular, both unanticipated and anticipated DSGE forecasts show a persistent positive bias. The BVAR and BVARX-based predictions also feature a positive bias, which increases over time. The AR model instead displays a bias of opposite sign that increases as the projection horizon draws out.

Figure 3 reports the historical evolution of the forecast bias in the period 2002Q3 - 2013Q1 (4 and 8 quarters ahead, with data up to 2014Q1). All models clearly underpredict the observed GDP fall of 2008Q4, with a similar forecast error at the two horizons reported in the table: up until 2007Q4 no model would have predicted the large fall in output that actually took place. Note in particular that the size of the error is virtually unchanged at four and eight quarters ahead (first column), reflecting the absence of new relevant information between 2006Q4 and 2007Q4. However, the BVAR (both specifications) and the AR clearly overestimate the inflation rate in 2008Q4, while the corresponding DSGE-based forecast bias is about half the size for the four-quarter-ahead projection and slightly larger for the eight-quarter-ahead forecast. Such result confirms the better performance of the DSGE model in predicting inflation, already signalled by the RMSFEs (see Table 2).

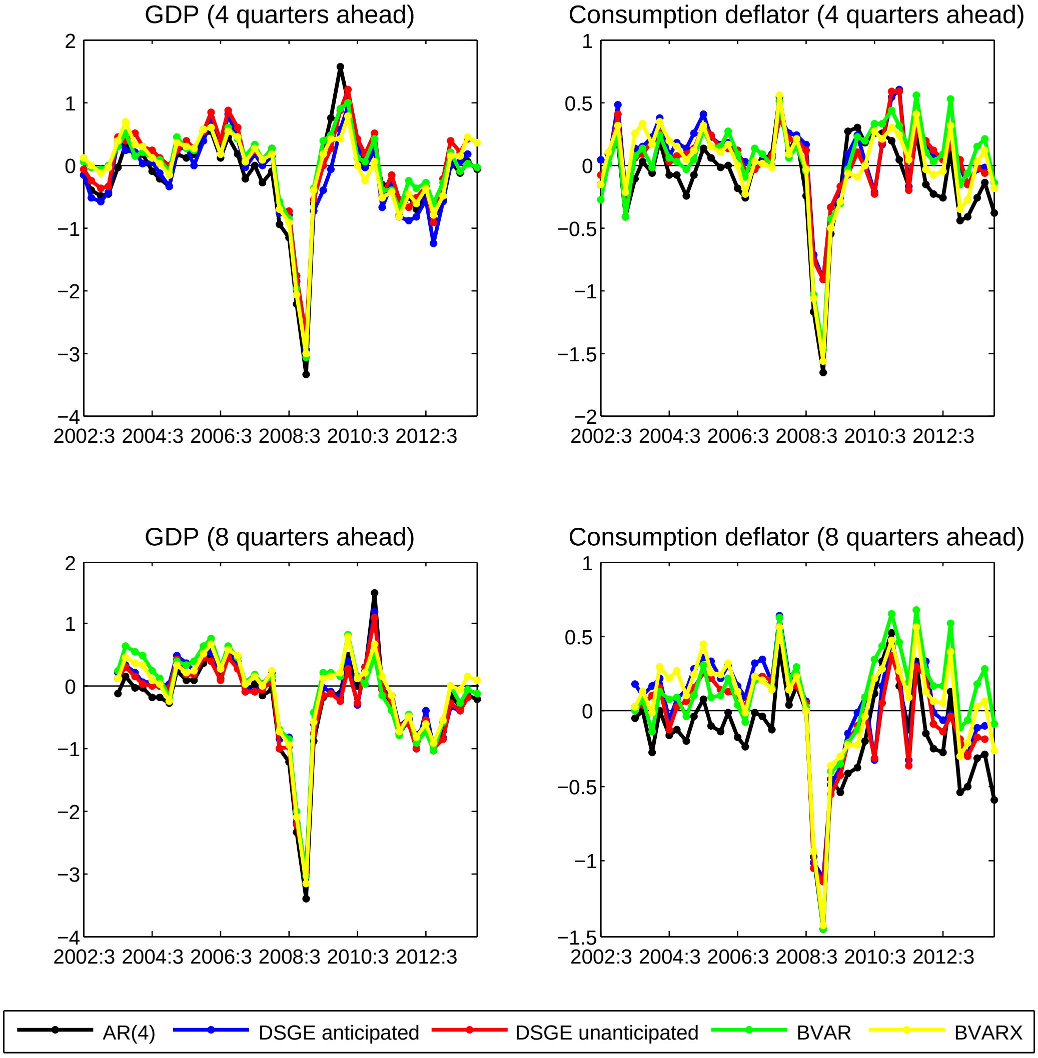
Figure 2: Forecast bias at different horizons.



3.1 Comparison of annual forecasts with the Eurosystem projections

Tables 3 and 4 report the 1 and 2-year ahead RMSFE generated by the different models against the corresponding Eurosystem projections' forecast errors. More precisely, the first column of each Table reports the RMSFE related to the one year ahead projection of the year-on-year growth rate of GDP and inflation, respectively. Such information also provides a complement to Table 1, Table 2, and Figure 1, in that it summarizes the performance of the

Figure 3: Forecast bias at different horizons.



different models in terms of year-on-year – as opposed to quarter-on-quarter – forecasts.

Concerning GDP, all models perform similarly in the first year. The result reflects, at least in part, the effect of using the same current-quarter information for all the alternative model specifications. For the 2-year ahead projections, the BVAR provides the most accurate performance, as already observed in Table 1. The DSGE model, under both specifications, provides a slightly larger RMSFE. The worst projection is the one obtained with the

Table 3: RMSFE 1 and 2 years ahead (GDP).

	1 year ahead	**2 years ahead**
Eurosystem	0.4982	1.9763
AR(4)	0.4925	2.2831
DSGE anticipated	0.4769	2.0080
DSGE unanticipated	0.5052	1.9185
BVAR	0.4824	1.8367
BVARX	0.4915	1.8967

Table 4: RMSFE 1 and 2 years ahead (Consumption deflator).

	1 year ahead	**2 years ahead**
Eurosystem	0.2716	0.9012
AR(4)	0.2303	1.0848
DSGE anticipated	0.2373	0.8235
DSGE unanticipated	0.2200	0.7555
BVAR	0.2398	0.9828
BVARX	0.2577	1.0041

AR(4). As to inflation, we also observe little variation in the RMSFE in the first year (only the BVARX provides a slightly worse performance), while the DSGE-based forecasts are the most accurate 2 years ahead.

Overall, the differences across forecasts are small. In particular, a standard Diebold-Mariano test yields no statistically significant difference between Eurosystem projections and the other models' forecasts, except for the 2 years-ahead GDP in the case of BVAR-based (i.e., without conditioning) forecast and for the 1 year-ahead inflation in the case of DSGE-based forecasts with unanticipated shocks. Note however that the DM test should not be interpreted as a model comparison device but simply as a forecast comparison device, as explained in Diebold (2012).[11]

[11] In our case, these exist several confounding factors such as, for example, the accuracy of the hypotheses underlying our forecasting exercise. Moreover, Eurosystem projections are not the result of a model-based forecast per se, so the model underlying the projections is unknown to the econometrician.

4 Conclusion

In this paper we analyze the relative forecasting performance of a DSGE and a BVARX model currently used at the Bank of Italy. We focus on quarterly forecasts of euro-area GDP and inflation for each quarter from 2002Q3 to 2014Q1, and exploit the access to the assumptions underlying Eurosystem projections. Our results are as follows. The DSGE-based forecasts are most accurate for inflation, whereas the BVARX provides the best performance in terms of GDP forecasting. In particular, the BVARX shows a systematically better performance from 4 to 8 quarters ahead. The DSGE-based projections tend to be more accurate when the path of the conditioning variables is not immediately anticipated by the agents. In terms of bias, the DSGE model tends to overestimate GDP dynamics after four quarters and underestimates them within the first year when shocks are not anticipated. The BVARX provides more accurate predictions overall, although consistently overestimating the evolution of GDP. The inflation rate is systematically underestimated by all models. From a historical perspective, all models would have failed to predict the magnitude of the fall in GDP observed in 2008Q4. However, the DSGE-based forecasts for inflation in the same quarter show a much smaller bias than the BVARX-based projections. We find that the forecasts of both models are comparable in terms of RMSFE with Eurosystem projections and are on average more accurate than those obtained by means of a simple univariate model.

A number of potentially relevant issues may be explored within our framework. For example, a forecast combination may help to improve the quality of our forecasts. Since the pioneering work of Bates and Granger (1969), it is well known that pooling several forecasts can yield a mean square forecast error lower than that of each individual forecast. Hence, rather than selecting a preferred forecasting model for a specific variable, it may be convenient to combine all the available projections. Several pooling procedures are available depending on how the various forecasts are weighted. Moreover, the increased attention to risks underlying the macroeconomic projections, such as those related to low and falling inflation rates, call for the use of density forecasts instead of point forecasts and for methods to combine density forecasts coming from different models.[12] We leave the investigation of these interesting issues for future research.

[12] See Hall and Mitchell (2007) and, more recently, Busetti (2014).

References

Adolfson, M., M. K. Andersson, J. Lindé, M. Villani, and A. Vredin (2007): "Modern Forecasting Models in Action: Improving Macroeconomic Analyses at Central Banks," *International Journal of Central Banking*, 3(4), 111–144.

Alessi, L., E. Ghysels, L. Onorante, R. Peach, and S. Potter (2014): "Central Bank Macroeconomic Forecasting During the Global Financial Crisis: The European Central Bank and Federal Reserve Bank of New York Experiences," *Journal of Business & Economic Statistics*, 32(4), 483–500.

Bates, J. M., and C. W. J. Granger (1969): "The Combination of Forecasts," *Operations Research Quarterly*, 20(4), pp. 451–468.

Busetti, F. (2014): "Quantile aggregation of density forecasts," Temi di discussione (Economic working papers) 979, Bank of Italy, Economic Research and International Relations Area.

Christoffel, K., G. Coenen, and A. Warne (2010): "Forecasting with DSGE models," Working paper series, European Central Bank.

Del Negro, M., and F. Schorfheide (2013): "Chapter 2 - DSGE Model-Based Forecasting," in *Handbook of Economic Forecasting*, ed. by G. Elliott, and A. Timmermann, vol. 2, Part A of *Handbook of Economic Forecasting*, pp. 57 – 140. Elsevier.

Diebold, F. X. (2012): "Comparing Predictive Accuracy, Twenty Years Later: A Personal Perspective on the Use and Abuse of Diebold-Mariano Tests," NBER Working Papers 18391, National Bureau of Economic Research, Inc.

ECB (2001): "A guide to Eurosystem staff macroeconomic projection exercises," Discussion paper, European Central Bank.

Edge, R. M., and R. S. Gürkaynak (2010): "How Useful Are Estimated DSGE Model Forecasts for Central Bankers?," *Brookings Papers on Economic Activity*, 41(2 (Fall)), 209–259.

Edge, R. M., R. S. Gürkaynak, and B. Kisacikoğlu (2013): "Judging a DSGE model by its forecast," *Mimeo.*

Edge, R. M., M. T. Kiley, and J.-P. Laforte (2010): "A comparison of forecast performance between Federal Reserve staff forecasts, simple reduced-form models, and a DSGE model," *Journal of Applied Econometrics*, 25(4), 720–754.

Forni, L., A. Gerali, A. Notarpietro, and M. Pisani (2012): "Euro area and global oil shocks: an empirical model-based analysis," Temi di discussione (Economic working papers) 873, Bank of Italy, Economic Research and International Relations Area.

Gürkaynak, R. S., B. Kisacikoğlu, and B. Rossi (2013): "Do DSGE Models Forecast More Accurately Out-of-Sample than VAR Models?," Cepr discussion papers, C.E.P.R. Discussion Papers.

Hall, S. G., and J. Mitchell (2007): "Combining density forecasts," *International Journal of Forecasting*, 23(1), 1 – 13.

Lees, K., T. Matheson, and C. Smith (2011): "Open economy forecasting with a DSGE-VAR: Head to head with the RBNZ published forecasts," *International Journal of Forecasting*, 27(2), 512–528.

Litterman, R. (1986): "Forecasting with Bayesian vector autoregressions – Five years of experience : Robert B. Litterman, Journal of Business and Economic Statistics 4 (1986) 25-38," *International Journal of Forecasting*, (4), 497–498.

Litterman, R. B. (1979): "Techniques of forecasting using vector autoregressions," Discussion paper.

Wieland, V., and M. Wolters (2013): "Chapter 5 - Forecasting and Policy Making," in *Handbook of Economic Forecasting*, ed. by G. Elliott, and A. Timmermann, vol. 2, Part A of *Handbook of Economic Forecasting*, pp. 239 – 325. Elsevier.