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2011

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CZECH NATIONAL BANK

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CNB WORKING PAPER SERIES

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Distributed by the Czech National Bank. Available at http://www.cnb.cz.

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Are Bayesian Fan Charts Useful for Central Banks? Uncertainty, Forecasting, and Financial Stability Stress Tests

Michal Franta, Jozef Baruník, Roman Horváth, and Kateřina Šmídková*

Abstract

This paper shows how fan charts generated from Bayesian vector autoregression (BVAR) models can be useful for assessing 1) the forecasting accuracy of central banks' prediction models and 2) the credibility of stress tests carried out to evaluate financial stability. Using unique data from the Czech National Bank (CNB), we compare our BVAR fan charts for inflation, GDP growth, interest rate and the exchange rate to those of the CNB, which are based on past forecasting errors. Our results suggest that in terms of the Kullback-Leibler Information Criterion, BVAR fan charts typically do not outperform those of the CNB, providing a useful cross-check of their accuracy. However, we show how BVAR fan charts can rigorously deal with the non-negativity constraint on the nominal interest rate and usefully complement the official fan charts. Finally, we put forward how BVAR fan charts can be useful for assessing financial stability and propose a simple method for evaluating whether the assumptions of banks' stress tests about the macroeconomic outlook are sufficiently adverse.

JEL Codes: E52, E58.

Keywords: Bayesian vector autoregression, fan chart, inflation targeting, stress tests, uncertainty.

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We thank Jan Brůha, Pär Österholm, Michael P. Clements, Lubomír Lízal, and seminar participants at the Czech National Bank for comments and helpful discussions. The views expressed in this paper are not necessarily those of the Czech National Bank.
This research was supported by Czech National Bank Research Project A2/10. Roman Horváth appreciates the support provided by the Grant Agency of the Czech Republic under Grant No. P402/11/1487.

Nontechnical Summary

In this paper, we assess the potential that Bayesian fan charts may have for the Czech National Bank (CNB). Fan charts have become an important communication tool for inflation targeters. According to our survey, most inflation-targeting central banks currently publish fan charts for inflation and quite a few publish them for GDP growth. Fan charts are used mainly to communicate the uncertainty relating to macroeconomic forecasts and monetary policy decisions that are based on these forecasts. In some cases, fan charts are also employed to facilitate internal discussions about forecast risks.

Inflation targeters produce fan charts mostly from their macroeconomic forecasts, which represent the most likely future development, and from past forecast errors. In cases where fan charts facilitate internal discussion, a subjective assessment of the forecast risks is incorporated into the fan charts after the forecast is created. The risks are typically assumed to have an asymmetric, but otherwise nearly normal distribution called a two-piece normal distribution.

Research papers offer several alternatives to these two main approaches to producing fan charts. From these alternatives, we select so-called BVAR fan charts, which are produced by Bayesian vector autoregression models. They differ from the fan charts produced by inflation targeters in two aspects. First, BVAR fan charts are not produced by the core forecasting model, which is usually quite complex and combines theory-based and empirical parts. Vector autoregression models are empirical and typically work with several key variables only. Second, uncertainty is represented neither by past forecasting errors nor by subjective assessments attached ex post to the forecast. BVAR fan charts employ Bayesian methodology to approximate uncertainty. Subjective assessments are incorporated during the process of fan chart creation.

These two features give BVAR fan charts a potential edge over the approaches currently applied. It might be more transparent to assess risks for several key variables than to frame the discussions of forecast risks by a large complex model. In addition, incorporating subjective assessments into fan charts during the process of their creation might increase their consistency.

We tested the BVAR methodology on the Czech data, since the CNB produces fan charts from past forecast errors, for all four key variables: inflation, GDP growth, the interest rate path, and the exchange rate. No other inflation targeter publishes a full set of fan charts.

We show that compared to the currently produced fan charts the BVAR fan charts are not more accurate (in terms of the Kullback-Leibler Information Criterion, which measures distance of probability densities). However, BVAR fan charts might be beneficial for monetary policy in situations such as when approaching the zero bound, when incorporating expert knowledge into fan charts is clearly desirable and the complex forecasting model does not capture asymmetric risks well. For such situations, we illustrate that combining the core fan chart with a complementary BVAR fan chart might be an interesting option.

In addition to alternative fan charts, we argue that BVAR fan charts might be useful for assessing the macroeconomic scenarios used in the stress testing of the Czech banking sector. Similarly to the potential benefits mentioned above in the inflation-targeting context, BVAR fan charts might

offer a transparent and consistent way of either producing or assessing macroeconomic stress-test scenarios.

Using BVAR fan charts, we illustrate that the recent stress-test scenarios employed by the CNB to check the health of the Czech financial system were rather demanding. The BVAR fan charts show that the combination of macroeconomic shocks assumed by these scenarios is very unlikely according to historical data.

1. Introduction

The recent financial crisis has been associated with a substantial increase in uncertainty about future economic developments. The risks in the economic outlook have often been far from symmetric. Nominal interest rates have reached historical lows and in many countries have converged to the zero bound constraint. Generating forecasts about the future economic environment has become a challenge. As a consequence, assessing as well as communicating forecast uncertainty has gained primary importance for inflation-targeting central banks. For these central banks, the release of the macroeconomic forecast is an integral part of the monetary policy framework, and efficient communication about the forecast uncertainty is crucial to their credibility (Geraats, 2010). Very recently, assessing macroeconomic forecast uncertainty has also gained importance in the macroprudential policy area (Haldane, 2009). Many inflation-targeting central banks have increased the emphasis on financial stability, and consequently, have started producing stress tests of their financial sectors. The macroeconomic scenarios that comprise an important part of these stress tests work extensively with macroeconomic uncertainty.

While some inflation-targeting central banks describe the uncertainty relating to their forecasts verbally or with the help of alternative scenarios (Šmídková, 2005), the majority convey the forecast uncertainty by publishing probability distributions known as fan charts. Fan charts were introduced by the Bank of England (BoE) in 1996 in order to improve communication and put more emphasis on the risks of the inflation forecast and their direction (Britton et al., 1998). Fifteen years later, about three quarters of inflation targeters communicate their inflation forecasts with the help of fan charts.

Inflation targeters use various methodologies to produce their fan charts, from calibrations based on past forecasting errors (Czech National Bank, 2008), to small-scale structural model simulations (Norges Bank, 2005) to subjective assessments made by monetary policy decision makers (Britton et al. 1998). Alternative methodologies have also been proposed by researchers. For example, Bayesian fan charts based on simulated predictive densities (Cogley et al., 2005) have been put forward as a potential improvement to current practice. This proposal seems especially attractive with the recent crisis in mind. Fan charts based on simulated predictive densities can exclude negative values of the nominal interest rate. As a result, they are more consistent with the nature of the forecasted variable than fan charts based on past forecast errors. Given the forecasting challenges mentioned above, the discussion of alternative fan chart methodologies is again topical.

In this paper, we use a Bayesian vector autoregression model (BVAR) to produce fan charts for the Czech economy. This methodology allows for risk asymmetries and the incorporation of expert judgment in the form of a non-negativity constraint on the nominal interest rate. The constraint is implemented by treating the interest rate as a censored variable. Moreover, the Bayesian approach allows prior information to be incorporated into the system of equations, thus mitigating the problem of estimation based on a short time data span (Geweke, 2001). We are motivated by the fact that BVAR fan charts could serve as a useful benchmark for the methodology currently employed by the Czech National Bank (CNB). The fan charts published in the CNB Inflation Reports are constructed using a completely different methodology. They are based on past forecasting errors, which reflect the quality of the model-based, but expert-augmented, macroeconomic forecasts (CNB, 2008b).

Another motivation for producing BVAR fan charts for the Czech economy relates to the communication strategy of the CNB. The CNB belongs to the group of advanced inflation targeters and is one of the most transparent central banks (Dincer and Eichengreen, 2009). Its communication strategy is unique in that it involves publishing fan charts for all four key macroeconomic variables: inflation, GDP growth, interest rates, and the exchange rate. Other inflation targeters working with fan charts publish them only for selected variables (typically for inflation and GDP growth, rarely for interest rates, and, to our knowledge, never for the exchange rate). We can therefore compare fan charts for more variables using the Czech data than using data from any other central bank.

Last but not least, there is an intense discussion among policy makers about whether the numerous financial stability stress tests carried out during the financial crisis were too easy. For example, many commentators put forward that the European stress tests were not sufficiently severe to evaluate the resilience of the banking sector (see, for example, Onado, 2011). Borio and Drehmann (2009) argue that stress tests without sufficiently severe scenarios may give rise to a false sense of security. In this respect, Goodhart (2006) raises the need for an analytical framework to evaluate whether the scenarios in stress tests are sufficiently adverse. We contribute to this discussion and propose a simple method based on Bayesian fan charts to evaluate to what extent the macroeconomic scenarios in stress tests are, or are not, sufficiently adverse. Furthermore, the "plausibility" of the scenarios is dealt with from the point of view of consistency with correlations estimated from the data. We use the Czech data for this exercise, but the approach is general and easy to apply in any central bank using fan charts.

Our results show that the CNB fan charts come out well by comparison with the BVAR methodology. For shorter horizons up to a year ahead, the CNB fan charts perform better than the BVAR benchmark in terms of the Kullback-Leibler Information Criterion (KLIC). For longer horizons, the BVAR fan charts sometimes outperform the CNB fan charts. This result reflects the fact that the BVAR fan charts benefit from high quality data while the CNB fan charts were constructed in real time without knowledge of subsequent data revisions. For shorter horizons, where the CNB forecasting errors were reduced by augmenting the model-based forecast with expert judgment, small-scale BVAR cannot compete unless expert judgment is incorporated on a much larger scale compared to the current expert input limited to the zero bound restriction only. Given these results, we conclude that BVAR fan charts could be used as a benchmark to assess the CNB fan charts, as a complementary input to create combined fan charts, or as a tool to create macroeconomic scenarios for the regular stress tests of banking sector stability carried out at the CNB. In this respect, our results show that the CNB stress tests were sufficiently severe.

The paper is organized as follows. Section 2 gives a brief description of the various fan chart methodologies employed by the CNB and other central banks and the methodologies proposed by researchers. Section 3 describes our BVAR model and discusses the basic properties of the model. Section 4 gives our fan charts and assesses their forecasting performance vis-à-vis the CNB fan charts. Section 5 describes how the two alternative fan charts could be combined should BVAR prove an interesting complement to the current CNB fan charts. It also illustrates how BVAR fan charts could be used to assess how stringent the assumptions about the macroeconomic outlook in stress testing are. It also shows how to incorporate expert judgment into the BVAR fan charts. Section 6 concludes. An appendix with additional results follows.

2. Inflation Targeters and Fan Charts

Since the BoE introduced them in 1996, fan charts have become widely popular with inflation-targeting central banks. This section provides a brief overview of the practices of inflation targeters in terms of publishing forecasts and the attendant fan charts. It also reviews proposals by researchers for alternative methodologies for producing fan charts.

Table 1: The Use of Fan Charts in Inflation-Targeting Central Banks: Are Forecasts and Fan Charts Publicly Available?

Country	*Inflation*	*GDP growth*	*Interest rate*	*Exchange rate*
Armenia	++	++	-	-
Australia	+	+	-	-
Brazil	++	++	-	-
Canada	++	+	-	-
Chile	+	+	-	-
Colombia	++	+	-	-
Czech Republic	++	++	++	++
Ghana	++	+	-	-
Guatemala	+	-	-	-
Hungary	++	++	-	-
Iceland	+	-	-	-
Indonesia	+	+	-	-
Israel	++	+	++	-
Mexico	++	++	-	-
New Zealand	+	+	+	-
Norway	++	++	++	-
Peru	++	++	-	-
Philippines	++	-	-	-
Poland	++	++	-	-
Romania	+	+	-	-
Serbia	++	-	-	-
South Africa	++	++	-	-
South Korea	++	++	-	-
Sweden	++	++	++	-
Thailand	++	++	-	-
Turkey	++	+	-	-
United Kingdom	++	++	-	-

Notes: The table shows whether the forecasts and fan charts for inflation, GDP growth (output gap), the interest rate, and the exchange rate are publicly available. ++ denotes that both the forecast and the fan chart are available, + denotes that only the forecast is available, and - denotes that neither the forecast nor the fan chart is available. Information as of July 2011.

Table 1 summarizes which forecasts are published by inflation-targeting central banks. It also summarizes whether fan charts are generated for these forecasts and made publicly available. Regarding the forecast, Hammond (2011) is the source of the data on which macroeconomic variables the forecasts are publicly available for. The results show that all inflation targeters publish forecasts of inflation, many of them publish forecasts of GDP growth, some publish forecasts of interest rates, and only the CNB publishes forecasts for the exchange rate.

Regarding the fan charts, we survey central banks' official publications, primarily their inflation reports. According to our survey, most central banks currently publish fan charts for inflation and quite a few publish them for GDP growth. Publishing fan charts for interest rates is much less common, and again, only the CNB makes a fan chart for the exchange rate publicly available.

To illustrate the practice of inflation targeters publishing fan charts, we select central banks in countries that score high in terms of transparency (Dincer and Eichengreen, 2009): the UK, Sweden, Canada, the Czech Republic, and Hungary. In addition, we added Norway to our sample since it publishes fan charts for inflation, GDP, and the interest rate path.

The CNB fan charts are largely based on the past forecast errors of inflation, GDP growth, the exchange rate, and the interest rate path from the CNB g3 model (CNB, 2008). The g3 model is a dynamic stochastic general equilibrium (DSGE) model used as the core forecasting tool since 2008 (Šmídková, ed., 2008). Therefore, only a few years of forecasting errors are available. In consequence, the resulting fan chart over the individual forecast horizons is smoothed linearly. The fan charts are symmetric and are available for horizons covering 1 to 7 quarters for CPI inflation, monetary-policy relevant inflation, GDP growth, the 3M PRIBOR, and the exchange rate (see Table 1). The confidence intervals for the relevant quantiles are generated using the normal distribution. To deal with the fact that uncertainty may change over time, the forecast errors and fan charts are updated on a yearly basis.

The BoE takes a very different approach. Its fan charts for inflation and output are based on a subjective assessment of the overall uncertainty outlook and the directions of the risks to the forecast as viewed by the members of the Monetary Policy Committee (Britton et al., 1998). The BoE introduced the two-piece normal distribution to represent uncertainty in order to allow for asymmetry. The three moments of this distribution (mode, standard deviation, and skewness) are determined by a combination of model-based and expert-judgment methods. The mode represents the single most likely outcome based on current knowledge and judgment. Uncertainties relating to input variables are aggregated into fan charts for inflation and GDP growth. Experts and policy makers focus on discussing the balance of risks, which is defined as the difference between the mean and the mode. The final fan chart is created using a “top-down” approach where policy makers have the final say.

The Swedish Riksbank produces fan charts in a similar way to the CNB. The uncertainty of the inflation and GDP forecast is related to the past forecast errors. For the interest rate (repo rate) forecast the uncertainty reflects the past forecast errors for implied forward rates, which are adjusted to take into account the corresponding risk premium (Sveriges Riksbank, 2007). The uncertainty bands are symmetric.

The National Bank of Hungary also generates its fan charts for inflation and GDP growth with the help of the two-piece normal distribution (Magyar Nemzeti Bank, 2004). The mode is represented by the baseline forecast as the most probable scenario. The standard deviation is calculated from the past forecast errors. The skewness is determined by experts according to alternative scenarios considered when the baseline forecast is generated.

In the case of Norway, the fan charts are model-based with an emphasis on historical uncertainty (Norges Bank, 2005). The uncertainties relating to important variables are assessed on the basis of past performance. Next, they are combined with the help of a small macroeconomic model that has been calibrated to obtain the desired aggregate system properties (Husebo et al., 2004). The performance of the fan charts has been evaluated several times. For example, in 2007, the fan charts were put to informal tests. They showed that a significant portion of the observed inflation data points were outside the fan chart (Norges Bank, 2007), which raised the question of how to calibrate the model to get the appropriate width of the fan charts.

The Bank of Canada also produces model-based fan charts to communicate its inflation forecasts (Bank of Canada, 2009). The Canadian fan charts are based on stochastic simulations of a core forecasting model called ToTEM (Murchison and Rennison, 2006). For the first two quarters, the fan charts combine these stochastic simulations with past staff forecast errors in order to reflect the fact that the short-term forecasts are produced by experts, not by the core model. The fan charts also incorporate the uncertainty relating to external variables, as captured by a complementary model. The Canadian fan charts are symmetric.

To sum up, there are two main approaches employed in practice by inflation targeters to generate fan charts. First, some central banks, such as the CNB, rely on past forecast errors, assuming a normal distribution of risks and generating the central path using their core forecasting model. Second, other central banks, such as the BoE, assess subjectively the uncertainty of future economic developments with the help of the two-piece normal distribution, assuming that the central forecast represents the mode of this distribution. In the first case, the fan charts are used solely as communication tools to inform the general public about the uncertainty relating to the forecast. In the second case, the fan charts have two roles. Internally, their preparation facilitates discussion among policy makers and experts about the distribution of forecast risks. Externally, fan charts both inform the general public about uncertainty (standard deviation) and send out a potential signal regarding future policy moves (skewness).

Researchers have added various proposals to these current practices. Some researchers propose modifications to the fan charts based on two-piece normal distributions. Some claim that the aggregation of input variables should be modified in order to consider joint distributions and avoid the omission of such important information as trade-offs between forecasts (Pinheiro and Esteves, 2011). Others propose that it is important to aggregate the predictive densities of individual policy makers into one (Osterholm, 2009) or argue that incorporating market information is important (Elekdag and Kannan, 2009).

An important branch of literature is focused on BVAR models, which could be used to produce fan charts similar to those produced so far by expert judgment, but model based. The first proposition in this area illustrated how to produce time-varying BVAR fan charts for the BoE (Cogley et al., 2005). More recently, a large structural BVAR, benefiting from a more than 20 year long data series for Sweden, has been put forward to formalize forecast uncertainty (Osterholm, 2008) and produce model-based fan charts.

To sum up, there are more approaches to the construction of fan charts than currently used by major inflation targeters. In addition to generating fan charts from either past forecast errors or expertly specified two-piece normal distributions, one can consider joint distributions of forecasting errors, market expectations, and BVAR fan charts.

BVAR fan charts seem an especially attractive option for the CNB. They allow for both model-based estimates of risk asymmetries, represented with a distribution that does not need to be two-piece normal, as well as formalized incorporation of expert judgment, for example, by applying the zero bound. All this is done without a requirement to transform the core forecasting model into a full-fledged stochastic one. In addition, small-scale constant-coefficient BVAR fan charts are also suitable for countries with rather short time data spans, which is the case of the Czech Republic.

3. The Czech Bayesian Vector Autoregression Model

The BVAR model is estimated using four endogenous variables – real output (year-on-year growth rate), monetary-policy relevant inflation (the year-on-year growth rate of the CPI adjusted for the first-round effect of indirect taxes), the short-term interest rate (3M PRIBOR), and the CZK/EUR exchange rate (year-on-year growth rate). The growth rate of the exchange rate is chosen to account for the appreciation trend of the Czech koruna (see Babecky et al., 2010, on the discussion about why many Central European economies are exhibiting trend appreciation of their currencies). Furthermore, to account for changes to the inflation target during the sample period the distance of monetary-policy relevant inflation from the target is employed instead of the simple level of monetary-policy relevant inflation.

As already mentioned, the set of endogenous variables coincides with the set of variables for which the CNB publishes its fan charts. The data are seasonally adjusted and cover the period 1998Q1–2010Q4. This coincides with the period during which inflation targeting was applied in the Czech Republic.[1]

To estimate the model we use the Bayesian approach. We employ the Minnesota prior (Doan, Litterman, and Sims, 1984, and Litterman, 1986), which leads to simple analytical expressions for the posterior distributions and thus facilitates the computation, especially when the recursive forecasting exercise is carried out. Moreover, such a prior implies a closed-form likelihood function and so the marginal likelihood can be computed easily.

We consider a vector autoregressive model of order *p*:

$$y_t = C + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t , \tag{1}$$

where y_t for $t = 1,...,T$ is an $M \times 1$ vector of endogenous variables, *C* denotes an $M \times 1$ vector of intercepts, A_j is an $M \times M$ matrix of coefficients, and ε_t is an $M \times 1$ vector of innovations. We assume that the innovations are i.i.d. $N(0, \Sigma)$.

[1] To ensure consistency, the variables are taken from the data set used by the CNB's core forecasting model.

The prior for the vector of the intercepts and elements of the coefficient matrices is assumed to be distributed normally with mean α^{PR} and variance V^{PR}:

$$\alpha \equiv vec\left([C\ A_1\ ...\ A_p]'\right) \sim N\left(\alpha^{PR}, V^{PR}\right).$$

In the equations with a left-hand side variable in growth rate (real output, CPI, exchange rate) the prior mean at all lags of all variables is set to zero – this assumption reflects our belief that the growth rate exhibits a low level of persistence.[2] In the equations for variables in levels (interest rate) a prior mean equal to one at the own variable first lag is assumed. At other lags and for other variables the prior mean is set to zero. So, variables in levels are assumed to be close to a random walk. Finally, the prior mean for intercepts is set equal to zero.

The prior variance suggests how much the observed time series are tightened around processes given by the vector of prior means, and is assumed to be diagonal. We assume the diagonal elements of the prior variance to be as follows:

$$V_{ij,l}^{PR} = \begin{cases} a/l^2 & \text{for the coefficient on own lags} \\ \dfrac{b\sigma_i}{l^2\sigma_j} & \text{for the coefficients on lags of variable } j \neq i \\ c\sigma_i & \text{for the coefficients on intercepts,} \end{cases}$$

where *i* is the index of the equation and *j* the index of the variable in the equation, while *l* denotes the lag of the variable. The ratios σ_i / σ_j account for different measurement units of endogenous variables. The value of σ_i is set to the estimated standard error of a univariate autoregressive model for a particular variable *i*. The elements $V_{ij,l}^{PR}$ are ordered according to the order of the variables in the vector α.

The prior variance is set using three hyperparameters *a*, *b*, and *c*. We impose an uninformative prior on the intercepts: $c = 10^2$. The other hyperparameters are chosen based on maximization of the marginal data density (Giannone et al., 2010). The marginal data density (marginal likelihood) measures the out-of-sample forecasting performance of the model. More precisely, the value of the hyperparameter maximizing the marginal data density maximizes the one-step-ahead out-of-sample forecasts of the model (e.g. Geweke, 2001). The derivation of the formula for the marginal data density for the Minnesota prior is given in Appendix A. Based on the full sample, the marginal data density maximization yields $a = 0.523$ and $b = 0.0362$. Note that $a > b$ implies that own lags are more important in the prediction of a particular variable than lags of the other variables.

[2] Here one could argue that inflation exhibits a certain level of persistence in the Czech Republic (see e.g. Franta et al., 2010). Inflation persistence, however, usually relates to the sum of autoregression coefficients and individual coefficients can take different values. Therefore, we decided to impose the zero prior on all of them.

The Minnesota prior implies a posterior that is also normally distributed:

$$\alpha \mid y \sim N\left(\alpha^{PO}, V^{PO}\right), \tag{2}$$

where

$$V^{PO} = \left[\left(V^{PR}\right)^{-1} + \left(\hat{\Sigma}^{-1} \otimes (X'X)\right)\right]^{-1}$$
$$\alpha^{PO} = V^{PO}\left[\left(V^{PR}\right)^{-1}\alpha^{PR} + \left(\hat{\Sigma}^{-1} \otimes X\right)' y\right].$$

X is a matrix of endogenous variables entering the right-hand side of equation (1), i.e.,

$$X = \begin{bmatrix} \left(1, y_0', .., y_{1-p}'\right) \\ \left(1, y_1', .., y_{2-p}'\right) \\ \vdots \\ \left(1, y_T', .., y_{T-p}'\right) \end{bmatrix},$$

and $\hat{\Sigma}$ denotes an OLS estimate of Σ.

For the estimation, we use five lags of the endogenous variables $(p = 5)$. The number of lags is determined using the marginal data density.[3] The post-estimation diagnostics are presented in Appendix B. They suggest that the data are informative in the sense that the prior and posterior distributions differ.

4. Fan Charts for Inflation, GDP, the Interest Rate, and the Exchange Rate

In the next step, we use the BVAR model to generate fan charts for GDP growth, monetary-policy relevant inflation (MPR inflation), the 3M PRIBOR, and the exchange rate for horizons covering 1 to 7 quarters $(h = 1, 2, ..., 7)$, corresponding to the time span of the CNB fan charts.

To generate the predictive probability density we produce a sample from the posterior distribution of the coefficients of the BVAR model stated in (2). The size of the sample is 10,000 draws[4] and for each draw ten forecasts up to seven quarters ahead are computed for all endogenous variables using draws from the distribution assumed for disturbances. Each forecast is computed on a

[3] Note that Litterman (1986), pp. 27–28, suggests using the maximum number of lags feasible. We take another approach here and use the marginal data density to determine the number of lags. Anyway, five lags could be viewed as the maximum number feasible given the short data sample.

[4] For the application of predictive densities for stress tests we use a sample of 50,000 draws.

period-by-period basis. The draws that lead to a nonpositive nominal interest rate are changed such that zero is imposed on the negative part of the interest rate forecast. The simulated predictive density is then described by the percentiles of the distribution constituted by the forecasts and is denoted as a fan chart.

Basically, there are three possible approaches to dealing with the zero lower bound on the nominal interest rate when constructing density forecasts. The first is to discard the whole path forecast of it reaches a negative value in any period over the forecasting horizon. The second possibility is to discard only the part of the path forecast that is below zero. In that case, the negative part of the path forecast can be either changed to zero or just discarded.

If only the negative part of the interest rate path forecast is discarded, then correspondingly more probability is assigned to forecasts reflecting the model parameters (coefficients and shocks) that do not push the interest rate below zero. So, for example, fixing the draw of the vector of coefficients α, let's consider two cases – the interest rate is close to zero and the interest rate is far from the zero lower bound. Then, given the same shocks to other endogenous variables, the probability of a positive shock to the interest rate is higher in the first case. This is not reasonable, as a central bank would not be more likely to unexpectedly tighten monetary policy when the economy is approaching the zero lower bound on the interest rate than when it is far from it.

Next, if the whole path forecast is discarded, then less probability is assigned to paths that lead in the future to negative values of the interest rate. This is not reasonable either, since our prior belief is that the interest rate follows a process close to a random walk.

The problem of choosing an appropriate approach to deal with the zero lower bound can also be formulated in terms of the distribution of disturbances of the model (1). We started with the assumption of independent and identically normally distributed disturbances. Discarding the whole path forecast if it reaches negative interest rate values in any period implies disturbances to the interest rate that are not i.i.d. and, moreover, are not necessarily normally distributed. Next, discarding just the negative part of the interest rate path forecast leads to a truncated normal distribution. Finally, imposing zero on the part of the interest rate path forecast that is negative implies a censored normal distribution for disturbances. We see the last possibility as the most realistic one for modeling the time series involved in our analysis.

Finally, note that the problem of how to deal with the zero lower bound is relevant for a few periods only, when the ratio of discarded/changed paths is high. For the majority of forecasting periods the ratio is less than 0.05. Only for forecasting starting in 2009Q2–2010Q2 does the ratio exceed 0.3, and for some periods even 0.9.

Figures 1–4 provide an example of the BVAR fan charts for different periods. The data are available since 1998Q1[5] and the periods differ in terms of the ending quarter of the sample included in the estimation. Figure 1 shows the BVAR fan charts based on the full sample, while Figure 2 is based on the estimation sample ending in 2009Q4, Figure 3 on that ending in 2008Q4 and Figure 4 on that ending in 2007Q4. The red vertical line denotes the period of the last observed value used for the estimation. The predictive density is characterized by the centered 95%, centered 68% and median of the marginalized joint distribution.

[5] Given our focus of forecasts, the series are displayed from 2006Q1 onwards.

The BVAR fan charts cover the past three years, i.e., the period before and during the recent financial and economic crisis and also the most recent period. For example, Figure 4 shows the fan charts based on the data for 1998Q1–2007Q4 and the time series observed during the recent economic crisis. The BVAR fan charts do not capture the unprecedented fall in economic activity during 2008. This is not surprising given that the economic crisis transmitted to the Czech Republic through shocks to foreign demand. The limitation implied by the zero lower bound on the nominal interest rate can be observed in Figure 2.

Figure 1: BVAR Fan Charts Starting in 2011Q1

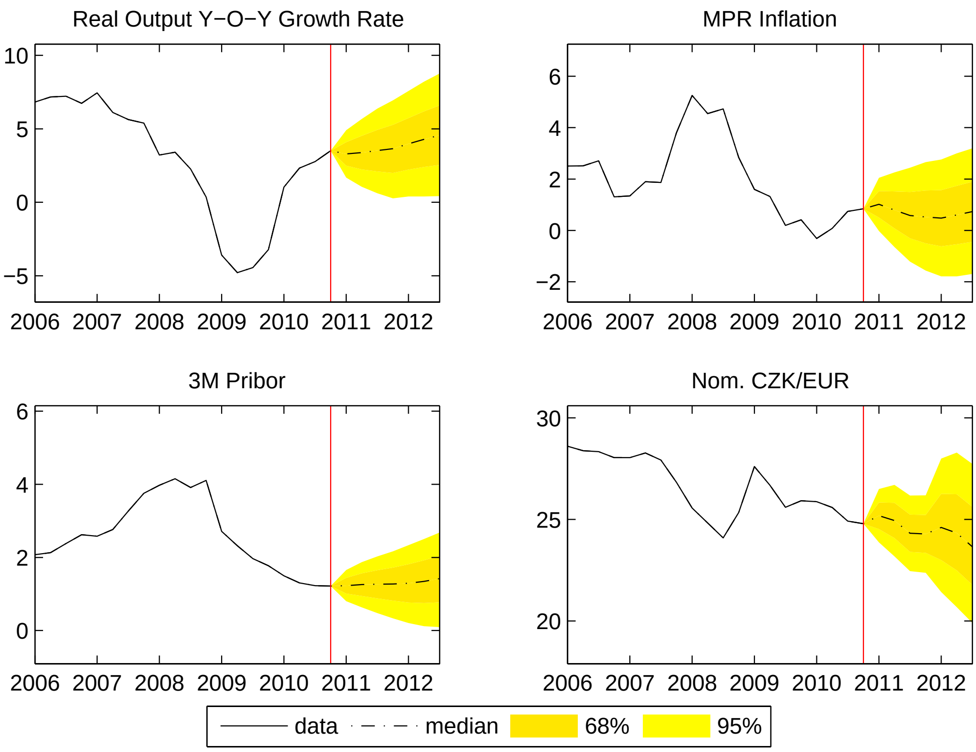


Figure 2: BVAR Fan Charts Starting in 2010Q1

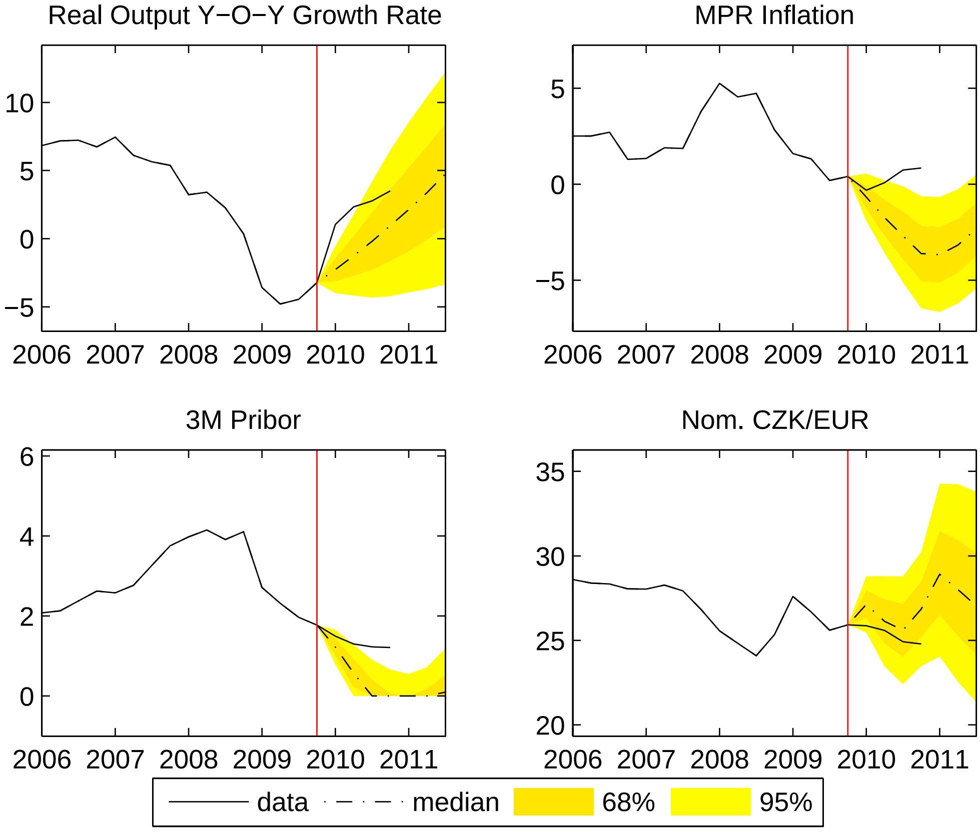


Figure 3: BVAR Fan Charts Starting in 2009Q1

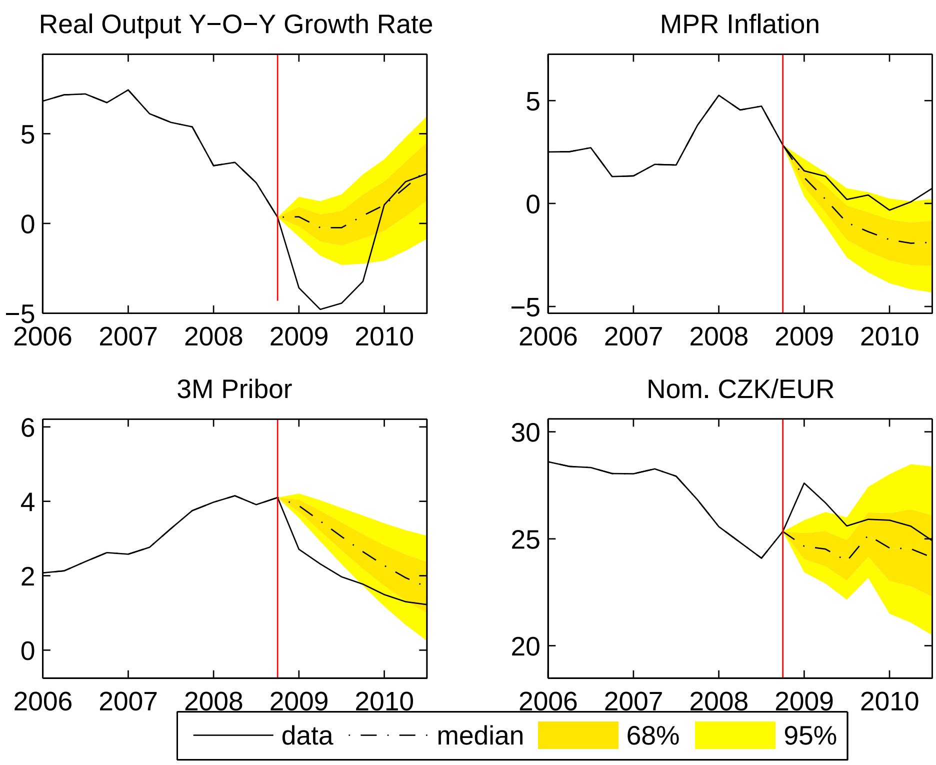
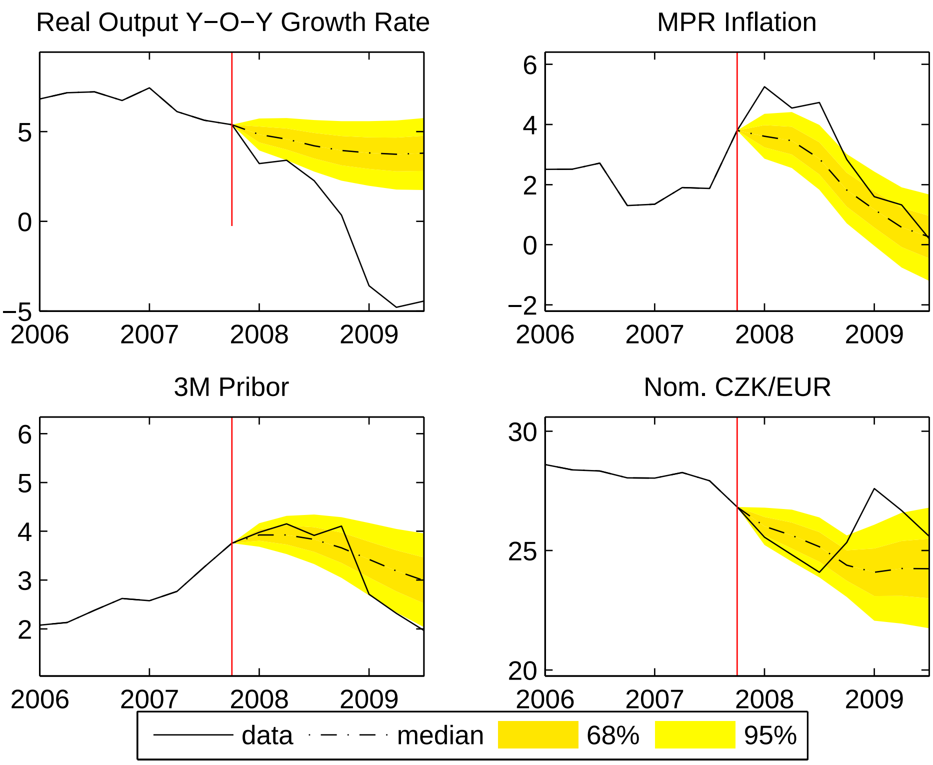


Figure 4: BVAR Fan Charts Starting in 2008Q1



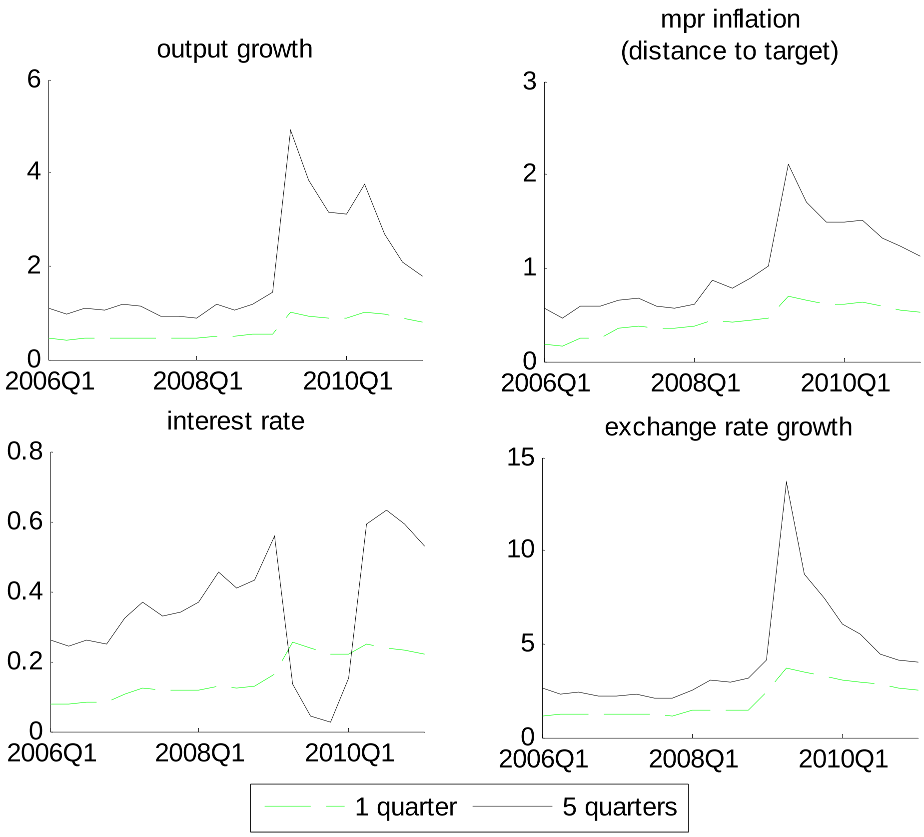
The examples of BVAR fan charts above suggest that the uncertainty relating to the forecasts is changing over time. Figure 5 reports the standard deviation of the BVAR fan charts for the horizons of one and five quarters. The zero lower bound on the interest rate accounts for the decrease in the standard deviation of the nominal interest rate at the end of 2009. In general, uncertainty is especially high for the BVAR fan charts starting in 2010Q1 and 2008Q1. While in 2010Q1 the uncertainty arises from uncertainty about future shocks, the uncertainty regarding the coefficients of the model is important for the BVAR fan charts starting in 2008Q1.[6] The observed change in uncertainty opens a discussion on the use of a model with time-varying volatility (e.g. Cogley et al., 2005). However, the "updating" of shock variance can be very slow, so the use of a model with changing volatility does not necessarily represent an improvement for the Czech case. Also, the number of coefficients to estimate would increase significantly in the case of a model with time-varying parameters.

In addition, the selected BVAR fan charts are not symmetric. Considerable positive skewness can be observed for the interest rate in the fan chart starting in 2010Q1. This skewness is a consequence of imposing zero for the interest rate forecasts, which may in principle reach negative values. The model itself is linear and Gaussian and thus produces symmetric density forecasts.

[6] The uncertainty relating to future shocks is measured by the variance matrix of the BVAR model, while the uncertainty relating to the coefficients is reflected in the standard deviations of their estimates. The detailed results are available upon request.

The presented figures and discussion on the basic properties of the BVAR fan charts represent an informal analysis only. Formal statistical testing involves density tests of whether the observed time series are drawn from the simulated distribution (see Elder, 2005, and Diebold et al., 1999). However, the small sample of data implies low power of the tests. The small-sample problem is exacerbated by the fact that for longer forecasting horizons even fewer observations are available. Therefore, formal statistical density tests are not carried out.

Figure 5: Standard Deviation of Fan Charts at Horizons of 1 and 5 Quarters



Note: The horizontal axes indicate the period in which forecasting starts.

One of the practical issues which we encounter and which is usual in macroeconomic forecasting is the timing of data releases. In our case the problem concerns output growth, which is published with a lag of one quarter in comparison with the other endogenous variables. To estimate the model based on the most recent quarter we use the estimate of output growth for 2010Q4 as used by the core CNB forecasting model.

The situation is slightly complicated when we want to compare the BVAR fan charts with those of the CNB. Two issues are worth emphasizing. First, the comparison is based on fan charts estimated on data sets that may differ. Specifically, the CNB fan charts use real-time GDP data at the time of release of the fan charts. On the other hand, our BVAR fan charts use the most recent data, i.e., all up-to-date revisions. However, the BVAR and CNB fan charts are based on the same data set for the forecasts starting in 2011Q1. Second, to reflect the one-quarter lag of the output growth release, for the BVAR fan charts the most recent data on output growth is estimated using the same BVAR model. So, we forecast output growth one quarter ahead using BVAR to obtain all the data for a particular quarter.

Figures 6–9 show a graphical comparison of the BVAR and CNB fan charts for the forecasts starting in 2011Q1, 2010Q1, 2009Q1, and 2008Q1, respectively. Note that the CNB fan charts are available since 2008Q1 (for the exchange rate since 2009Q1). First, the BVAR fan charts suggest less uncertainty in general than those used by the CNB for the full sample estimation (Figure 6). The reason is that the CNB fan charts reflect past forecast errors, which attained high values during the recent crisis and are therefore reflected in the uncertainty in the fan charts constructed after the crisis. Second, the CNB fan charts based on the CNB core forecasting model and extensive expert judgment seem to capture the observed outcomes better than the BVAR fan charts. This is not surprising since the BVAR fan charts were equipped with much less expert knowledge. The only expert judgment incorporated into the BVAR fan charts so far is the zero lower bound for the nominal interest rate. In Section 5.3 additional ways of incorporating expert judgment are discussed. Finally, looking at the medians of the fan charts for longer forecasting horizons there are cases where the BVAR fan charts seems to predict better than the CNB fan charts (e.g. the forecast of inflation starting in 2008Q1).

Figure 6: Comparison of BVAR and CNB Fan Charts, Forecasting Starts in 2011Q1

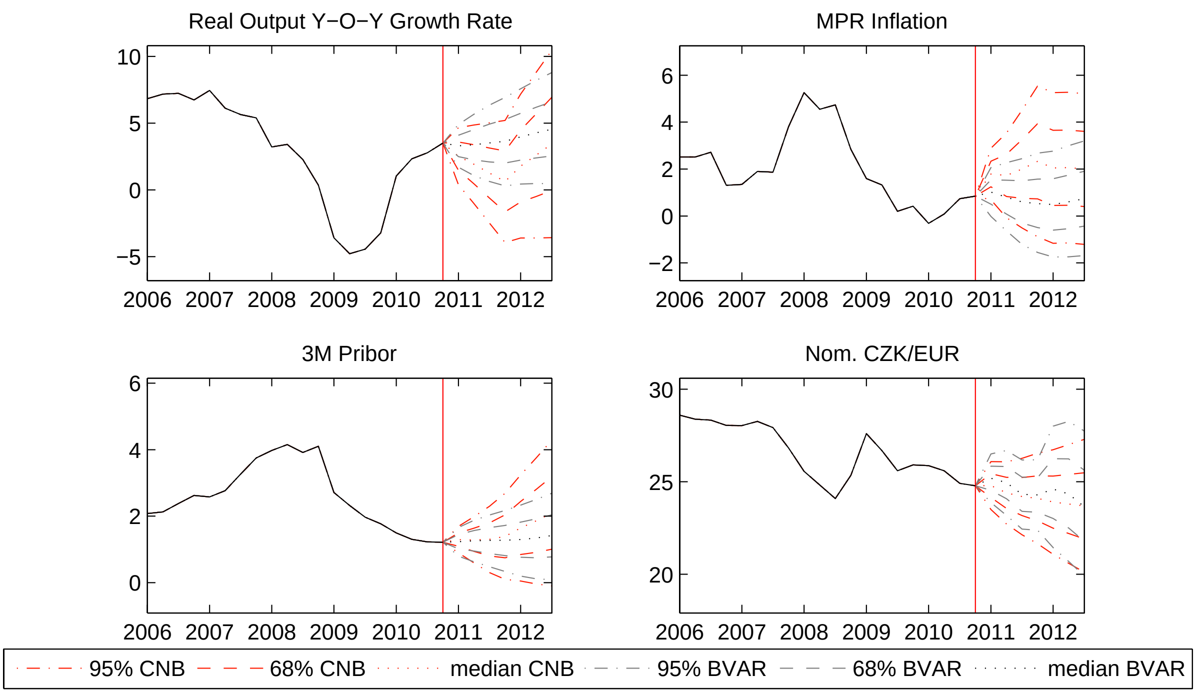


Figure 7: Comparison of BVAR and CNB Fan Charts, Forecasting Starts in 2010Q1

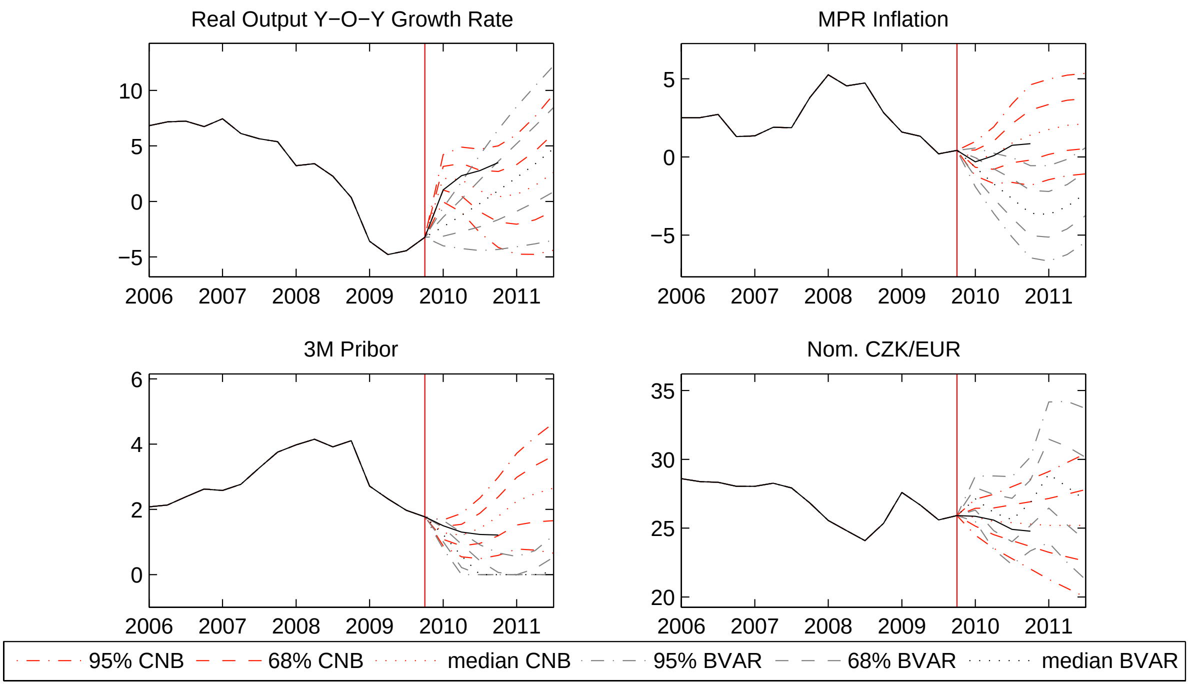


Figure 8: Comparison of BVAR and CNB Fan Charts, Forecasting Starts in 2009Q1

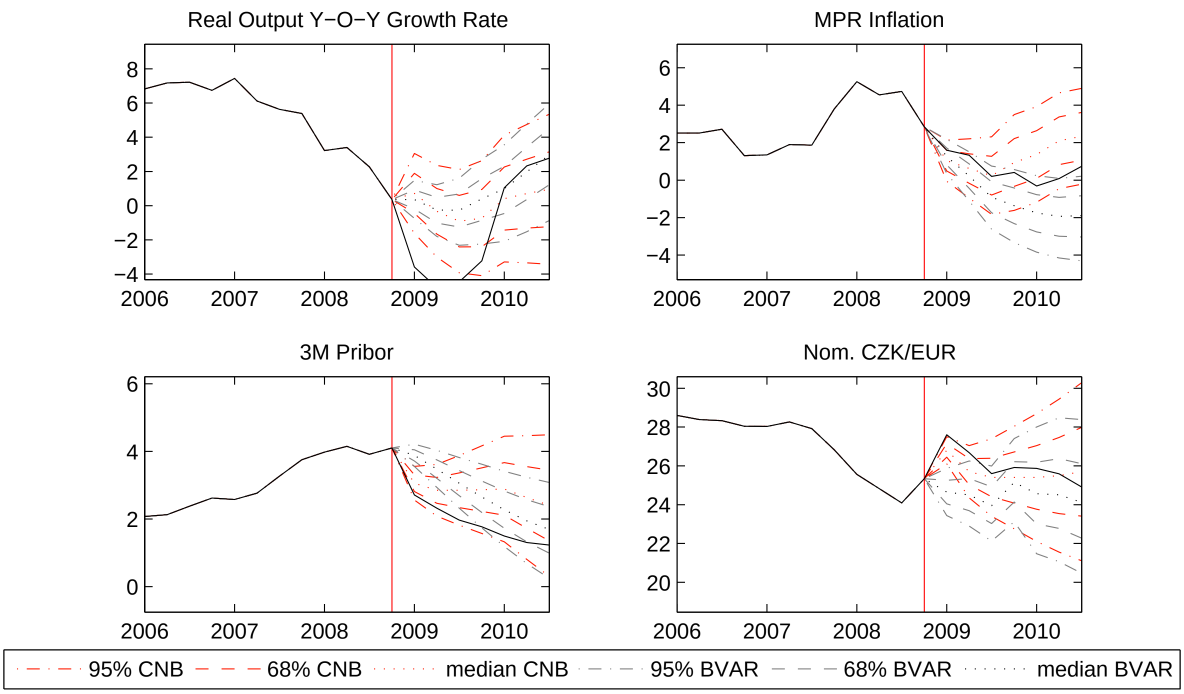
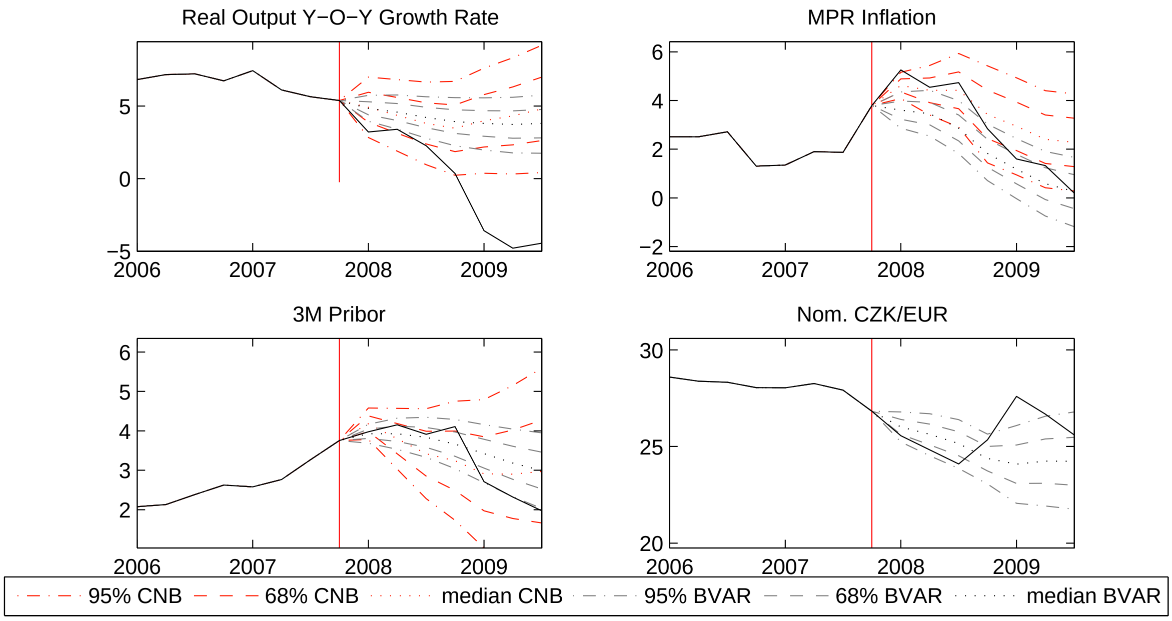


Figure 9: Comparison of BVAR and CNB Fan Charts, Forecasting Starts in 2008Q1



The formal comparison of the CNB and BVAR fan charts is based on the Kullback-Leibler Information Criterion (KLIC) (Mitchell and Hall, 2005). The advantage of the approach based on the KLIC is that one does not need to know the predictive density of the true model.

Following Kascha and Ravazzolo (2008), the $\mathrm{KLIC}^{x}_{i,h}$ distance for model i at the forecasting horizon h and for an endogenous variable x is defined as follows:

$$\mathrm{KLIC}^{x}_{i,h} \equiv \int f_{t+h,t}\left(x_{t+h}\right) \ln \frac{f_{t+h}\left(x_{t+h}\right)}{f_{t+h,t,i}\left(x_{t+h}\right)} dx_{t+h} = E\left[\ln f_{t+h,t}\left(x_{t+h}\right) - \ln f_{t+h,t,i}\left(x_{t+h}\right)\right], \tag{3}$$

where $f_{t+h,t}$ denotes the predictive density of the true model in period t for forecasting horizon h, and $f_{t+h,t,i}$ represents the predictive densities relating to model i, $i=1,2$. The densities are assumed to be strictly positive. Basically, the KLIC is a weighted average of the true density values, with the weights being equal to the distance between the logs of the true and model-based density values, i.e., the bigger the difference between the true and estimated predictive densities, the greater the weight. The formula in (3) implies that to compare the KLIC for two models it is enough the compare the expected logarithmic score:

$$\mathrm{ElnS}^{x}_{i,h} \equiv E\left[\ln f_{t+h,t,i}\left(x_{t+h}\right)\right]. \tag{4}$$

Minimization of the KLIC over the models is then equivalent to maximization of the expected logarithmic score. To estimate the expected logarithmic score, the average sample information is taken:

$$\frac{1}{N}\sum_{t\in A}\ln f_{t+h,t,i}\left(\overline{x}_{t+h}\right). \tag{5}$$

So, the average log of the density for a realization of the endogenous variable, $\overline{x}_{t+h}$, is taken for all available periods. All available periods constitute the set *A* and the size of the set is *N*. So, for example, for a forecasting horizon of 4 quarters the expected logarithmic score involves density forecasts starting in 2008Q1, when the CNB fan charts started to be published, and ending in 2010Q1.

A systematic comparison of the BVAR and CNB fan charts is provided in Table 2. The table suggests that in the short run (up to a year) the CNB fan charts are, in terms of the KLIC, closer to the true densities. For longer horizons and for some endogenous variables (inflation and output growth) the BVAR fan charts sometimes outperform the CNB fan charts in terms of the KLIC. Such a result is not so surprising, as the expert knowledge that is included in the CNB fan charts does not affect the CNB forecasts at longer horizons. Note that GDP revisions should affect the comparison in the direction of worse performance of the CNB fan charts.

Table 2: Average Logarithmic Score for BVAR and CNB Fan Charts

Horizon (QTRs)	1		2		3		4	
	BVAR	CNB	BVAR	CNB	BVAR	CNB	BVAR	CNB
Output growth	-7.92	-4.71	-6.64	-5.13	-6.92	-5.64	-6.86	-6.52
MPR inflation	-8.25	-4.27	-6.43	-4.05	-6.42	-3.72	-5.90	-3.88
Interest rate	-4.98	-4.89	-5.99	-3.95	-6.58	-3.81	-6.48	-3.75
Exchange rate	-10.88	-6.47	-10.86	-6.47	-10.81	-6.62	-10.75	-7.02

Horizon (QTRs)	5		6		7	
	BVAR	CNB	BVAR	CNB	BVAR	CNB
Output growth	-5.99	-7.54	-5.30	-6.94	-5.08	-6.01
MPR inflation	-5.24	-4.19	-4.43	-4.59	-3.67	-5.07
Interest rate	-5.91	-3.82	-5.11	-3.87	-4.36	-3.93
Exchange rate	-11.51	-7.47	-	-	-	-

Note: The average logarithmic score for the exchange rate computed since 2009Q1. The average logarithmic score is not reported for the exchange rate at the horizons of 6 and 7 quarters because only a few observations are available.

Note that the formal comparison based on the KLIC has to be taken with caution because the CNB has been publishing its fan charts for only 4 years so far, and so not many observations are available for the comparison. Moreover, the difference in the KLIC should be tested statistically (see, for example, Billio et al., 2010). Still, the low number of observations for particular variables and forecasting horizons weakens the power of the tests and so the test is not carried out here.

5. Three Applications: CNB-BVAR Combined Fan Charts, Fan Charts in Stress Testing of the Banking Sector, and Incorporating Expert Judgment

In this section, three applications of BVAR fan charts directly related to regular tasks of the CNB are discussed. The first application deals with the CNB fan charts. We discuss the possibility of combining the CNB fan charts with BVAR fan charts, which could increase the robustness of communication in some circumstances. Second, we show how the distribution of predictive densities can serve as a basis for assessing the probability of the various macroeconomic scenarios used by the CNB for stress testing of the financial sector. Third, we discuss an example of how to incorporate expert judgment into BVAR fan charts.

5.1 CNB-BVAR Combined Fan Charts

Regarding the first application, Kascha and Ravazzolo (2008) provide a detailed discussion on the approaches to combining density forecasts. Our aim is just to illustrate the possibility of such combination and so the simplest setup is chosen. We combine the two fan charts linearly with equal weights:

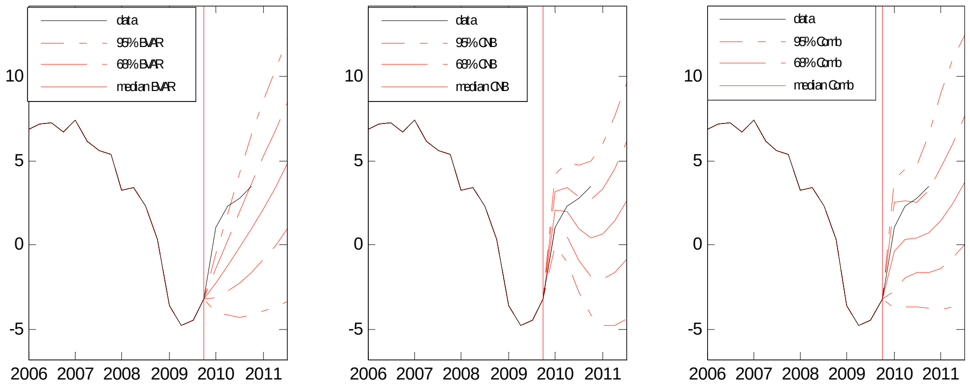
$$f_{t+h,t}^{Comb}(x_{t+h}) = \frac{1}{2} f_{t+h,t}^{BVAR}(x_{t+h}) + \frac{1}{2} f_{t+h,t}^{CNB}(x_{t+h}), \tag{6}$$

where $f_{t+h,t}^{BVAR}$, $f_{t+h,t}^{CNB}$, and $f_{t+h,t}^{Comb}$ are density forecasts at forecasting horizon h relating to the BVAR model, the CNB fan charts, and the combination of the two, respectively. Hendry and Clements (2004) show that the use of deterministic weights implies that the combination of densities is (in terms of the KLIC) never worse than the worst individual density. So, linear combination with equal weights represents a safe way to minimize large errors.[7]

Figure 10 shows the two types of fan charts and their combination. The presented fan charts are for output growth and capture the forecasting period starting in 2010Q1. The figure demonstrates that even though one model produces a fan chart that does not cover the observed output growth even for the centered 95% of the distribution, the combination of the two fan charts performs better. Combining fan charts can be a safe technique when the uncertainty is communicated with the public. Multiple models generating fan charts can help to avoid situations in which one model clearly fails.

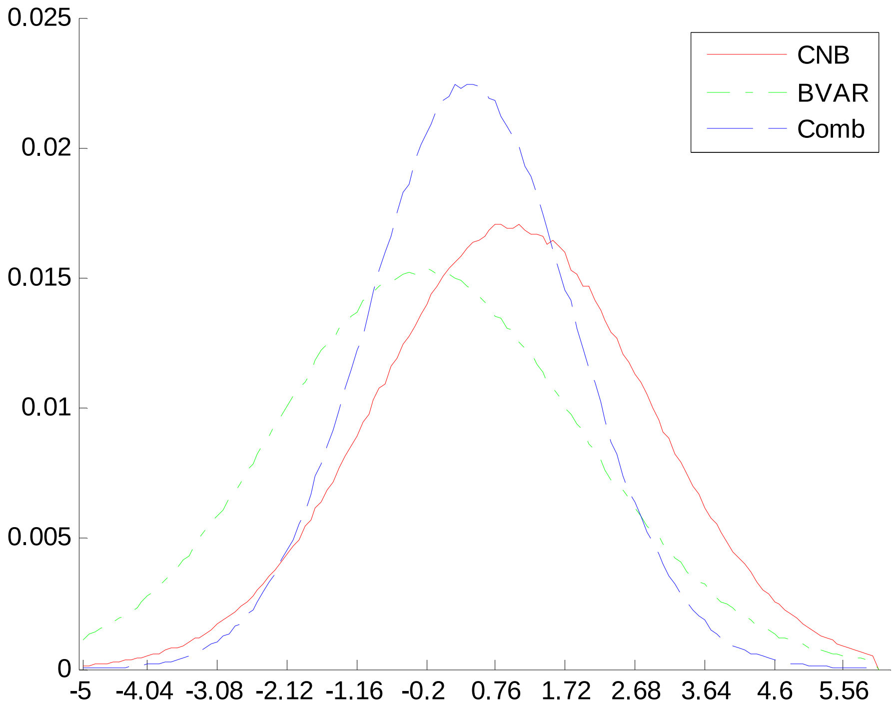
[7] On the other hand, linear combination of fan charts can produce a multimodal distribution. To avoid this, logarithmic combination could be used.

Figure 10: The Combination of the CNB Fan Chart and the BVAR Fan Chart for Output Growth



As an illustration we also present in Figure 11 the three simulated densities for output growth at the forecasting horizon of 3 quarters.

Figure 11: Example of Simulated Densities for Output Growth Forecasted at a Horizon of 3 Quarters for the Forecasts Starting in 2010Q1



5.2 BVAR Fan Charts and Stress Tests of the Banking Sector

In the second application, we assess the usefulness of BVAR fan charts for evaluating selected aspects of the credibility of financial stability stress tests. The current financial crisis has reminded us of the important role that banks play in the economy. The stability of banks is regularly evaluated by many central banks, international organizations as well as the private sector. The stress-test scenarios need to be sufficiently adverse to provide a real test of banking sector stability (Goodhart, 2006, Alfaro and Drehmann, 2009, or Borio and Drehmann, 2009). On top of that, it has been put forward that a proper analytical framework needs "to assess the probability, virulence and speed of occurrence of potential shocks" (Goodhart, 2006). We take a step in this direction and illustrate how the probability of a macroeconomic stress-test scenario can be evaluated by BVAR fan charts. We draw on the fact that fan charts can be interpreted as density of path forecasts. Therefore, any particular forecasted path can be assessed in terms of the percentiles of the simulated density. A related stream of literature proposes a formal evaluation of the severity of stress tests based on risk factor distribution (Breuer et al., 2009, or Breuer et al., 2011).

Alternative scenarios of the macroeconomic outlook serve as an input into the CNB's financial sector stress-test framework.[8] All four endogenous variables of the BVAR model are included in the stress-test scenarios. We take the first 7 quarters of the macroeconomic scenarios so that they are comparable with our BVAR fan charts (the scenarios are presented for a slightly longer horizon of 8 quarters).

The problem of assessing the probability of a macroeconomic scenario can be divided into two parts. First, the scenario need not necessarily be fully consistent with the correlations captured by the BVAR model. Therefore, from the set of all forecasted (model-consistent) paths, we take the path which is the minimum distance from the scenario. Second, the probability assessment of this "nearest" path forecast can be done in several ways. We present the probabilities for each forecasting horizon and variable separately and discuss the probabilities of the scenarios based on the joint density of path forecasts.

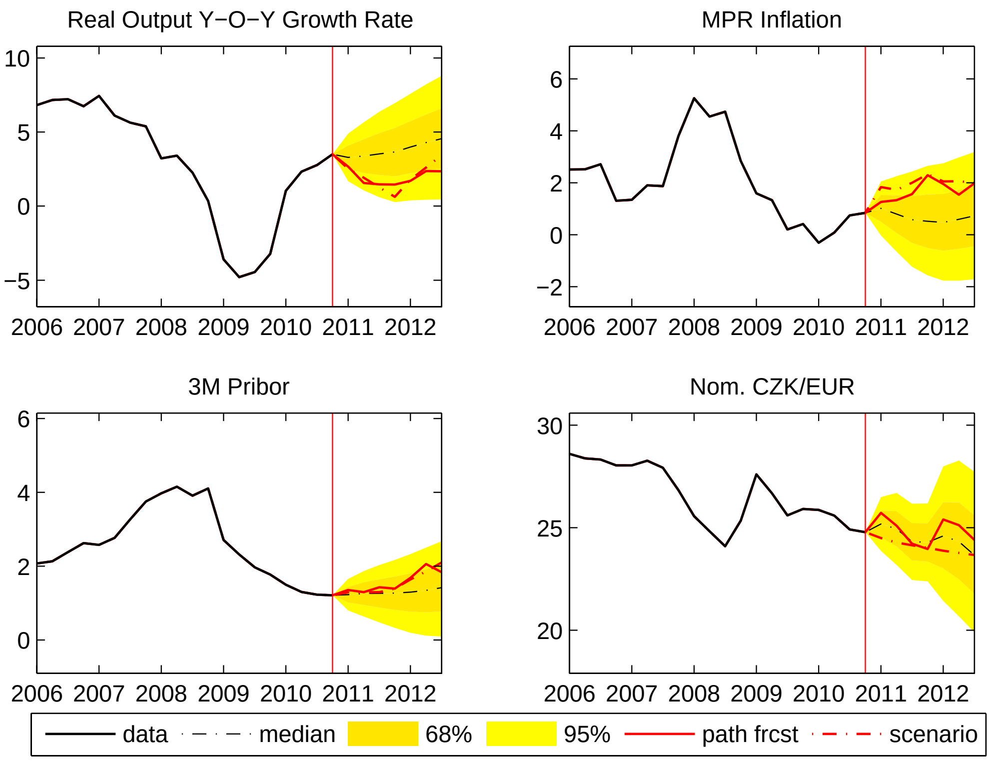
The construction of the minimum-distance path forecast follows Fry and Pagan (2005), who conducted a similar exercise for the distance between the set of impulse responses identified by sign restrictions and their median. First, the set of path forecasts generated by the BVAR model is normalized to be unit-free, i.e., for each endogenous variable and forecasting horizon the values of the scenario are subtracted and the result is divided by the standard error of the forecasted paths. Then the forecasted path characterized by the lowest normalized distance over the whole forecasting horizon and over all four endogenous variables is drawn.

Figures 12 and 13 present the BVAR fan charts, the two stress-test scenarios and the minimum-distance path forecast. We assess the two macroeconomic scenarios from the CNB's stress test of February 2011. First, the baseline scenario corresponds to the CNB's macroeconomic outlook. Second, the "Unexpected Recession" scenario is characterized by a significant drop in economic

[8] The macroeconomic scenarios of the financial sector stress tests can be found at http://www.cnb.cz/en/financial_stability/stress_testing/index.html.

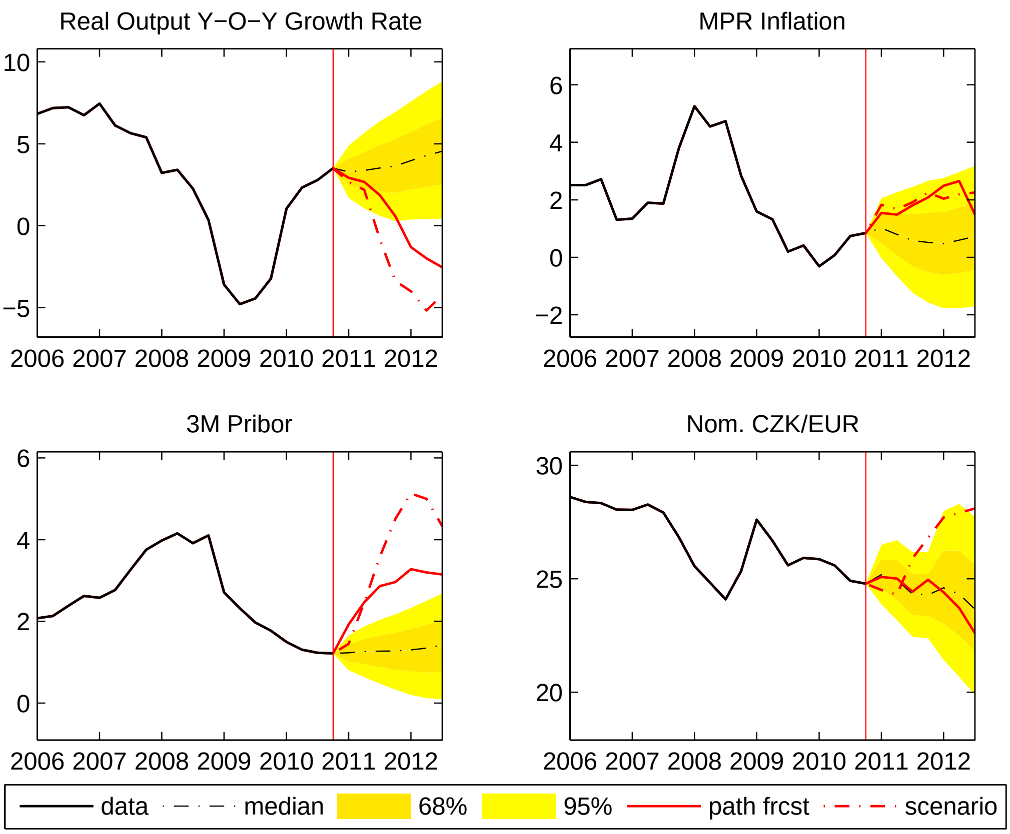
activity in 2011H2 caused by an external shock, exchange rate depreciation, and, in reaction to inflation pressures, a marked increase in the monetary policy rate reflected in a rise of short-term interest rates. Both scenarios are based on the data set to 2010Q4 and thus we use the BVAR model with the first forecasting period 2011Q1.

Figure 12: The Baseline Scenario and the Minimum-Distance Path Forecast



While Figure 12 demonstrates that the baseline scenario corresponds to the BVAR model, since it fits in the 95% interval, Figure 13 suggests that the alternative, "Unexpected Recession" scenario indeed represents an extreme stress for the financial sector. The "nearest" path forecast lies far from this scenario (especially for the 3M PRIBOR and output growth), which does not seem to be consistent with the model and the estimated shock variances. Even the unlikely situation of a misspecified BVAR model and an unprecedented set of shocks (given our data sample) that is consistent with the forecasting density (i.e., a path forecast consistent with a very low posterior probability of the parameter vector and the set of draws from the error variance matrix with low probability) does not yield a path forecast close to the scenario. Therefore, the "Unexpected Recession" scenario is likely to represent a sufficiently adverse scenario. The plausibility of the scenario, however, could be questioned. The exchange rate path, for example, does not seem to be consistent with the paths for the other variables.

Figure 13: The "Unexpected Recession" Scenario and the Minimum-Distance Path Forecast



Figures 12 and 13 are accompanied by Table 3, which reports the value of the marginalized distribution (the particular horizon and variable) at the value of the path forecast that is the minimum distance from the respective scenario. These marginalized distributions suggest the probabilities of the scenarios. The probabilistic assessment of the scenarios stated in terms of a simultaneous outlook for several variables has to be based on the joint forecasting density. Note that the set of path forecasts constitutes a sample from the joint distribution over all variables and forecasting horizons. The various marginalized versions can be computed easily. For example, the probability that the path forecast of output growth *and* inflation is below the path forecast at the minimum distance from the baseline for the first two quarters is 0.19. The probability of being above is 0.02.[9]

[9] In such a way, we can assess the probabilities of all possible combinations of horizons and variables. The low probability of both path forecasts being either above or below the baseline from the example is due to the high uncertainty of the future development reflected in the high shock variance estimates. There is, therefore, a high probability of the path forecast switching from below to above the baseline (and vice versa).

Table 3: Marginalized Distribution of Path Forecasts

	Baseline stress-test scenario				"Unexpected Recession" scenario			
Horizon	Output growth	MPR inflation	Interest rate	Exchange rate	Output growth	MPR inflation	Interest rate	Exchange rate
1	0.15	0.87	0.48	0.56	0.27	0.83	0.86	0.99
2	0.32	0.84	0.83	0.33	0.16	0.92	1.00	1.00
3	0.20	0.91	0.62	0.33	0.04	0.98	1.00	0.98
4	0.12	0.86	0.66	0.23	0.06	1.00	1.00	0.93
5	0.31	0.86	0.83	0.35	0.02	1.00	1.00	0.46
6	0.18	0.74	0.91	0.70	0.02	0.98	1.00	0.32
7	0.22	0.91	0.88	0.66	0.00	0.94	1.00	0.37

Note: The table shows the probability that the forecasted variable is below the stress-test scenario path, approximated by the "nearest" BVAR path forecast. For example, in the baseline scenario, this probability for output growth is 11% for Q1.

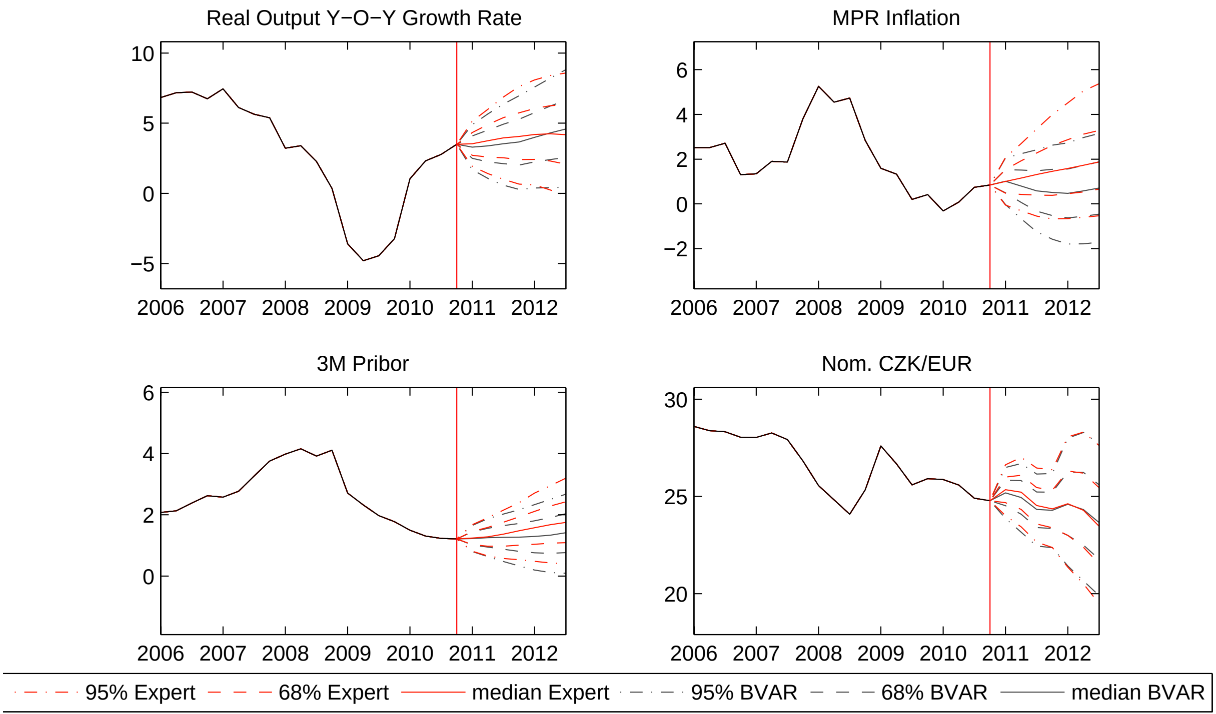
5.3. Incorporating Expert Judgment into BVAR Fan Charts

The last application of BVAR fan charts incorporates expert judgment into the forecasts. Judgment can generally be any "information, knowledge and views outside the scope of a particular model" (Svensson and Williams, 2005). Since the BVAR model is purely backward looking, its forecasts do not account for expectations or known events, i.e., decisions on cuts in value-added tax or expected appreciation of the exchange rate. If this information is available to a forecaster, it may be useful to incorporate it into the BVAR forecasts. So far, the only judgment imposed in this paper is a non-negativity constraint on the nominal interest rate.

There are several ways of incorporating judgment into the density forecasts. From the economic point of view, one can either impose a condition on the forecasted variables and let the model find suitable innovations, or directly impose conditions on innovations. From another perspective, one can impose either a concrete value for a variable (hard conditioning) or a non-empty set of values (soft conditioning) – see Waggoner and Zha (1999). Another branch of approaches imposes moment conditions on predictive densities instead of particular values (see Robertson et al., 2005).

In our application, we assume a scenario in which the inflation mean will attain the value of the inflation target (2%) at the horizon of monetary policy (the 7th forecasted quarter). To incorporate judgment into the BVAR fan charts, we follow the methodology of Cogley et al. (2005) and Robertson et al. (2005). The basic idea of how to generate the predictive density associated with our scenario is to take a random sample from the BVAR predictive density and to transform it into a random sample from another predictive density that contains outside information. Cogley et al. (2005) suggest finding the transformed distribution by finding the new probability weights for the BVAR random sample. This can be done by minimizing the KLIC distance (Eq. 3) between the BVAR density forecast and the new transformed density, given the constraint imposed on the mean of inflation. Using the new weights obtained from the minimization problem, we are able to resample the original BVAR distribution into a new one associated with the scenario using the multinomial re-sampling algorithm of Gordon et al. (1993). The technical details of the procedure can be found in the above references. In this simple case, the probability weights that minimize the KLIC distance of the two density forecasts for inflation can be applied to other variables, because the implied transformation of the density forecasts for other variables is still minimal in terms of the KLIC.[10]

Figure 14: BVAR Fan Charts Incorporating Expert Judgment: Imposing the Inflation Target



The results are available in Figure 14. Clearly, the fan chart for inflation heads toward the inflation target, which is attained at the end of the forecasting horizon. The change in the fan charts for other variables is negligible. This is because the uncertainty for the fan charts starting in 2011Q1 is driven mainly by the high estimate of the shock variance and the role of the estimated cross correlations is minimal.

This example shows how the flexibility of the BVAR methodology can be increased. Incorporating expert judgment also makes it more in line with how forecasting is carried out in practice. Central banks typically generate forecasts as a combination of a model-based approach and expert judgment. In this respect, Svensson and Tetlow (2005) suggest that such an approach typically yields superior outcomes.

[10] Note that Cogley et al. (2005) focus solely on the inflation predictive density and do not discuss the implications of the imposed moment restriction for the other variables included in their model.

6. Conclusions

Fan charts have become important communication tools for inflation-targeting central banks around the world. According to our survey, about three quarters of inflation targeters publish fan charts for inflation and some publish them for other important macroeconomic variables. The recent financial crisis increased the importance of assessing and communicating forecast uncertainty well. While the fan charts used by inflation-targeting central banks for this purpose are mostly based on past forecast errors and subjective assessment of risk scenarios, alternative methodologies have been put forward, too. We find it useful to cross-check the currently employed methodology with an alternative offered by the BVAR approach.

We carry out a comprehensive analysis of the usefulness of BVAR fan charts for central banks and examine two main questions: 1) Can BVAR fan charts outperform the official fan charts? 2) Can BVAR fan charts help assess the resilience of the financial sector through regular stress tests? We use the Czech data for this exercise, but the methods as well as the findings are applicable to any other inflation-targeting central bank. The choice of the Czech data is motivated by the transparency of the Czech central bank, which publishes fan charts for inflation, GDP growth, the interest rate, and the exchange rate. This allows us to investigate fan charts for more macroeconomic variables than if we use fan charts from different central banks. In addition, a detailed description of the stress-test scenarios is publicly available and the severity of these scenarios can therefore be evaluated.

As concerns the first question, we examine whether BVAR fan charts can outperform the official fan charts produced by the CNB, which are based on past forecasting errors. Our results suggest that in terms of the Kullback-Leibler Information Criterion BVAR fan charts do not improve the accuracy of CNB fan charts for shorter horizons up to a year ahead. In our opinion, this is not so surprising, since the CNB forecasting errors are reduced by augmenting the model-based forecast with expert judgment, so the small-scale BVAR cannot compete unless expert judgment is incorporated on a much larger scale. For longer horizons, the BVAR fan charts sometimes outperform the CNB fan charts. This result reflects, at least to a certain extent, the fact that the BVAR fan charts are based on revised data while the CNB fan charts are constructed in real time.

Our paper also discusses the benefits and costs of combining BVAR fan charts with official fan charts. We show that combining the fan charts reduces the risk of large errors. In addition, we show how expert judgment can be incorporated into fan charts using the method of Robertson et al. (2005). The incorporation of expert judgment can further increase the flexibility of BVAR fan charts.

As concerns the usefulness of BVAR fan charts for assessing financial stability, we contribute to the literature putting forward that the scenarios in stress tests need to be sufficiently adverse in order not to give a false signal of safety (Borio and Drehmann, 2009). It is noteworthy that the scenarios are typically based on the expert judgment of a group of financial stability experts interacting with the board members. Using our BVAR fan charts, we propose a simple method based on the minimum-distance path forecast which allows the severity of expert judgment-based scenarios to be assessed. As a consequence, this analysis may shed light on the credibility of any stress tests in general.

All in all, our results suggest that BVAR fan charts not only are helpful for evaluating the forecast accuracy of the fan charts employed in central banks, but may also contribute to a more formal assessment of the severity of financial stability stress tests.

In terms of future research, two possible routes can be taken to extend the presented research. The first possibility is to improve the BVAR model itself. A model that better captures the dynamics of the data should provide better fan charts in terms of both higher accuracy and lower uncertainty. The improvement of the BVAR model involves, for example, imposing an informative prior on the deterministic part of the VAR model specification (Villani, 2009) and extending the VAR to include additional endogenous and exogenous variables.

Second, instead of focusing on the BVAR model, attention could be directed at fan charts themselves. Improvement of the fan charts could be based on the incorporation of outside information directly into the fan charts. The conditional forecast of an endogenous variable can be constructed in such a way as to attain a particular value at some horizon or a set of values (Waggoner and Zha, 1999). Such an approach is thoroughly discussed for fan charts in Osterholm (2009). Another possibility is to prescribe moment conditions for the predictive density (Robertson et al., 2005). Such outside information can be taken from central banks' core forecasting models or from experts' judgments. The approaches for incorporating outside information are currently being discussed intensively. For a recent contribution see, for example, Andersson et al. (2010).

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Appendix

Appendix A: Marginal Data Density for a BVAR with the Minnesota Prior[11]

We work with the following system of equations described in the main text:

$$y_t = C + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t$$
$$\varepsilon_t \sim N(0, \Sigma) .$$

The system can be rewritten as follows:

$$Y = X\beta + \mathrm{E}$$
$$\mathrm{E} \sim N\left(0, \Sigma \otimes I_T\right)$$

where $Y \equiv vec\left([y_1,...,y_T]'\right)$, $x_t \equiv [1, y'_{t-1},..., y'_{t-p}]'$, $x \equiv [x_1,...,x_T]'$, $X \equiv I_M \otimes x$, $\varepsilon \equiv [\varepsilon_1,...,\varepsilon_T]'$, $\mathrm{E} \equiv vec\left(\varepsilon\right)$, $\alpha \equiv vec\left([C, B_1,..., B_p]\right)$.

Prior density: $\alpha \sim N\left(\alpha^{PR}, V^{PR}\right)$ i.e.,

$$p(\alpha) = \left(2\pi\right)^{-\frac{1}{2}M(Mp+1)} \left|V^{PR}\right|^{-\frac{1}{2}} e^{-\frac{1}{2}\left(\alpha-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha-\alpha^{PR}\right)}$$

Given the distribution of innovations E, the likelihood can be expressed as:

$$p(Y \mid \alpha) = \left(2\pi\right)^{-\frac{1}{2}MT} \left|\Sigma\right|^{-\frac{1}{2}T} e^{-\frac{1}{2}\left(Y-X\alpha\right)'\left(\Sigma\otimes I_T\right)^{-1}\left(Y-X\alpha\right)}$$

[11] The derivation of the marginal data density for the more general case of conjugate priors can be found in Giannone et al. (2010).

Un-normalized posterior:

$$p(\alpha \mid Y) = (2\pi)^{-\frac{1}{2}M(Mp+T+1)} \left|V^{PR}\right|^{-\frac{1}{2}} |\Sigma|^{-\frac{T}{2}} \cdot$$
$$\cdot e^{-\frac{1}{2}\left[(Y-X\alpha)'(\Sigma\otimes I_T)^{-1}(Y-X\alpha)+\left(\alpha-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha-\alpha^{PR}\right)\right]}$$

Let α^{PO} denote the mean of the posterior distribution of the coefficient vector. Then we can rearrange the terms in the exponent of the exponential function as follows:

$$\begin{aligned}
&(Y-X\alpha)'(\Sigma\otimes I_T)^{-1}(Y-X\alpha)+\left(\alpha-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha-\alpha^{PR}\right)= \\
&=\left(Y-X\alpha^{PO}+X\alpha^{PO}-X\alpha\right)'(\Sigma\otimes I_T)^{-1}\left(Y-X\alpha^{PO}+X\alpha^{PO}-X\alpha\right)+ \\
&+\left(\alpha-\alpha^{PO}+\alpha^{PO}-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha-\alpha^{PO}+\alpha^{PO}-\alpha^{PR}\right)= \\
&=\left(\alpha^{PO}-\alpha\right)'X'(\Sigma\otimes I_T)^{-1}X\left(\alpha^{PO}-\alpha\right)+\left(\alpha-\alpha^{PO}\right)'\left(V^{PR}\right)^{-1}\left(\alpha-\alpha^{PO}\right)+ \\
&+\left(Y-X\alpha^{PO}\right)'(\Sigma\otimes I_T)^{-1}\left(Y-X\alpha^{PO}\right)+\left(\alpha^{PO}-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha^{PO}-\alpha^{PR}\right)= \\
&=\left(\alpha-\alpha^{PO}\right)'\left[X'(\Sigma\otimes I_T)^{-1}X+\left(V^{PR}\right)^{-1}\right]\left(\alpha-\alpha^{PO}\right)+ \\
&+\left(Y-X\alpha^{PO}\right)'(\Sigma\otimes I_T)^{-1}\left(Y-X\alpha^{PO}\right)+\left(\alpha^{PO}-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha^{PO}-\alpha^{PR}\right)
\end{aligned}$$

The marginal data density is defined as:

$$p(Y) \equiv \int_\alpha p(\alpha \mid Y)d\alpha = \int_\alpha \; (2\pi)^{-\frac{1}{2}M(Mp+T+1)} \left|V^{PR}\right|^{-\frac{1}{2}} |\Sigma|^{-\frac{T}{2}} \cdot$$
$$\cdot\exp\left\{-\frac{1}{2}\left[\begin{array}{l}\left(\alpha-\alpha^{PO}\right)'\left[X'(\Sigma\otimes I_T)^{-1}X+\left(V^{PR}\right)^{-1}\right]\left(\alpha-\alpha^{PO}\right)+ \\ +\left(Y-X\alpha^{PO}\right)'(\Sigma\otimes I_T)^{-1}\left(Y-X\alpha^{PO}\right)+\left(\alpha^{PO}-\alpha^{PR}\right)'\left(V^{PR}\right)^{-1}\left(\alpha^{PO}-\alpha^{PR}\right)\end{array}\right]\right\}d\alpha$$

So, we need to integrate an exponential function with a quadratic function in the exponent, which is a standard exercise. It holds that

$$\int_\infty e^{-ax}dx = \sqrt{\frac{\pi}{a}}\,.$$

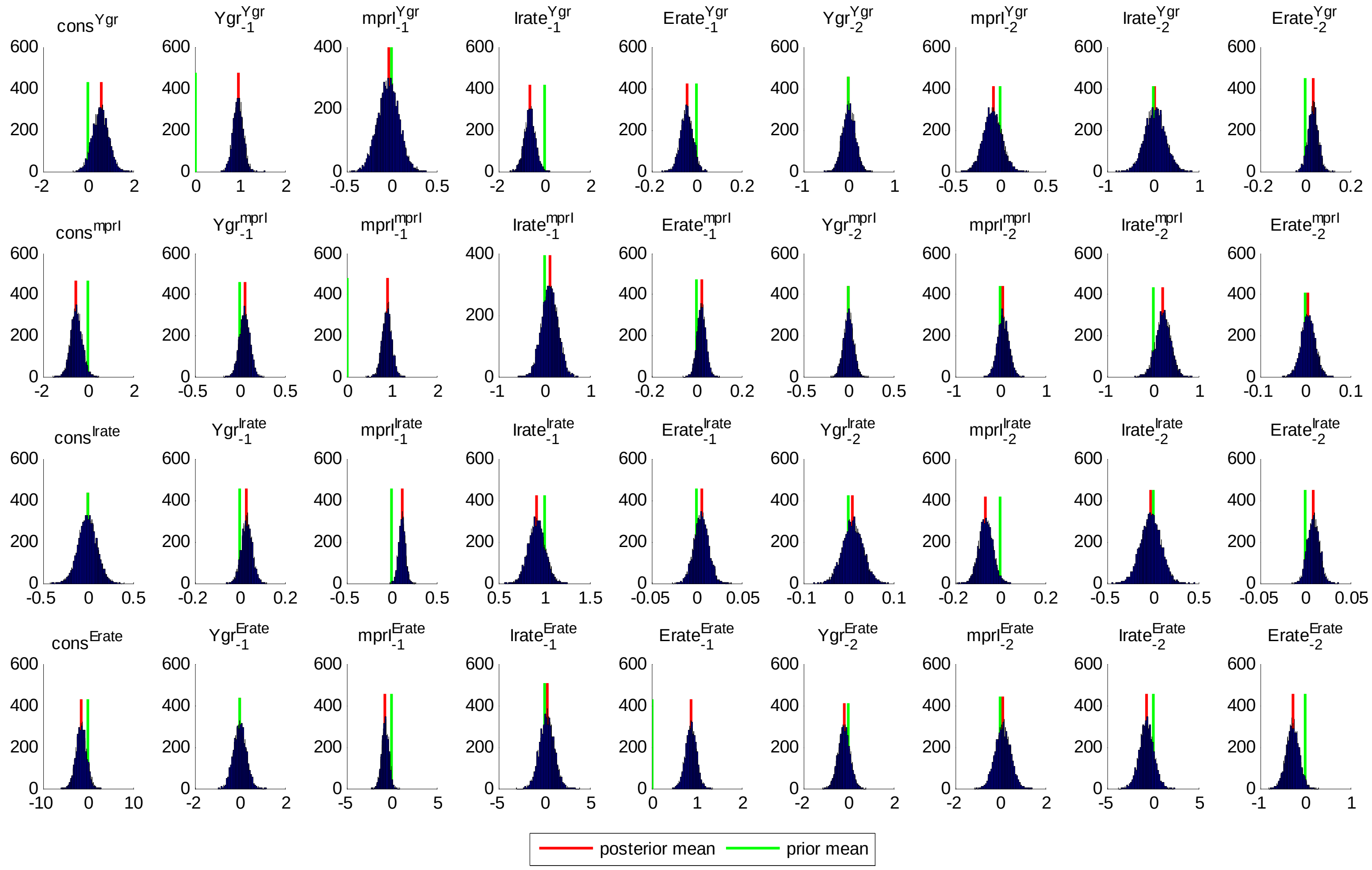
So, applying this formula we get for the marginal data density:

$$p(Y) = (2\pi)^{-\frac{1}{2}M(Mp+T+1)} \left|V^{PR}\right|^{-\frac{1}{2}} \left|\Sigma\right|^{-\frac{T}{2}} \cdot$$
$$\cdot \exp\left\{-\frac{1}{2}\left[\left(Y - X\alpha^{PO}\right)' \left(\Sigma \otimes I_T\right)^{-1} \left(Y - X\alpha^{PO}\right) + \left(\alpha^{PO} - \alpha^{PR}\right)' \left(V^{PR}\right)^{-1} \left(\alpha^{PO} - \alpha^{PR}\right)\right]\right\} \cdot$$
$$\cdot \left|\frac{1}{2\pi} X' \left(\Sigma \otimes I_T\right)^{-1} X + \frac{1}{2\pi}\left(V^{PR}\right)^{-1}\right|^{-\frac{1}{2}}$$

Appendix B: Post-Estimation Diagnostics for the BVAR Model

This appendix presents the post-estimation diagnostics of the reduced form BVAR(5) estimated on the full data set covering the period 1998Q2–2010Q4. The following figure shows the simulated posterior distribution of the parameters and the prior and posterior mean of the distributions. The coefficient notation is the following: $Irate_{-2}^{mprI}$ denotes the coefficient on the second lag of the interest rate in the equation for monetary-policy relevant inflation (mprI). To save space, only the coefficients for the first two lags are presented. The figure suggests that the data are informative, i.e., the prior and posterior distributions differ.

Figure B1: Simulated Posterior Distributions



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ISSN 1803-7070