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A BVAR Model for Forecasting of Czech Inflation

František Brázdik and Michal Franta *

Abstract

Bayesian vector autoregressions (BVAR) have turned out to be useful for medium-term macroeconomic forecasting. Several features of the Czech economy strengthen the rationale for using this approach. These include in particular the short time series available and uncertainty about long-run trends. We compare forecasts based on a small-scale mean-adjusted BVAR with the official forecasts published by the Czech National Bank (CNB) over the period 2008q3–2016q4. The comparison demonstrates that the BVAR approach can provide more precise inflation forecasts over the monetary policy horizon. For other macroeconomic variables, the CNB forecasts either outperform or are comparable with the forecasts based on the BVAR model.

Abstrakt

Bayesovské vektorové autoregrese (BVAR) se ukázaly být užitečné pro střednědobé makroekonomické prognózy. Použití takového přístupu podporuje několik rysů české ekonomiky, zejména existence pouze krátkých časových řad a nejistota související s vývojem dlouhodobých trendů. Porovnáváme prognózy založené na modelu BVAR malého rozsahu upraveném o ustálený stav s oficiálními prognózami zveřejněnými Českou národní bankou (ČNB) za období 2008q3–2016q4. Srovnání ukazuje, že přístup BVAR může poskytovat přesnější inflační prognózy na horizontu měnové politiky. U ostatních makroekonomických proměnných přesnost prognóz ČNB buď převyšuje prognózy založené na modelu BVAR, nebo je s nimi srovnatelná.

JEL Codes: E37, E52.
Keywords: BVAR, forecast evaluation, inflation targeting, real-time forecasting.

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Nontechnical Summary

DSGE models have become an important analytical tool in central banks in recent decades. While their micro-foundations make them suitable mainly for policy analysis, they are also often used for forecasting purposes. However, recent literature suggests that forecasts based on Bayesian Vector Autoregressions (BVARs) can be superior to forecasts built on DSGE models.

Following this line of research, the aim of this paper is to examine the medium-term forecasting performance of a BVAR model and compare it with that of the forecasts officially published by the Czech National Bank (CNB), which are based on a DSGE model. The forecasting performance exercise is based on forecasts produced quarterly during the period 2008q3–2016q4, i.e., the whole period in which the DSGE model has been used for forecasting. Importantly, the exercise draws on historical data vintages, so the information set used for the BVAR model is comparable to that employed for the corresponding CNB forecast and ex-post data revisions do not play an important role.

Several features of the BVAR model specification make it a suitable tool for forecasting the Czech economy. First, the BVAR model is set into the mean-adjusted form, where the steady state of the model is treated explicitly, leading presumably to more accurate medium-term forecasts. Second, the Bayesian approach to estimating the model can help deal with the only short time series available. This approach allows out-of-data information to be incorporated into the estimation process in the form of priors.

The results show that the various specifications of the BVAR deliver lower inflation forecast errors over the monetary policy horizon than the CNB forecasts, although the difference is not statistically significant. If the inflation forecast is conditioned for the first forecasted quarter on the CNB inflation nowcast, which combines expert judgment and various data-intensive models, forecasting dominance of the BVAR model inflation forecasts is observed for all forecasting horizons. For the exchange rate growth forecasts and short-term interest rate forecasts, the results are mixed. For GDP growth, the official CNB forecasts are superior. Although it is not possible to quantify the possible reasons for the difference in forecasting performance, it turns out that the different steady states – especially those of foreign variables – that are assumed/estimated in the two forecasting frameworks can lead to differences in the inflation forecast.

1. Introduction

Recent literature suggests that forecasts based on Bayesian Vector Autoregressions (BVARs) can be superior to those built on DSGE models. For example, Iversen et al. (2016) show that for medium-term forecasts of inflation and the policy rate a BVAR model outperforms both the DSGE model and Sveriges Riksbank's judgmental forecasts over the period 2007–2013. Next, Bloor (2009) discusses the medium-term forecasting used at the Reserve Bank of New Zealand and demonstrates that inflation forecasts from a large-scale BVAR model outperform forecasts based on a structural model. On the other hand, higher forecasting accuracy of the DSGE approach with respect to Fed staff and time-series models is found in a pseudo real-time exercise for the U.S. in Edge et al. (2010).[1] Since medium-term forecasting is of crucial importance for central banks targeting inflation, any approach having the potential to generate more precise medium-term forecasts of inflation should be explored.

The aim of this paper is to examine the medium-term forecasting performance of variants of a small-scale mean-adjusted BVAR model and compare it with that of the forecasts officially published by the Czech National Bank (CNB). The CNB forecasts are based on the CNB's core forecasting model, known as the g3 model. The g3 model is a medium-scale DSGE model of a small open economy featuring real and nominal rigidities (see Andrle et al. (2009), for more details on the model). It should be emphasized that forecasting is not the sole task of the g3 model, so its forecasting performance should be viewed accordingly. The g3 model also serves as a tool for monetary policy analysis, and the aim of accurate policy analysis is often achieved at the cost of reduced forecasting accuracy.[2]

The forecasting performance exercise is based on forecasts produced quarterly during the period 2008q3–2016q4. It covers the period over which the structural g3 model has been used as the main forecasting tool at the CNB. Our exercise draws on historical data vintages, so the information set for the BVAR model is comparable to that employed for the corresponding forecast based on the structural model. Furthermore, the start of our forecasting performance exercise coincides with the onset of the financial crisis. This fact makes the comparison of forecasts even more important, because the nature of macroeconomic fluctuations presumably changed and previous results relating to the forecasting performance of different modeling approaches may also have changed.

The Bayesian approach to the estimation of VAR models is preferable because only short time series are available for the estimation of the model parameters. Also, this approach is able to incorporate expert information in the form of priors. Following Villani (2009), the BVAR model is set into the mean-adjusted form, where priors are imposed directly on the steady state of the model variables. This form allows information about the inflation target and other equilibrium values to be used and expert information on the evolution of the steady state over the considered period to be imposed, leading presumably to more precise estimates of steady states. As argued by Faust and Wright (2013), more accurate estimation of steady states results in more accurate medium- to long-term

[1] Furthermore, a recent real-time forecasting accuracy comparison of a BVAR model and the Bank of England's DSGE model COMPASS can be found in Domit et al. (2016). The study found similar forecasting accuracy for inflation, but for GDP the BVAR model outperforms COMPASS.

[2] Structural policy models are story-telling devices and in comparison to empirical models they can be used more straightforwardly for policy experiments and counterfactual analyses and when expert judgments need to be incorporated (see, for example, Bruha et al. (2013)). From the point of view of forecasting, empirical models can be used as a check for structural models. If the forecasting performance of the empirical model is systematically better than that of the structural model, the underlying reasons should be examined and a modification of the structural model can be proposed.

forecasting. Next, the Bayesian approach allows conditions to be imposed on forecasts intuitively. Specific structural shocks are chosen to impose the prescribed conditions in line with the hard conditioning introduced in Waggoner and Zha (1999). Similarly to the CNB forecasts, the BVAR forecasts are conditioned on the foreign outlook and, for the period of the exchange rate floor, also on the officially announced exchange rate and interest rate commitments.

The results show that the various specifications of the mean-adjusted small-scale BVAR deliver lower inflation forecast errors over the monetary policy horizon than the CNB forecasts, although the difference is not statistically significant. If the inflation forecast is conditioned for the first forecasted quarter on the inflation nowcast, which combines expert judgment and various data-intensive models, forecasting dominance of the BVAR model inflation forecasts is observed for all forecasting horizons. For the exchange rate growth forecasts and short-term interest rate forecasts, the results are mixed. For GDP growth, the official CNB forecasts are superior. Possible reasons for the differences in inflation forecast precision are discussed. Although it is not possible to quantify the particular sources, it turns out that the different steady states – especially those of foreign variables – that are assumed/estimated in the two forecasting frameworks and the conditioning procedure itself can lead to differences in the inflation forecast.

The rest of the paper is organized as follows. Section 2 introduces the BVAR model in mean-adjusted form and the forecasting procedure. Section 3 describes the data set and the exact specification of the priors. Section 4 presents the results on the steady-state estimates and forecasting performance. Finally, section 5 concludes. Additional information and results can be found in Appendixes A–G.

2. Model

The VAR model in mean-adjusted form is as follows:

$$A(L)(y_t - Fx_t) \quad = \quad \varepsilon_t, \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables, $A(L)$ is a matrix lag polynomial, and F is an $n \times m$ matrix of coefficients for the $m\ times1$ vector of deterministic trends or other exogenous variables x_t. The term Fx_t represents an unconditional mean of the process y_t. The error term ε_t is i.i.d. following $N(0,\Sigma)$.

A diffuse prior for the error covariance matrix is assumed for estimation of the model:

$$p(\Sigma) \quad \propto \quad |\Sigma|^{-(n+1)/2}, \tag{2}$$

together with the normally distributed prior for the AR parameters and the steady state:

$$vec(A) \quad \sim \quad N(\theta_A, \Omega_A), \tag{3}$$
$$vec(F) \quad \sim \quad N(\theta_F, \Omega_F), \tag{4}$$

where $vec(.)$ denotes the operator that stacks the columns of a matrix into a vector.[3]

[3] The diffuse prior is an improper prior and thus precludes the computation of marginal likelihood. However, it is the only prior implemented for mean-adjusted VAR in the BEAR toolbox.

Posterior distributions are simulated using the Gibbs sampler described in Villani (2009). We assume four lags in model given by Equation 1.[4] The block exogeneity assumption, reflecting the fact that the Czech economy is a small open economy, is implemented in such a way that the block submatrices in $A(L)$ corresponding to the effects of domestic variables on foreign variables are set to zero.

The forecasting performance of the BVAR model is compared with the CNB forecasts (denoted by CNB), which are based on the structural DSGE model by the means of the forecast errors. The forecasting performance is also discussed with respect to two naïve benchmarks – random walk model and a univariate AR(4) model.

2.1 Forecasting

Iterated BVAR forecasts for up to 7 quarters in the form of a posterior predictive distribution are simulated using draws from the marginal posterior distributions of the model parameters produced by the Gibbs sampler. For each set of draws, the residuals are simulated and a forecast is produced from the drawn parameters and simulated residuals. Based on all the draws from the Gibbs sampler, the predictive distribution is simulated and various percentiles can be computed. For details see Algorithm 2.1.1 in Dieppe et al. (2016).

The conditioning of forecasts is done in line with the hard conditioning introduced in Waggoner and Zha (1999) using the solution suggested by Jarocinski (2010). This method uses a specific subset of structural shocks to implement forecast conditioning. The intuition behind the method of conditioning is as follows: first, shocks that are not selected as those for imposing the conditions (non-constructive shocks) are drawn according to the estimated variance of the relevant normal distribution. Second, shocks that are selected by the forecaster to deliver the condition (constructive shocks) are drawn. The conditional probabilities of the constructive shocks are then taken into account to maximize the likelihood of the data. The implementation in the BEAR toolbox is such that blocks of variables are defined. Each block is constituted by variables with the prescribed condition and the same shocks intended to fulfil the condition. The conditioning exercise is then conducted for each block in turn. Details of the algorithm can be found in Dieppe et al. (2016), Algorithm 3.4.2.

For all forecasting rounds, the BVAR forecasts are conditioned on foreign variables for 7 quarters ahead. All shocks relating to the foreign block are considered as constructive. In forecasting rounds where the exchange rate and interest rate commitments are in effect, interest rate and exchange rate shocks are added to the set of constructive shocks. The length of the prescribed condition on the two variables can be found in Appendix A and is in accordance with the commitments officially announced by the CNB. When conditioning on monetary policy-relevant inflation in the current quarter, real economy shocks are additionally considered (supply and demand shocks).

There are two points worth emphasizing when discussing conditional forecasts. First, forecast conditioning works with structural shocks and identification is thus necessary. We assume recursive identification based on a Cholesky decomposition of the error covariance matrix. Second, the prescribed conditions try to mimic the conditions employed in the forecast based on the g3 model. However, the implementation of conditioning differs between the core model and the BVAR model.

[4] As a robustness check, the specification with two lags is estimated. The results are hardly affected at all and are available upon request.

In the g3 model, conditioning is also implemented via independent structural shocks. However, a feature of the g3 model forecasting framework is that the conditioning is based on the identity between the shock and the variable used for delivering the condition. This identity relation is beneficial for interpretation of the forecast, as the conditioning is uniquely linked to the structural shock. Conditioning in the g3 framework is also applied as hard conditioning, but there are two modes for doing so. It can be applied in either anticipated or unanticipated mode, so it is able to reflect the nature of the information used for the conditioning. For example, outlooks for foreign variables are applied as anticipated or partially anticipated information in the CNB forecasting framework.

As the BEAR toolbox does not allow for anticipated information handling, the use of anticipated information conditioning is one of the points where the application of conditioning differs from the BVAR implementation. This limitation of BVAR-approach forecast conditioning also explains why the conditioning is only done over 7 quarters, while longer horizons for conditions are used in the CNB forecasting framework. Conditions prescribed for horizons beyond 7 quarters thus do not affect the BVAR forecasts over a horizon of 1 to 7 quarters.

3. Data

The vector of endogenous variables in the BVAR model consists of a foreign block and four domestic variables. The foreign block includes foreign demand growth, foreign PPI inflation, and the foreign short-term interest rate. Foreign demand and PPI inflation are in effective terms, i.e., they are trade-weighted aggregates of the individual countries' GDP or PPI. In addition, foreign demand growth is approximated by scaled effective foreign GDP growth. The short-term interest rate is represented by the 3-month EURIBOR and is intended to capture foreign monetary policy. Unconventional monetary policies such as the asset purchases introduced in the Eurozone in the last few years are not directly included in the data. The list of variables represents the order considered by the recursive identification scheme.

The vector of domestic variables consists of real GDP growth, monetary policy-relevant inflation, the short-term interest rate, and CZK/EUR exchange rate growth. Monetary policy-relevant inflation is headline inflation adjusted for the first-round effects of indirect tax changes. It is the type of inflation to which the central bank reacts. So, we are interested primarily in the forecast of this type of inflation.

The short-term interest rate is represented by the 3-month PRIBOR and a positive value of exchange rate growth means depreciation of the Czech koruna.

The growth variables are in annualized q-o-q terms. The results based on growth variables formulated in y-o-y terms are very similar to the benchmark and can be found in Appendix D.

The time series entering the BVAR estimation procedure represent a subset of the time series entering the CNB's forecasting procedure built on the g3 model. Due to the publication lag, the missing GDP observation for the last quarter before the start of a forecast is completed by the nowcast. This completion of the data set is also used for BVAR forecasts. The other domestic variables for the quarter that precedes the quarter of the forecast are observed.

The data set starts with 1998q1, which coincides with the period of introduction of inflation targeting. This restriction implies estimation of the model within a single monetary policy regime. The probability of changes in coefficients in the reduced-form VAR due to regime changes is thus

lower. However, in the period considered, monetary policy hit the zero lower bound (2012q4) and the central bank introduced exchange rate and interest rate commitments (2013q4). The graph of the data can be found in Appendix B.

3.1 Parameter Priors

The prior distribution of the dynamic coefficients in the BVAR model given by Equation 1 is set in line with Litterman (1986). The vector of endogenous variables contains the variables both in levels (domestic and foreign interest rates) and in growth rates (the remaining variables). Litterman (1986) suggests setting the prior mean for the coefficients on the first own lag of variables in growth rates at zero and the prior mean for variables in levels at one. However, the usual random walk prior with the AR coefficient equal to one is not consistent with imposing a prior on the steady state because the steady state does not exist. Moreover, the BEAR toolbox requires us to use the same prior mean on the coefficient on the first own lag in all the equations. So, we assume the prior mean on the coefficient on the first own lag to be 0.2, as this number is close enough to zero and allows for some persistence of the process.

The hyperparameters that define the prior variance Ω_A are set to the usual values – the overall tightness to 0.1, the cross-variable weighting to 0.5, and the lag decay to 1.

The prior on the steady state is normally distributed, with the mean following the setup of the long-run trends assumed in the g3 model. There were two significant changes in the assumed long-run trends over the period of use of the g3 model. Starting with the forecast in 2010q2, the long-run growth rate of real domestic variables was changed to reflect considerations about the speed of recovery of the domestic economy after the Great Recession. Next, from 2013q4 another change was made. Again, this was due to considerations about the speed of recovery after the crisis together with the fact that the economic convergence of the domestic economy had reached an advanced stage.

While setting the means for the priors on steady states is straightforward, setting the variance of those priors is challenging. Few studies discuss the setup of the variance of steady-state priors for Czech macroeconomic variables. Variances from similar studies carried out for other countries are therefore used. Two papers contain explicitly stated priors for mean-adjusted BVARs: Beechey and Österholm (2008) for the Australian economy and Villani (2009) for Sweden. We follow Beechey and Österholm (2008), who use slightly looser priors, because the uncertainty about the equilibrium values in the Czech economy is presumably higher due to economic convergence and structural changes. The prior distributions of the steady-state values in the BVAR model are normal, with means and standard deviations specified in Table 1. Results based on the tighter priors given by Villani (2009) are reported in Appendix C.

The change in the prior on the steady state is implemented using dummy variables as additional exogenous variables stored in the vector x_t . So, in addition to the constant term a dummy variable indicating the period until 2009q4 and another indicating the period until 2013q2 are added. They are included in the set of exogenous variables only if the data set used for the estimation covers the relevant period. The coefficient on the dummies then represents the change in the prior with respect to the intercept. So, for example, the prior on the steady state for the period after 2013q4 is made up of the prior on the constant and the priors on the coefficients on the two dummy variables. The total prior mean is the sum of the prior means on the constant and the two dummy variables. This is also why the standard deviations presented in Table 1 are increasing in the direction of earlier periods. When computing the standard deviations for the sum of the intercept and the dummy variables,

Table 1: Prior Distributions for the Steady States

	2008q3–2010q1		2010q2–2013q3		2013q4–2016q4	
Variable	Mean	95%	Mean	95%	Mean	95%
Foreign Demand Growth	9.4	(3.4,15.4)	8.9	(4.9,12.9)	7.2	(5.2,9.2)
Foreign Inflation	2.0	(-1.0,5.0)	2.0	(0.0,4.0)	2.0	(1.0,3.0)
3M EURIBOR	4.0	(1.0,7.0)	4.0	(2.0,6.0)	3.5	(2.5,4.5)
Output Growth	5.0	(2.0,8.0)	4.0	(2.0,6.0)	3.0	(2.0,4.0)
MP Relevant Inflation	3.0	(1.0,5.0)	2.0	(1.0,3.0)	2.0	(1.5,2.5)
3M PRIBOR	3.0	(-0.5,15,4)	3.0	(0.5,5.5)	3.0	(1.5,4.5)
CZK/EUR Change	-2.4	(-8.4,3.6)	-2.4	(-6.4,1.6)	-1.5	(-3.5,0.5)

independence of priors is assumed. We do not view the change in the standard deviations of the priors as a problem, as higher uncertainty of the priors corresponding to earlier periods seems to be a reasonable assumption.

Note that in the g3 model the long-run trends are often adjusted over the forecasting horizon to reflect expected changes in the medium term. Thus, a particular g3 model forecast can effectively assume medium-term deviations from long-run trends over the forecasting horizon. Such assumptions are not contained in the BVAR model. Next, starting with 2013q4, time-varying long-run growth of real variables is introduced in the g3 model. This feature is used when explaining the observed data. Within the mean-adjusted BVAR model, the change in the steady-state values is imposed in all the relevant forecasts as indicated by Table 1.

4. Results

For inference and forecasting, 10,000 iterations of the Gibbs sampler are carried out, with the first 5,000 iterations serving as burn-in. The posterior estimates of the steady state are discussed in Subsection 4.1. The forecasting performance is examined in Subsection 4.2. The inflation forecasts are discussed in detail in subsection 4.3. Some additional results and robustness checks are presented in Subsection 4.4.

The results relating to the steady state are based on the reduced-form VAR and structural shock identification does not play any role. On the other hand, the conditional forecasts draw on the shock identification scheme used to obtain the structural shocks. Impulse responses based on recursive identification are reported in Appendix E. A robustness exercise with respect to the ordering of variables is carried out in Appendix G.[5]

[5] It is possible to create conditional forecasts without structural identification. This approach can be reasonable for conditioning on variables where not much information is available on the type of structural shocks. However, this approach would be inappropriate for conditioning on the exchange rate and interest rate, as we have strong support for the identification of shocks over the commitment period. We therefore stick to the structural VAR model in forecast conditioning. Finally, we carry out a robustness check to ensure that the results are robust to the identification scheme used.

4.1 Steady State

Mean-adjusted VAR allows for direct estimation of the steady-state values of the system.[6] Table 2 reports the prior and posterior medians and the 95% confidence bands for the steady state in 2016q4. More precisely, the model is estimated on the full data set covering 1998q1–2016q4 with two changes in the steady state imposed. Only the posterior estimates of the steady state for 2016q4 are presented, because they are of the main interest due to the fact that they are assumed for the whole forecasting horizon in the forecasting procedure.

Table 2: Prior and Posterior Distributions of the Steady States for 2016q4 Forecast

	Prior		Posterior	
Variable	Median	95%	Median	95%
Foreign Demand Growth	7.2	(5.2,9.2)	7.1	(5.5,8.8)
Foreign Inflation	2.0	(1.0,3.0)	2.0	(1.2,2.9)
3M EURIBOR	3.5	(2.5,4.5)	2.7	(2.0,3.5)
Output Growth	3.0	(2.0,4.0)	2.5	(1.7,3.4)
MP Relevant Inflation	2.0	(1.5,2.5)	1.9	(1.4,2.4)
3M PRIBOR	3.0	(1.5,4.5)	2.6	(1.9,3.3)
CZK/EUR change	-1.5	(-3.5,0.5)	-1.7	(-3.4,0.0)

There are some differences between the prior and posterior medians of the steady state for 2016q4 which are worth discussing. Regarding the foreign variables, the median of the posterior of the steady state for the foreign interest rate is 0.8 percentage point lower than that of the prior. The 95% confidence band does not include the prior median, suggesting that the difference between the prior and the posterior is substantial. As for the domestic variables, the posterior distributions suggest lower steady-state growth, a lower steady-state value of the short-term interest rate, and a slightly more pronounced appreciation trend. The median of the posterior distribution for the steady-state growth of prices is very close to the 2% inflation target.

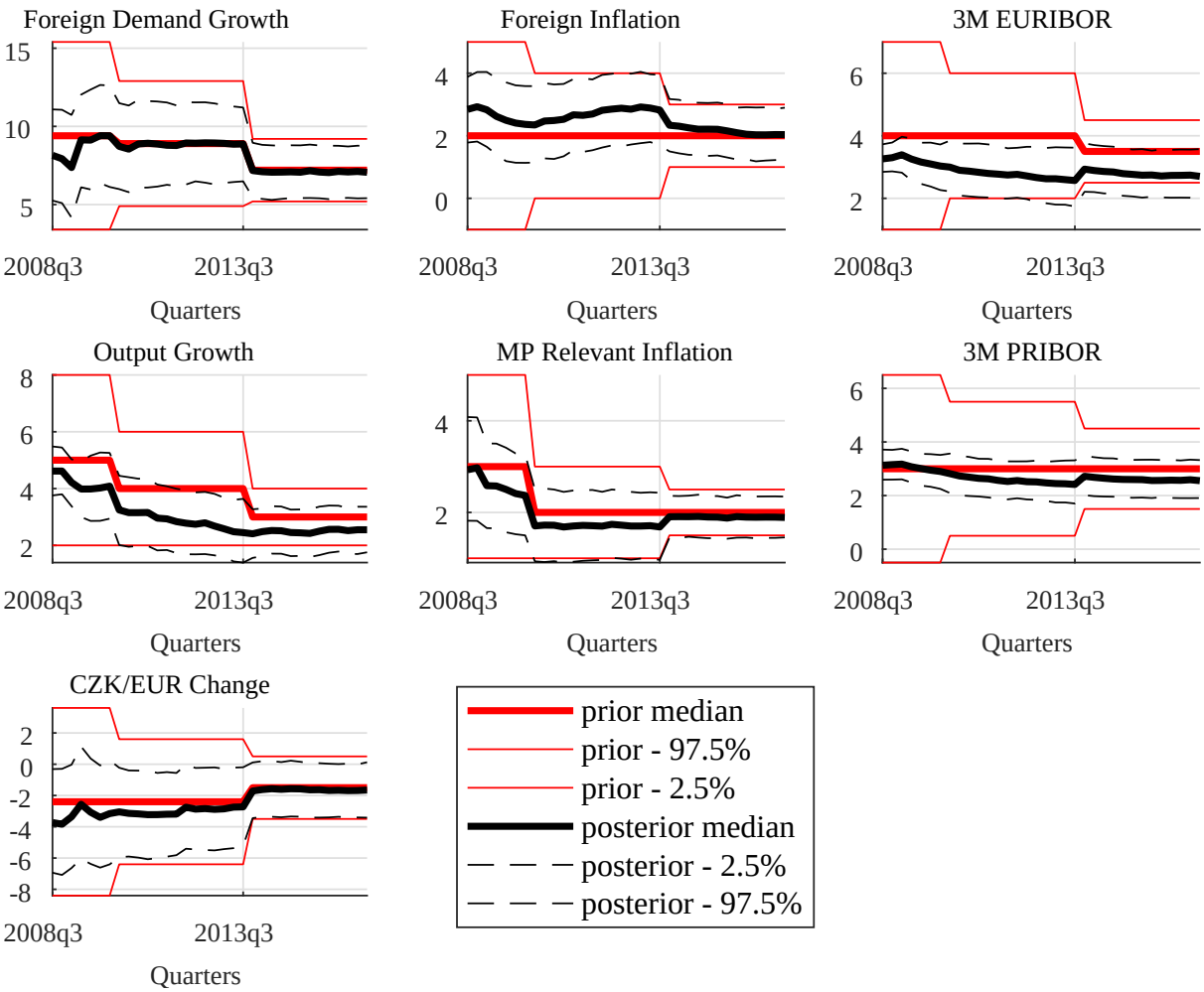
The steady state estimated using the BVAR model is re-estimated in each forecasting round, ensuring that the most recent data developments are considered in the steady-state estimation. On the other hand, the estimated steady state for a given quarter can change if the data set used for the estimation is extended. Figure 1 reports the evolution of the posterior distribution of the steady state for the last quarter of the data set used for the estimation, i.e., it shows how the estimated steady state for the last quarter of the data set changes over the forecasts made from 2008q3 to 2016q4. It demonstrates the decline in the steady-state value of the foreign interest rate corresponding to the recently estimated decline in the real equilibrium interest rate in the euro area after 2008 (see for example Holston et al. (2016)).

Next, the decrease in the steady state for domestic inflation between 2008 and 2010 reflects the change in the domestic inflation target from 3% to 2% at the end of 2008. Moreover, the posterior median of the steady state for domestic inflation suggests the presence of a difference between the prior and posterior values that disappeared at the end of 2013. The lower steady-state estimates of inflation in 2010–2013 could be explained by too restrictive monetary policy that was not able to

[6] Mean-adjusted VAR is one possible approach to estimating the steady-state values of macroeconomic variables. In contrast to the semi-structural and structural multivariate approaches, the BVAR model does not impose any cross-coefficient restriction. The precision of this approach then relies on meeting the restrictions in the data-generating process.

cope with the anti-inflationary pressures and shocks over this period. Figure 1 also shows a declining appreciation trend corresponding to the slowdown or even halt in the economic convergence of the domestic economy after 2008.[7]

Figure 1: Sequential Prior and Posterior Median Distributions of the Steady State Over Time



Note: The specification with growth data in q-o-q terms is considered; the horizontal axis denotes the quarter in which the forecast is made.

4.2 Forecasting Performance

In this subsection, the forecasting performance of the BVAR model vis-à-vis the official CNB forecasts is examined. For this purpose, 34 official CNB forecasts are compared with forecasts based on the BVAR model using the same data set available for each particular forecast. In addition, the

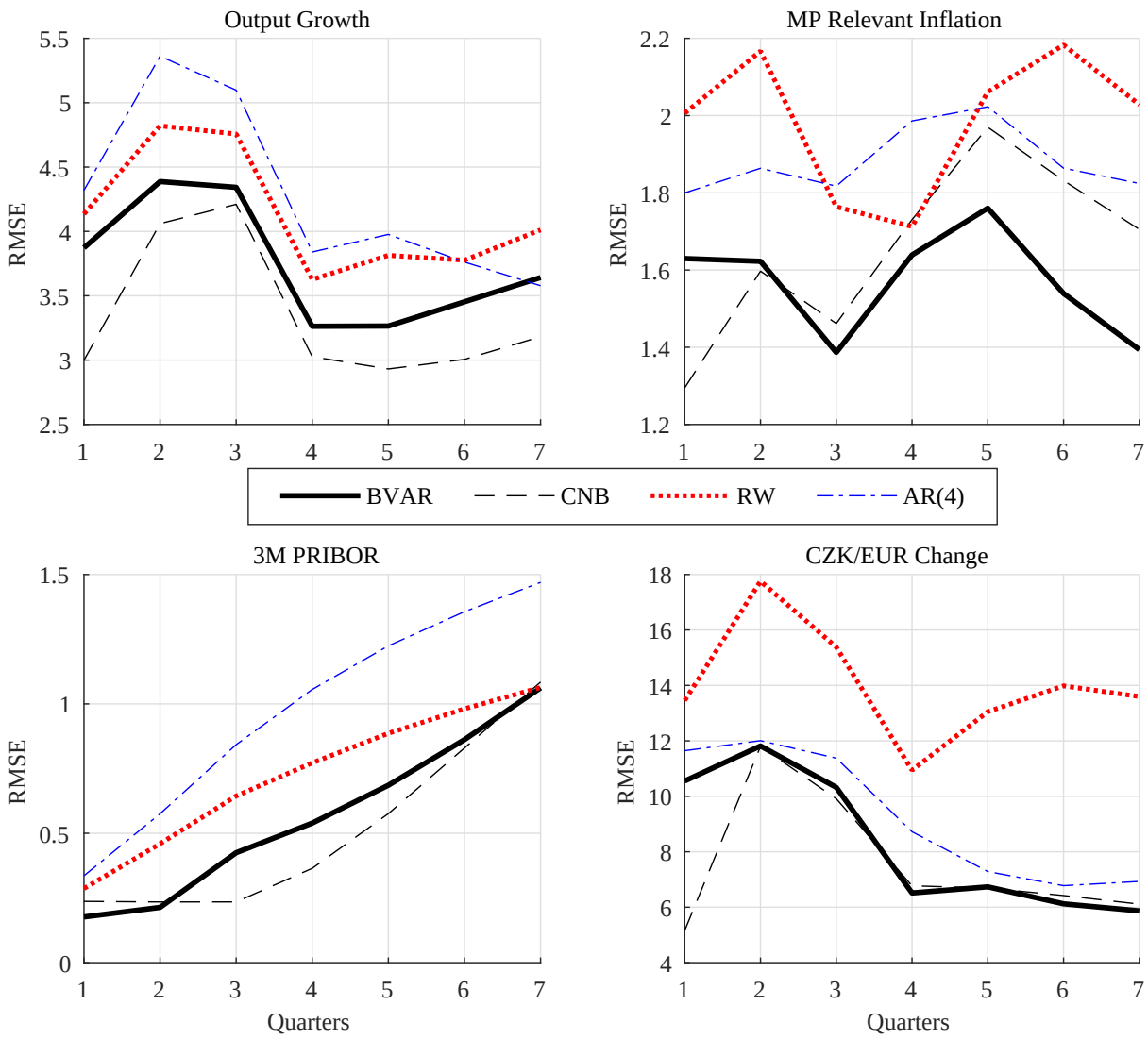
[7] Note that the differences between the estimated/assumed steady states in the BVAR and g3 models do not necessarily say anything about the quality of the model-based policy recommendations. For example, the lower value of the steady state of the domestic interest rate estimated in the BVAR model with respect to the value assumed in the g3 model suggests *ceteris paribus* that the policy recommendation regarding the interest rate setting should change because the same interest rate represents tighter monetary policy under the lower steady-state value. However, at the same time steady-state output growth is estimated to be lower in the BVAR model, suggesting that the real economy is more inflationary, implying, in turn, that more restrictive monetary policy is needed to fulfil the inflation target. Other differences in steady states may affect the policy conclusion as well. In this paper, the focus is on forecasting performance rather than on in-sample data fit. The differences in steady states between the modeling frameworks are discussed only if they can help explain systematic differences in forecasting performance.

forecasting performance is compared with two univariate benchmarks – a random walk model and an AR(4) model. Note that for the two univariate benchmarks no conditions are imposed on the forecasts.

The root-mean-square error (RMSE) is employed as the measure of forecasting performance. Two types of data are considered as actual values. First, the last observed vintage – the data available in 2016q4 – is taken. Second, in order to improve the forecast error properties in terms of the number of revisions considered, the vintage released two years after the production of each forecast is used as the actual value. The release after two years is basically the first release of the actual values for the forecasts for the horizon of 7 quarters. The forecasting performance based on the final vintage is presented in the main text, while results relating to the vintage released after two years are given in Appendix F.

There are no substantial differences between the two approaches to assessing forecasting accuracy. In addition to forecasting accuracy measurement, the equal forecasting accuracy of the modeling frameworks is statistically tested using the Diebold-Mariano test.

Figure 2: RMSE Over the Forecasting Horizons



The forecasting performance of the BVAR model and the CNB forecasts is reported in Figure 2 and Table 3. In the case of output growth, the CNB forecasts are superior in terms of RMSE over all forecasting horizons, whereas for exchange rate growth and the 3M PRIBOR the forecasting accuracy of the two approaches is similar. However, for inflation the BVAR forecasts outperform the CNB forecasts in the interval from 3 to 7 quarters. From the point of view of a central bank targeting the inflation forecast the observed difference is important. At the horizons of 6 and 7 quarters, the inflation forecast based on the BVAR model is on average more than 0.3 p.p. closer to the ex-post observed value in comparison to the CNB inflation forecasts. The decrease in the RMSE relative to the CNB inflation forecast is almost 20% at the monetary policy horizon (5–7 quarters). Note that the difference is not statistically significant (see Table 3).

Regarding GDP growth, the CNB forecasts outperform the BVAR forecasts for all the horizons considered. This finding could be a consequence of the fact that the CNB forecasting process works with the components of GDP separately and thus deals with a broader information set. Regarding the exchange rate, the forecasting accuracy is on average similar and relatively low, except for the horizon of one quarter ahead, where the CNB forecasts are statistically significantly more accurate than the BVAR forecasts. Finally, the BVAR forecasts and the CNB forecasts beat the naïve benchmarks for all horizons and variables. The poor performance of the RW for exchange rate growth forecasting could be viewed as surprising, as the RW is often difficult to beat (Rossi (2013)). However, the existing appreciation trend leads to a preference for frameworks that are able to deal with such a trend, i.e., models that include at least an intercept.

Table 3: RMSEs for the CNB Forecasts and the BVAR Model Forecasts

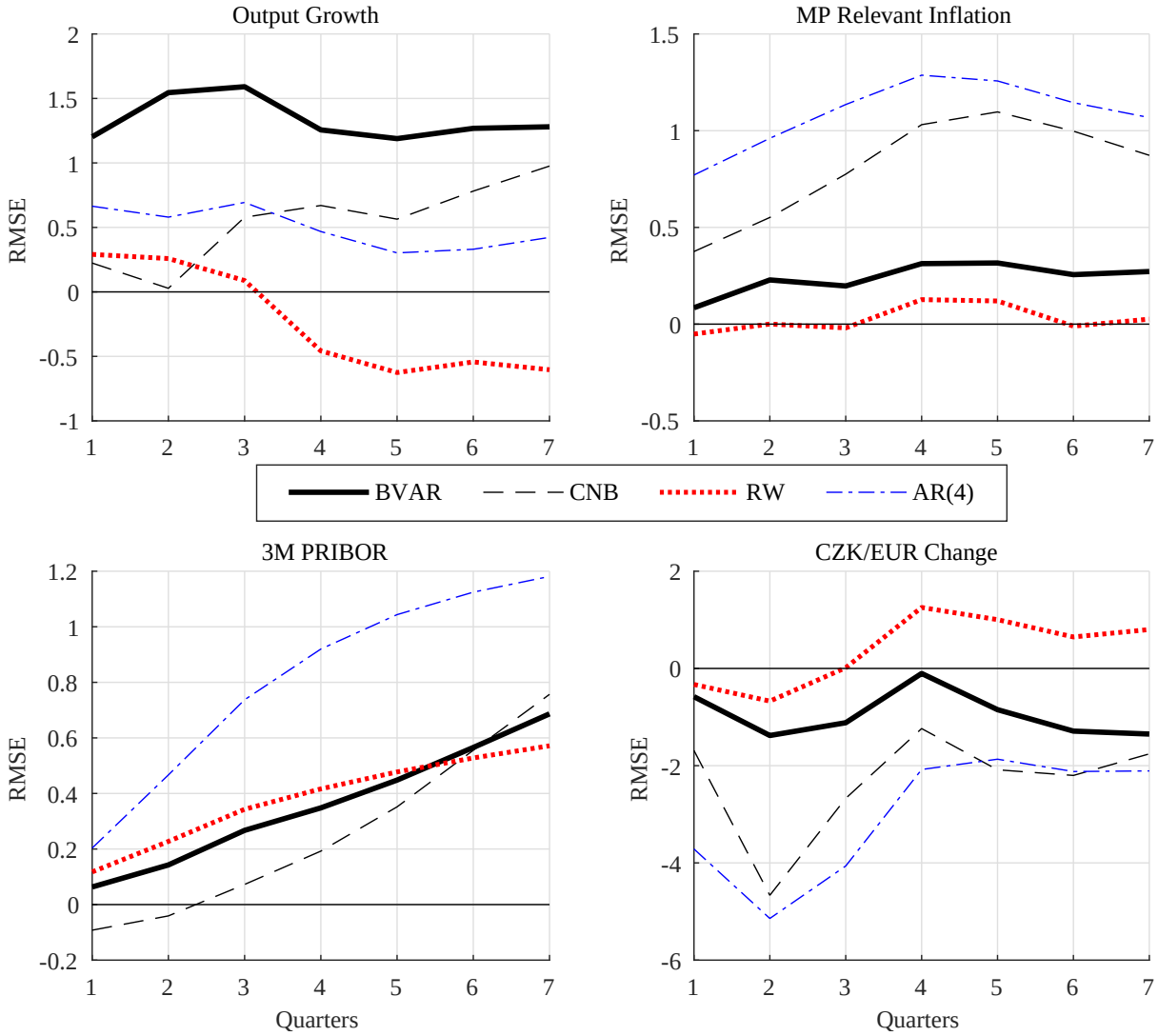
	Output Growth		MP Relevant Inflation		3M PRIBOR		CZK/EUR Change	
Horizon	CNB	BVAR	CNB	BVAR	CNB	BVAR	CNB	BVAR
1	3.00	3.87	1.30	1.64	0.24	0.17	**5.16**	10.53
2	4.06	4.39	1.60	1.62	0.23	0.21	11.80	11.85
3	4.21	4.35	1.46	1.38	0.23	0.42	9.91	10.38
4	3.03	3.27	1.73	1.64	0.36	0.54	6.77	6.57
5	2.93	3.27	1.97	1.76	0.58	0.68	6.69	6.76
6	3.01	3.45	1.83	1.53	0.83	0.86	6.42	6.10
7	3.18	3.64	1.71	1.39	1.08	1.06	6.11	5.86

Note: Bold indicates a statistically significant difference in forecasting performance at the 95% level according to the Diebold-Mariano test.

A more detailed picture beyond the aggregate measure represented by the RMSE can be obtained if we focus on the forecast bias (Figure 3). The forecast bias is the average forecast error for a given variable and horizon, where the forecast error is defined as the difference between the forecasted value and the ex-post observed value. A forecast bias close to zero suggests that positive and negative errors average out. A non-zero bias indicates a possible "systematic" difference between the forecasts and the ex-post observed values. For the BVAR model no bias can be observed for the inflation and exchange rate growth forecasts, but this is not the case for the CNB forecasts, which exhibit a positive bias for inflation, i.e., the forecasts are systematically above the ex-post observed values, and a negative bias for the exchange rate.

Finally, an even more detailed view is provided by Figure 4, which shows all the CNB and BVAR forecasts and observed values (last vintage). In general, the BVAR forecasts are smooth in comparison to the CNB forecasts, probably because additional expert knowledge is included in the CNB forecasts (for example, knowledge of the fiscal policy outlook can affect output growth even at

Figure 3: Forecast Bias Over the Forecasting Horizons



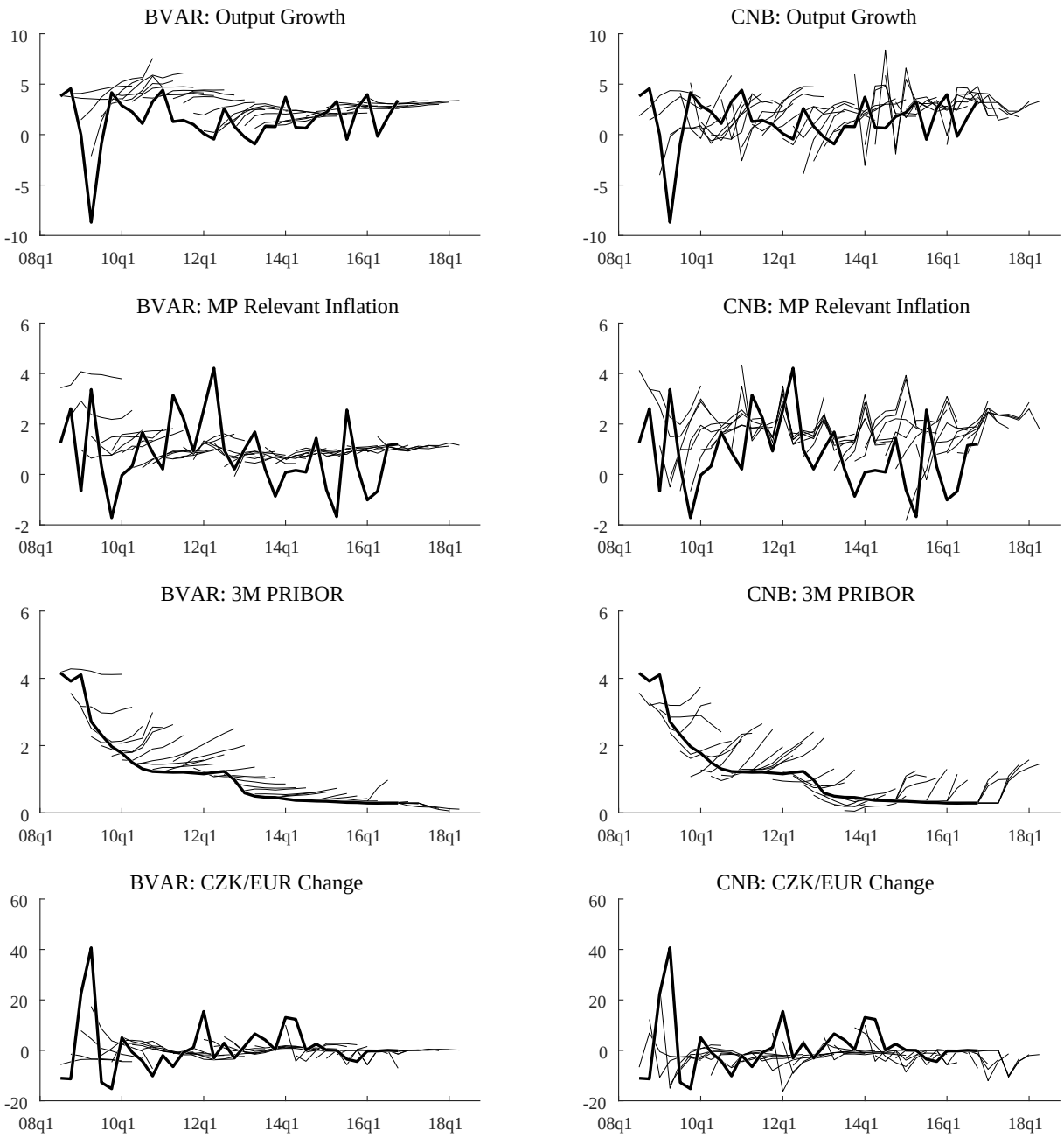
longer forecasting horizons). Next, an effect of the different steady states in the two frameworks can be observed. For example, the CNB forecasts of the 3M PRIBOR tend to rise more, reflecting the higher steady state underlying the CNB forecasts.

4.3 Inflation Forecasts

The most striking difference between the BVAR forecasts and the CNB forecasts is the forecasting performance for inflation at the monetary policy horizon. To get a more nuanced view, we focus on the profile of the forecast errors. Note that we deal primarily with the difference in the inflation forecast errors between the two frameworks rather than their magnitude, which is determined mainly by the shocks that occur over the forecasting horizon after the forecast is made.

Focusing on the forecasting horizon of 7 quarters, a lower forecast error for inflation in the case of the BVAR model can be observed starting with the forecast conducted in 2010 (Figure 5). The negative BVAR inflation forecast error indicates a lower-than-forecasted value of inflation. Since the start of 2011, the forecast error of the BVAR model is approximately half that of the CNB

Figure 4: Point Forecasts of Domestic Endogenous Variables

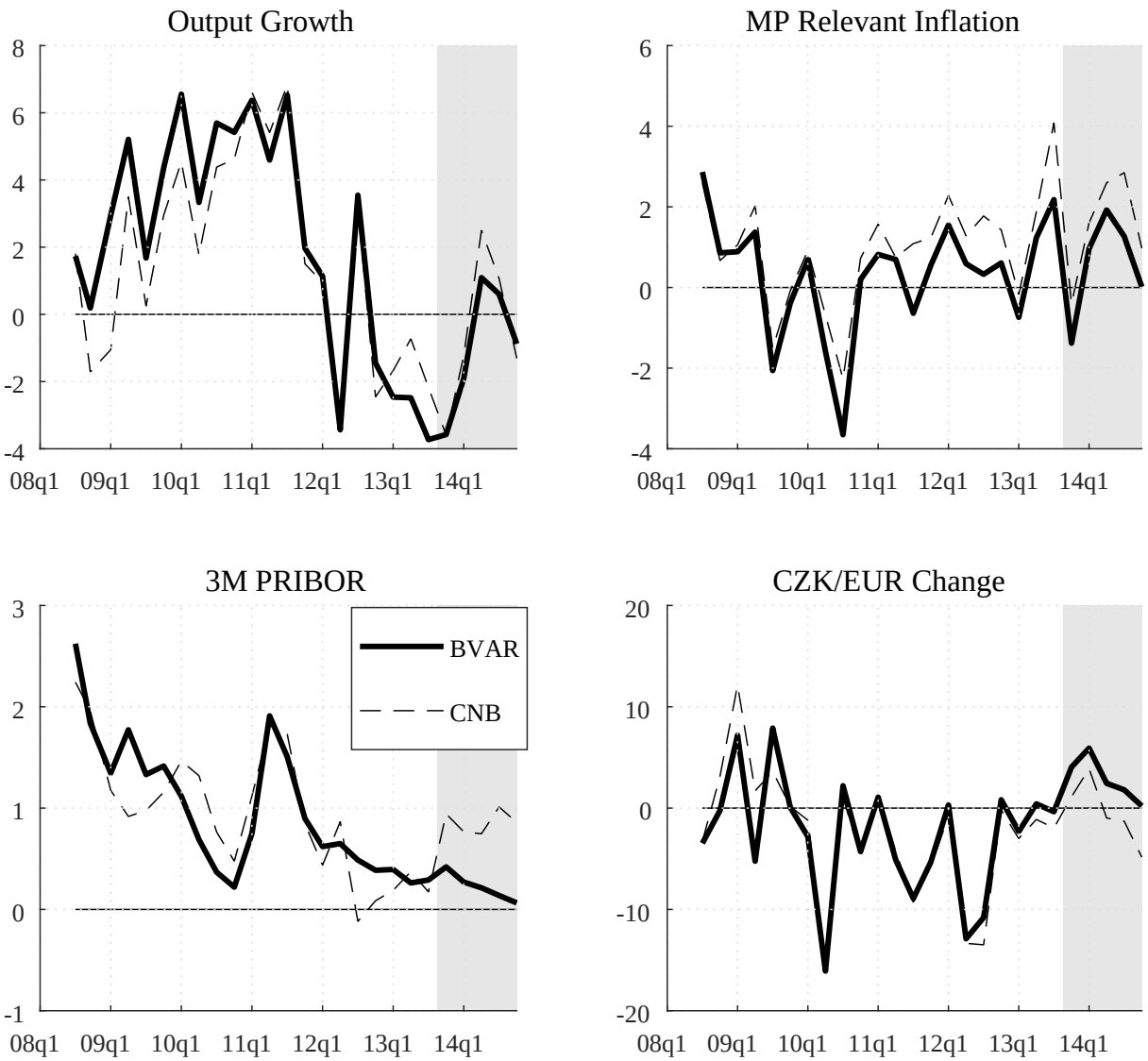


Note: The thick line indicates the observed data and the thin lines indicate forecasts.

inflation forecasts.[8] During the period 2008–2010, the differences in the inflation forecast error are very small.

[8] In addition, Figure 5 shows superior performance of the interest rate forecasts based on the BVAR model for the forecasts made since the end of 2013 at the horizon of 7 quarters. The forecast error for the CNB forecasts reflects an increase in the interest rate prediction for that period after the end of the exchange rate commitment. This increase did not materialize. Over this period, the CNB communicated that the more probable outlook was a slower rise in the interest rate – see Czech National Bank (2015). On the other hand, for the same period the BVAR exchange rate growth forecasts suggested a more depreciated exchange rate than that observed ex-post, while the CNB forecasts predicted exchange rate growth at the horizon of 7 quarters more accurately.

Figure 5: Forecast Error at the Horizon of 7 Quarters.

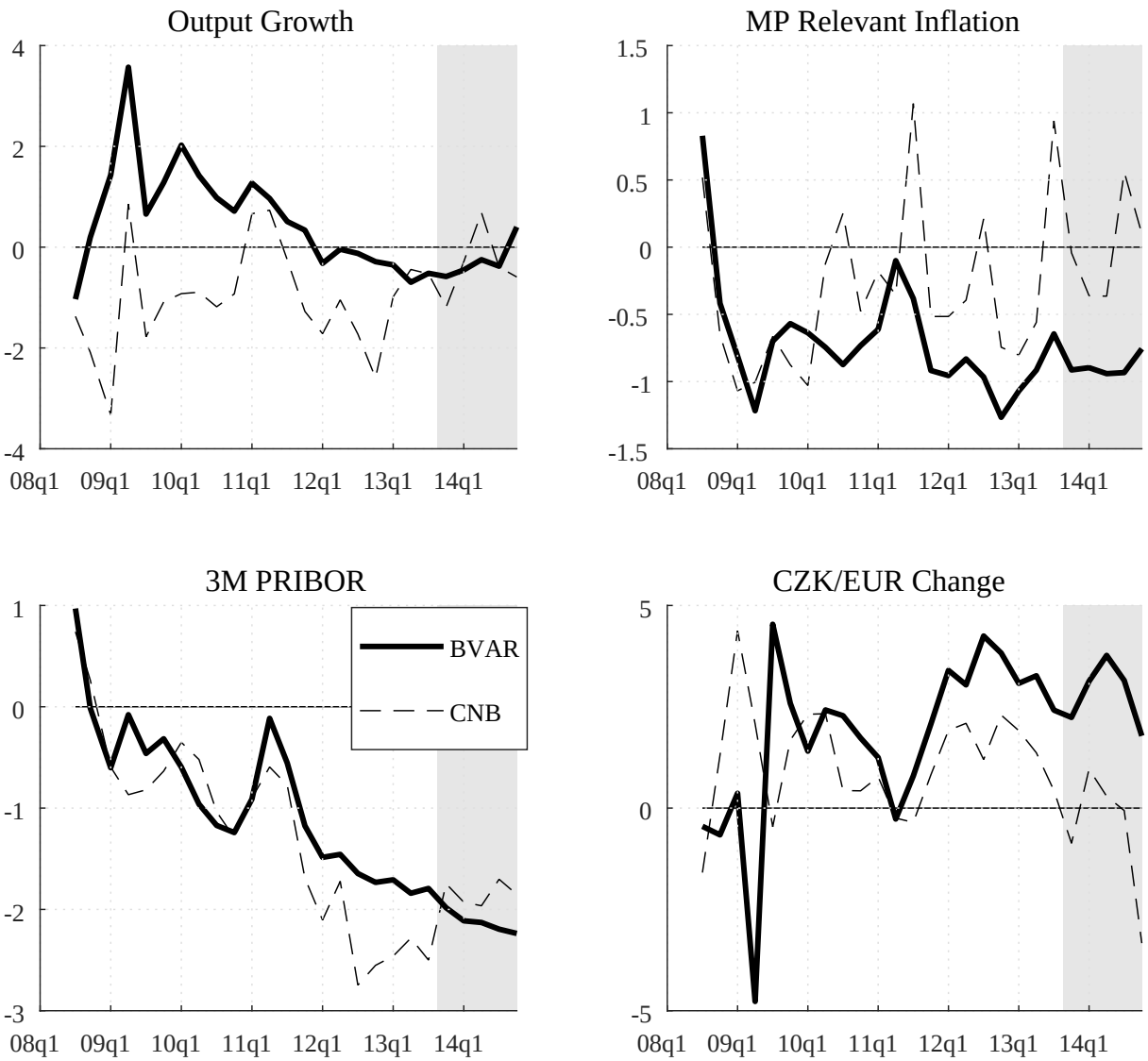


Note: Forecast error is defined as the difference between forecasted value and ex-post observed value. The shaded area denotes conditioning of the interest rate and exchange rate forecasts.

Drawing on the same observed data, the performance of the two forecasting frameworks can differ due to different dynamics implied by the model, different structural shock identification considered during forecast conditioning, and different judgments incorporated into forecasts. Judgments on top of the conditions imposed on forecasts are not included in the BVAR model. In addition, it is not possible to separate the effect of judgments in CNB forecasts because forecasts without judgments are not available. Therefore, we only discuss the first two reasons for the different forecasting performance.

As suggested by Faust and Wright (2013), from the point of view of forecasting accuracy the dynamics implied by the model can be simplified to the initial condition and the steady-state value. The assumed/estimated steady state for inflation is almost the same in both models and thus the observed difference in the medium-term inflation forecasts cannot be explained by different steady states of inflation.

Figure 6: Distance of the Forecast at the Horizon of 7 Quarters from the Steady State



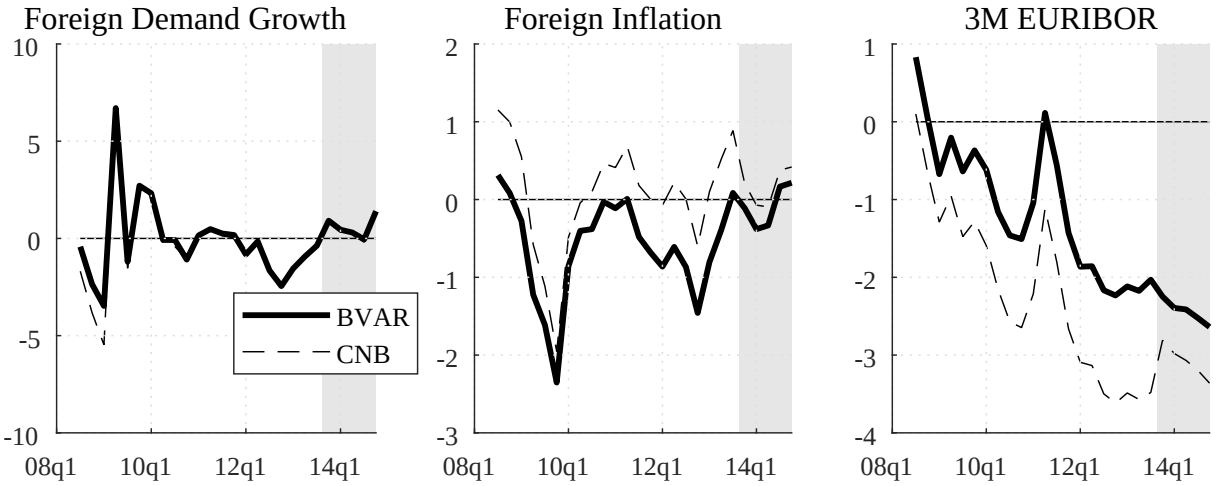
Note: The steady state estimated/assumed within the particular forecasting round is considered. The shaded area denotes conditioning of the interest rate and exchange rate forecasts.

Iversen et al. (2016) point out another reason for different forecasting accuracy relating to the model dynamics. Even though the steady state can be the same in both forecasting frameworks, the speeds at which the system approaches its steady state can differ. They argue that the BVAR model has a tendency to return more slowly to its steady state. Figure 6 reports the distance of the forecasts at the horizon of 7 quarters from the steady state. Note that the estimated steady state is assumed over all the forecasting horizons within a particular forecasting round. It turns out that the CNB inflation forecasts are closer to the inflation target than the BVAR inflation forecasts in the vast majority of cases, i.e., the distance is closer to zero.

So, the superior precision of the inflation forecast in the medium term could be a consequence of a faster return of the CNB forecast to the steady state. However, as we work with a multivariate system, all the endogenous variables should be closer to their steady states if the explanation built on model dynamics can be taken as plausible.

Figure 7 shows that the CNB inflation forecasts and exchange rate growth forecasts are often closer to the relevant steady state. However, this is not the case for the CNB GDP growth and interest rate forecasts.

Figure 7: Distance of the Forecast Condition at the Horizon of 7 Quarters from the Steady State



Note: The steady state estimated/assumed within the particular forecasting round is considered. The shaded area denotes conditioning of the interest rate and exchange rate forecasts.

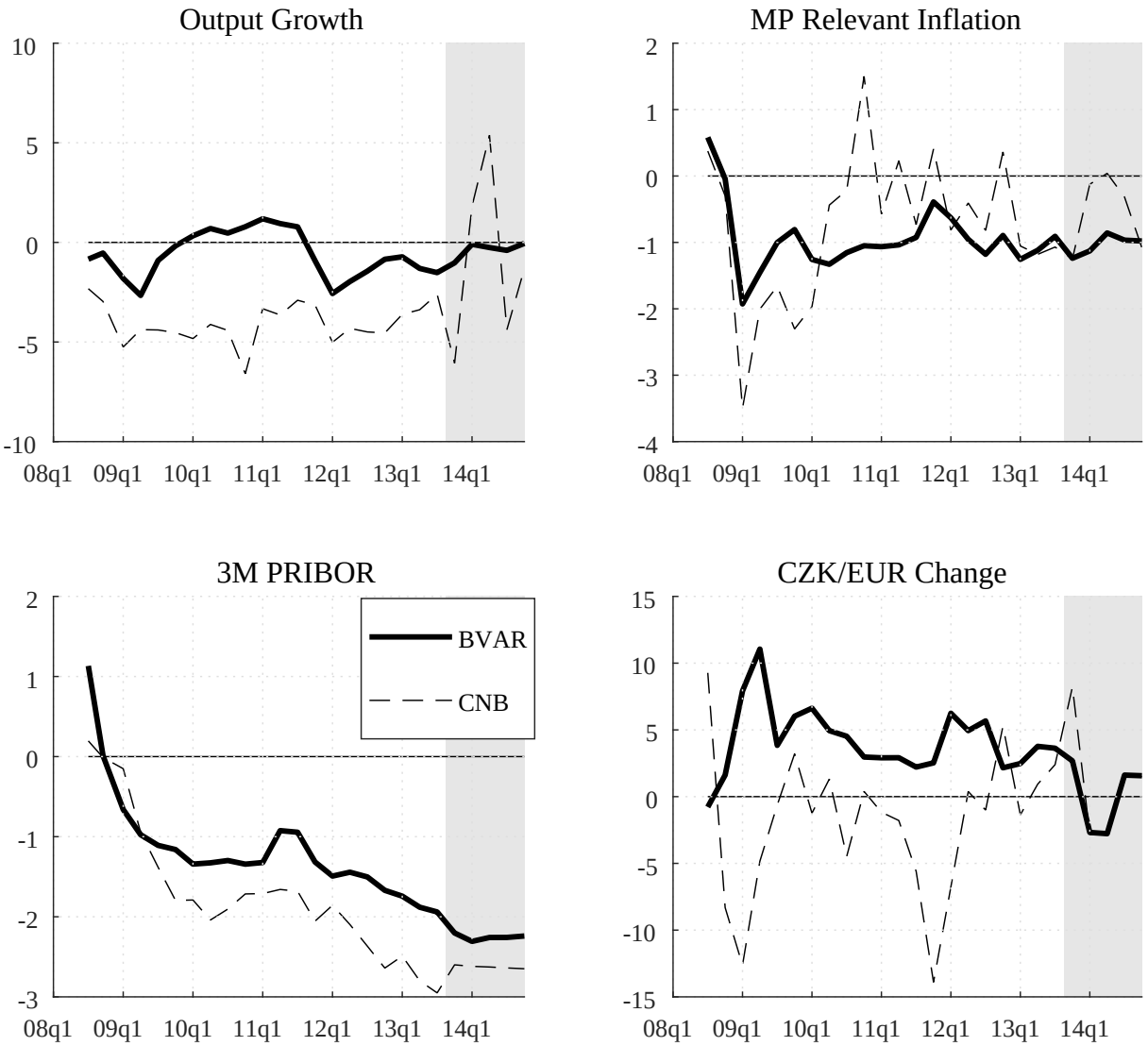
The degree to which the medium-term forecasts are close to their steady state is affected by the forecast conditioning, especially at the monetary policy horizon. Both the BVAR and CNB forecasts are conditioned on the outlook for foreign variables over all forecasting horizons, i.e., including the monetary policy horizon. If the foreign variables used for conditioning are not at their steady state at the monetary policy horizon, the BVAR inflation forecast cannot be at the inflation target because the forecast conditioning procedure interprets the difference between the foreign outlook and the unconditional forecast of foreign variables as a source of unexpected shocks that subsequently affect domestic inflation.

The fact that the foreign outlook is out of its steady state for almost all the forecasting rounds is demonstrated in Figure 7. The distance between the condition for a foreign variable at the horizon of 7 quarters and its steady-state value is sizeable for several forecasting rounds. For inflation, the distance can even exceed 1 percentage point. Unconditional foreign inflation forecasts tend to move closer to their steady state, and the resulting gap between the unconditional forecast and the condition imposed on foreign inflation represents an unexpected shock with an effect on domestic inflation. The shock is more profound, the larger is the distance from the steady state. Putting it differently, a greater distance to the steady state implies a larger size of the shock imposed during conditioning.

The distance of the foreign inflation outlook from the CNB steady state (the dashed line) is less negative or more positive than that from the BVAR steady state (the solid line) in all the forecasting rounds. This means that the foreign inflation outlook represents a more inflationary environment in the CNB framework than in the BVAR framework. Therefore, the effect of the foreign inflation outlook on domestic inflation is less inflationary for the BVAR forecasts. The different steady state of foreign inflation (see Figure 1) is thus a possible reason for the lower BVAR inflation forecast error at the monetary policy horizon.

There is another possible reason why the CNB inflation forecasts are in general closer to the inflation target at the monetary policy horizon. In the CNB forecasting framework, the structural shocks behind the conditions imposed on foreign variables are treated as partially anticipated, with the effect on endogenous variables moved backwards in time due to the fact that economic agents to some degree expect a forthcoming shock. In consequence, the effect of the conditions on domestic inflation at the monetary policy horizon is not as strong as in the BVAR framework, which considers shocks as fully unanticipated. The inflation forecast errors at the horizon of 7 quarters arise mainly from the fact that the CNB inflation forecasts are closer to the inflation target than the BVAR inflation forecasts. Therefore, the specific way of conditioning on foreign variables can play a role.

Figure 8: Distance of the Forecast Condition at the Horizon of 2 Quarters from the Steady State



Note: The shaded area denotes conditioning of the interest rate and exchange rate forecasts.

The effect of conditioning on the outlook for foreign variables in the case of different steady states can be generalized to all the forecasting conditions used in our exercise. It can be argued that the differences in the steady states of the interest rate and exchange rate affect the differences in the inflation forecast error if conditioning on the interest rate and exchange rate is carried out. Note that conditioning on the interest rate and exchange rate is done for the forecast starting with 2014q1.

For the interest rate, the underlying steady state is lower for the BVAR forecasts than for the CNB forecasts over almost the whole period (see Figure 1). The distance of the condition to the assumed steady state at the horizon of 2 quarters is reported in Figure 8.During conditioning, values further from the steady state imply a larger shock to fulfil the condition. So, the higher steady state of the interest rate in the g3 model implies more accommodative monetary policy, which is consistent with higher g3 model inflation forecasts in the medium term. At the horizon of 7 quarters, the BVAR inflation forecasts are lower than the CNB forecasts (see Figure 5).[9] For the exchange rate, the distance of the conditions from the steady state is very similar in both approaches after 2014q1, so the conditioning should not contribute to different medium-term inflation forecasts.

4.4 Forecasting Performance - Other Specifications

The CNB forecasts use a short-term inflation forecast obtained from a battery of econometric models together with expert judgments. This short-term inflation forecast is used in the first quarter of the forecast in the form of information on which the core model forecast is conditioned. As they account for a broader information set, the CNB short-term inflation forecasts should be more precise than those based on the small-scale BVAR model. This is confirmed empirically in Table 3.

Figure 9: RMSE - Inflation Conditioning

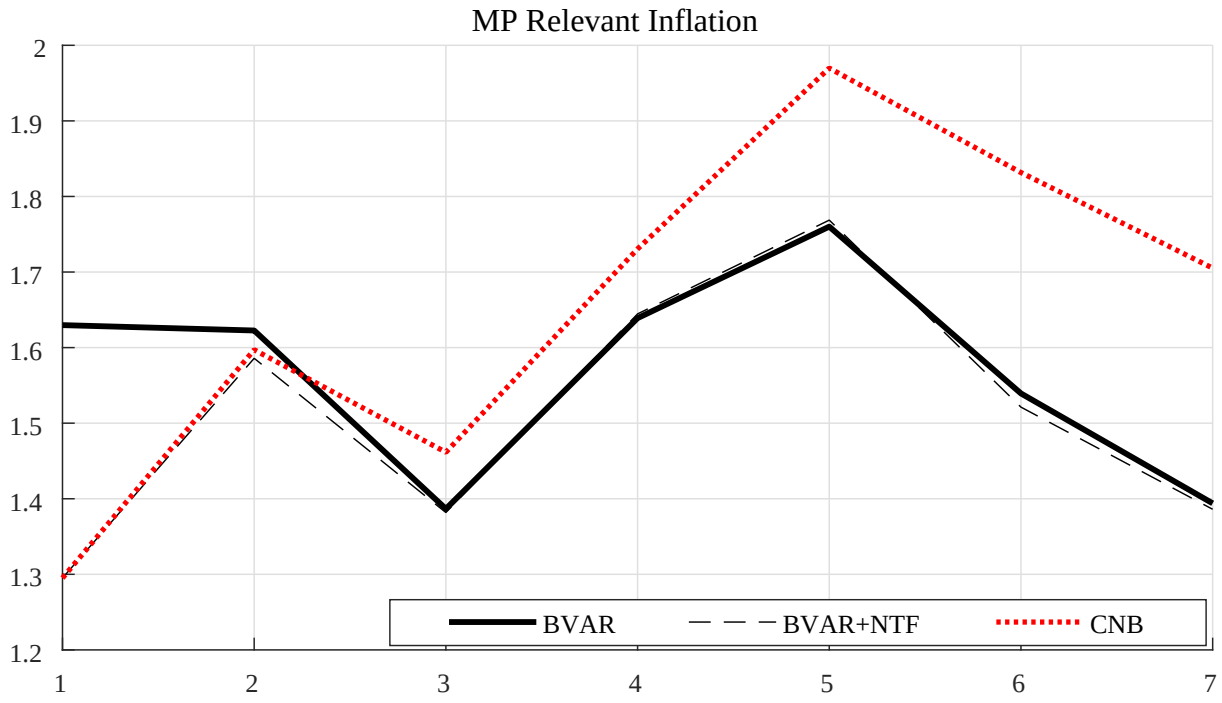


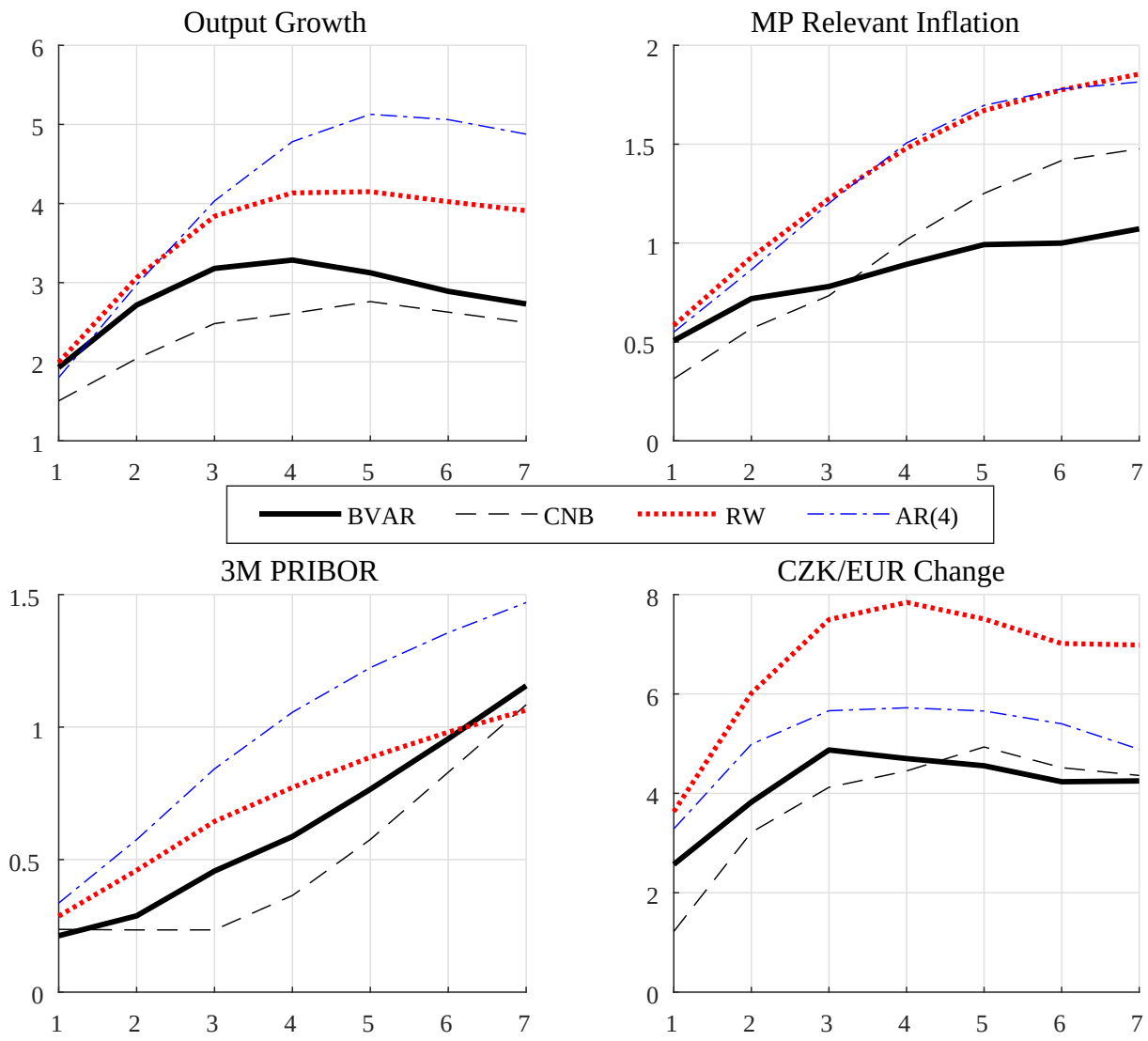
Figure 9 demonstrates how conditioning on inflation nowcast (NTF) improves forecasting accuracy for the first two quarters in the BVAR model. Longer forecasting horizons are unaffected. The result is that BVAR inflation forecast extended for inflation nowcast outperforms CNB inflation for all horizons.

Next, the benchmark specification is based on growth data in annualized q-o-q changes. As a robustness check, the forecasting performance exercise is also done for the specification with growth

[9] The situation after 2014Q1 from the point of view of the g3 model is unusual. For a standard DSGE model of New-Keynesian type, the combination of negative foreign interest rates far from the assumed steady state and positive inflation and economic growth is difficult to reconcile and consequently to forecast.

data in y-o-y changes. As demonstrated by 10, the RMSEs provide similar results to the case of the specification with data in q-o-q changes. The inflation forecasts are more accurate in the BVAR model starting with the fourth quarter.

Figure 10: RMSE - Y-o-Y Model Specification

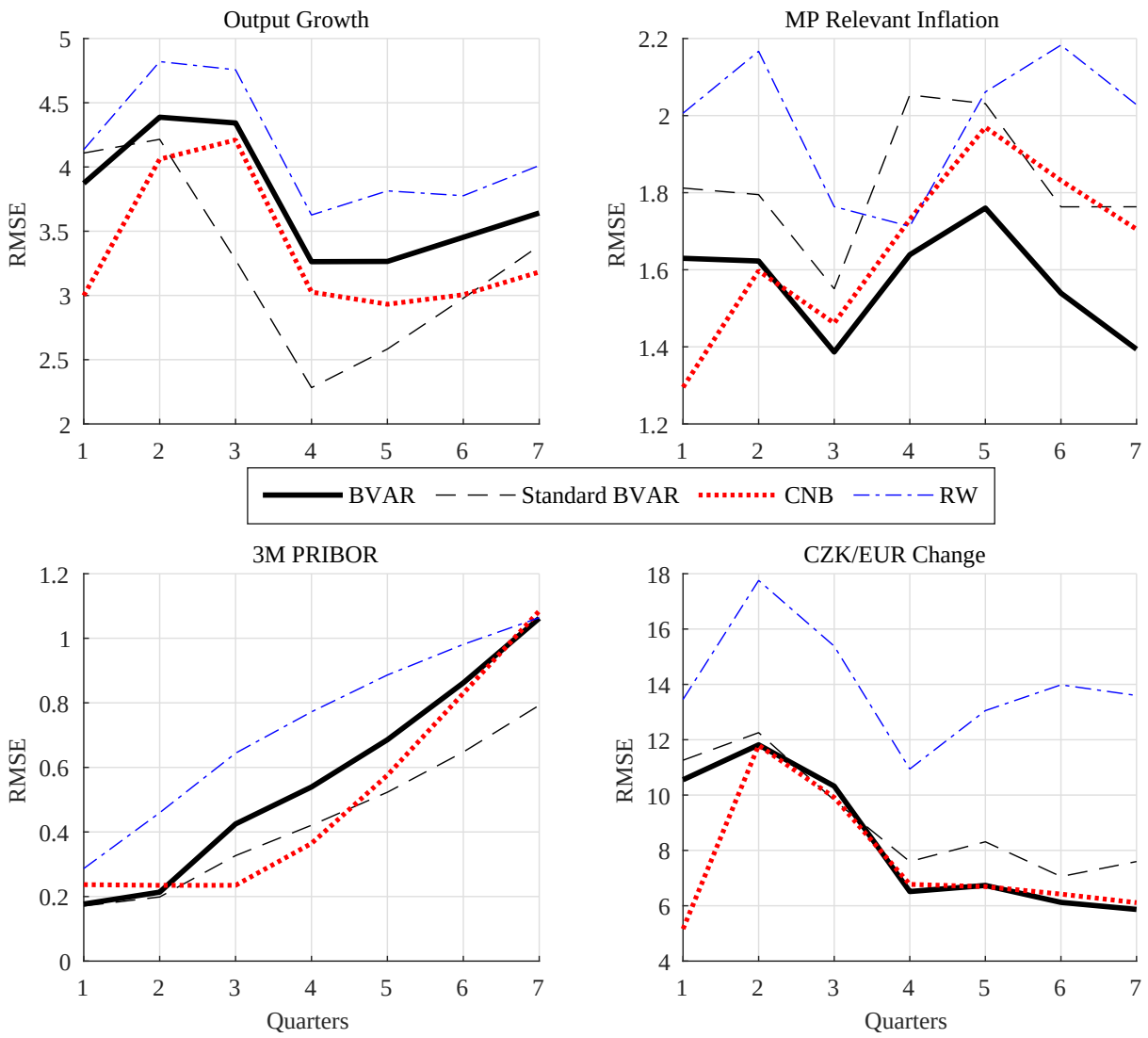


Finally, the standard, non-mean-adjusted BVAR forecasts are examined to shed some light on the role of the explicit treatment of the steady state in the mean-adjusted BVAR.[10] As argued above, such treatment should improve the forecasting ability in the medium and long term because the forecasts tend to approach the relevant steady state with increasing horizon, so an accurate estimate of the steady-state values could help.

Figure 11 reports the RMSEs of the benchmark mean-adjusted BVAR model (BVAR) and the standard BVAR without mean-adjustment (standard BVAR). It also reports all the other modeling approaches discussed above. For inflation and exchange rate growth, the medium-term forecasting performance worsens when the steady state of the model variables is not estimated directly. The opposite is true for the 3M PRIBOR. For all the variables except inflation, the short-term forecasting

[10] The standard BVAR is estimated using the same priors (Normal-diffuse) as the mean-adjusted BVAR.

Figure 11: RMSE - Role of the Mean-Adjustment



Note: BVAR denotes the mean-adjusted BVAR and standard BVAR denotes the BVAR without mean-adjustment.

ability is not affected much by switching between the mean-adjusted and standard BVAR. This is consistent with the idea that steady states affect forecasting mainly in the medium and long term.

5. Conclusions

In this paper, the forecasting performance of small-scale mean-adjusted Bayesian VAR was explored. The model was estimated using the Czech economy time series and its conditional forecasts were compared with the official CNB forecasts. We found that the BVAR approach can be useful for inflation forecasting at the horizon of 3–7 quarters, which covers the monetary policy horizon, i.e., the horizon at which CNB targets its inflation target.

The results are similar to the findings in Iversen et al. (2016), who found that the BVAR model generates superior forecasts for inflation and the repo rate in comparison to Sveriges Riksbank's forecasts and DSGE model forecasts. Iversen et al. (2016) state two possible reasons for the higher accuracy of BVAR inflation and interest rate forecasts in comparison to the DSGE model. First,

the higher accuracy could be a consequence of the fact that the BVAR model is re-estimated each forecasting round while the core model was estimated once on pre-crisis data. The core model that underlies the CNB forecasts is partly calibrated, so the advantage of re-estimation could be even more pronounced. The second reason for the superior performance of the BVAR model noted by Iversen et al. (2016), which is not confirmed by our analysis, is the slow speed at which the BVAR model returns to its steady state.

In this paper, another possible reason is explored. We found that the two forecasting approaches work with different steady states having different impacts during the forecast conditioning procedure. In addition, the conditioning procedure, which is different due to the treatment of the shocks needed to get the condition, can itself play a role.

It should be stressed that our forecasting comparison is done on a very short time period. The period covers an unusual recession and the findings should be generalized with caution. On the other hand, the analysis suggested that the forecasting comparison exercise can teach us a lot about the particular modeling approach and should therefore be conducted in the future as new data and forecasts appear.

Finally, the comparison of the CNB forecasts and BVAR forecasts is hindered by the fact that judgments are included in the CNB forecasts and it is difficult to distinguish what part of the forecast error is due to judgment and what part is due to the underlying core model. In this paper, we tried to incorporate judgments if they take the form of forecast conditioning. However, this procedure does not account for all judgments and extra model information in general. Also, the BVAR model framework lacks the option of applying conditioning in anticipated mode, while the inclusion of anticipated information is an integral part of the CNB forecast.

In general, mean-adjusted BVAR can be viewed as a tool to improve forecasting due to its explicit treatment of the steady state that the forecast approaches in the medium to long term. Future research could focus on short-term forecasting ability in the form, for example, of large BVARs or factor models. The combination of a data-intensive model for the short run and mean-adjusted VARs for the long run is definitely worth examining.

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Appendix A: Duration of Conditions Imposed on Forecasts of Interest and Exchange Rate Forecasts

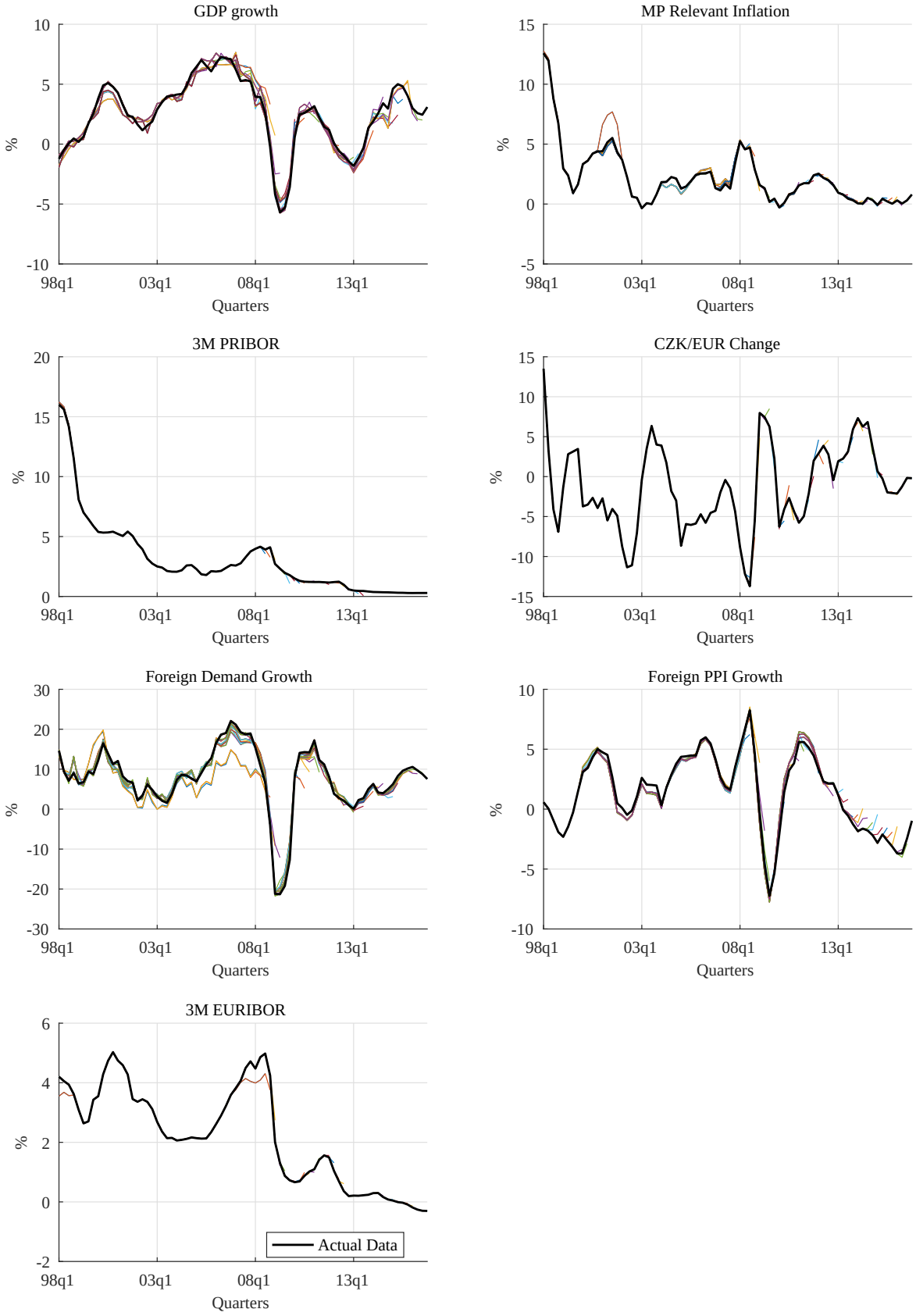
Table A1: Conditioning of Forecasts (Interest rate, Exchange rate Change)

Forecast	Length of Conditioning	Note
2014q1	4	Commitment announced until beginning of 2015.
2014q2	3	Commitment announced until beginning of 2015.
2014q3	5	Commitment announced until beginning of 2015q3.
2014q4	6	Commitment announced until beginning of 2016q1.
2015q1	8	Commitment announced until end of 2016.
2015q2	7	Commitment announced until end of 2016.
2015q3	6	Commitment announced until end of 2016.
2015q4	5	Commitment announced until end of 2016.
2016q1	4	Commitment announced until end of 2016.
2016q2	5	Commitment announced until mid-2017.
2016q3	4	Commitment announced until mid-2017.
2016q4	3	Commitment announced until mid-2017.

Note: The exchange rate commitment includes a commitment to keep the interest rate at technical zero at least for the period specified for the exchange rate commitment.

Appendix B: Data

Figure B1: Data and Revisions in Q-o-Q Terms



Appendix C: Results – Specification in Q-o-Q Changes and Tighter Priors

As noted in the text, it is not clear what prior variance should be assumed for the steady-state values. In the main text, the variances follow Beechey and Österholm (2008). Here, we use the tighter priors from Villani (2009) and set the prior variances on the steady-state values as reported in Table C1.

Table C1: Prior Distributions for Steady States

	2008q3–2010q1		2010q2–2013q3		2013q4–2016q4	
Variable	Mean	95%	Mean	95%	Mean	95%
Foreign Demand Growth	9.4	(7.8,11.0)	8.9	(7.6,10.2)	7.2	(6.7,7.7)
Foreign Inflation	2.0	(0.9,3.1)	2.0	(1.2,2.8)	2.0	(1.5,2.5)
3M EURIBOR	4.0	(2.9,5.1)	4.0	(3.2,4.8)	3.5	(3.0,4.0)
Output Growth	5.0	(3.9,6.1)	4.0	(3.2,4.8)	3.0	(2.5,3.5)
MP Relevant Inflation	3.0	(1.4,4.6)	2.0	(1.4,2.6)	2.0	(1.7,2.3)
3M PRIBOR	3.0	(1.9,4.1)	3.0	(2.2,3.8)	3.0	(2.5,3.5)
CZK/EUR Change	-2.4	(-3.4,-1.5)	-2.4	(-3.0,-1.8)	-1.5	(-1.8,-1.2)

Note: The exchange rate commitment includes the interest rate commitment on the interest rate to be at the technical zero at least for the period specified for the exchange rate commitment.

Figure C1: RMSE - Tighter Priors

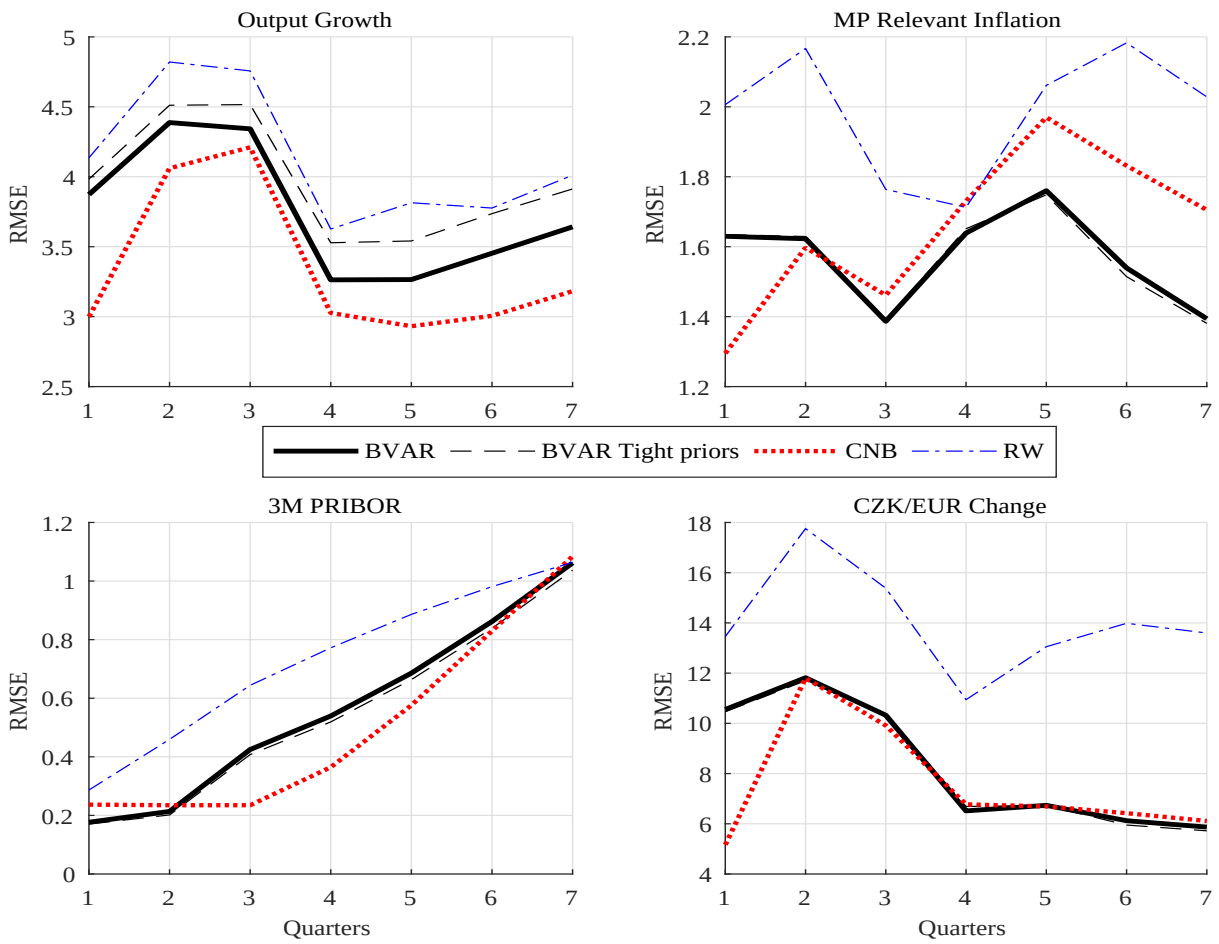
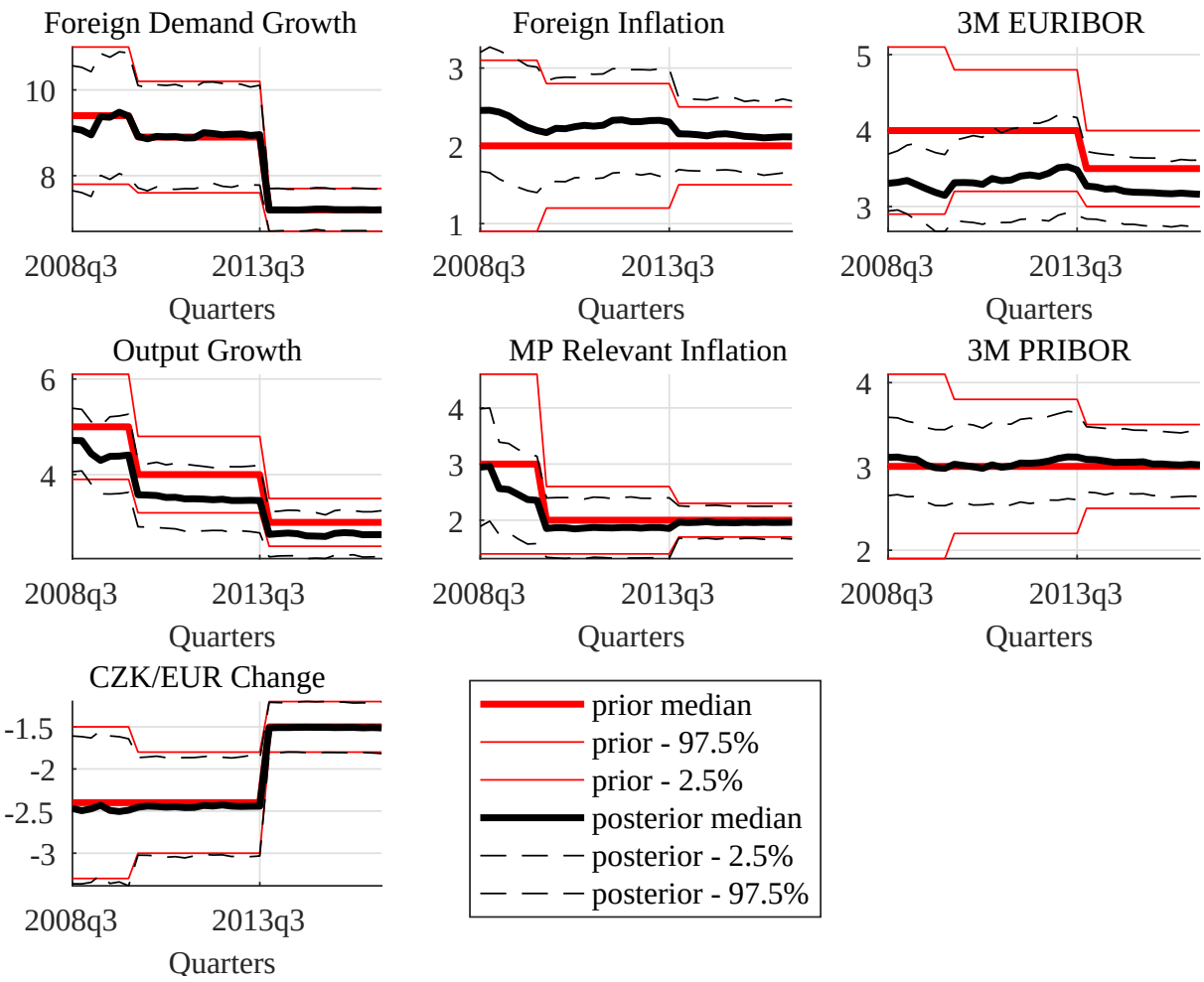


Figure C1 shows the forecasting performance of the BVAR model with tighter priors. The evolution of the estimates of the steady-state values are reported in Figure C2. For some variables the posteriors closely follow the priors, suggesting that the latter are too restrictive and that the specification of the prior variance from Beechey and Österholm (2008) is preferable.

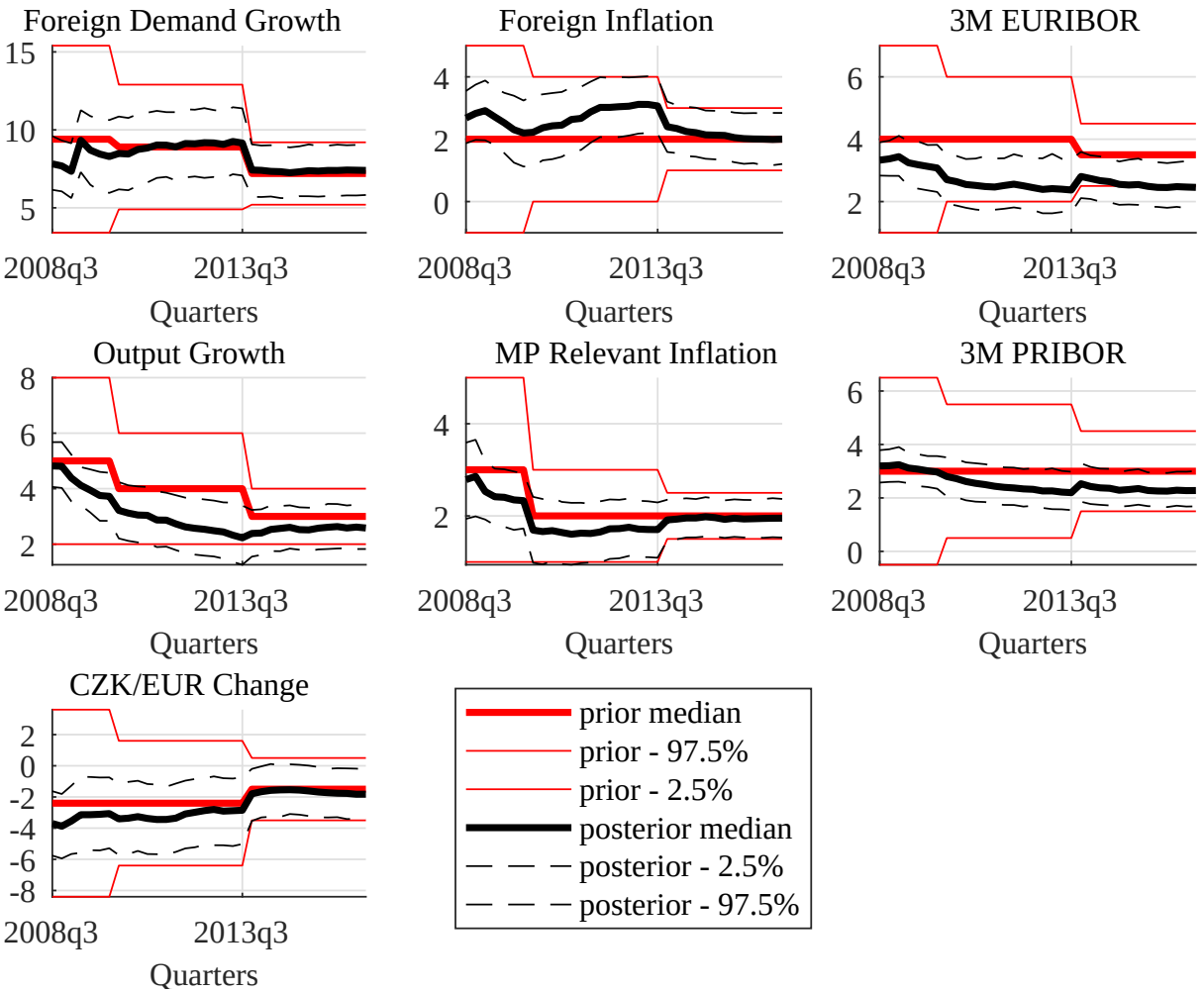
Figure C2: Sequential Prior and Posterior Median Distributions of the Steady State Over Time: Tighter Priors



Note: The specification in q-o-q terms is considered; the horizontal axis denotes the quarter in which the forecast is made.

Appendix D: Steady State – Y-o-Y Changes Specification

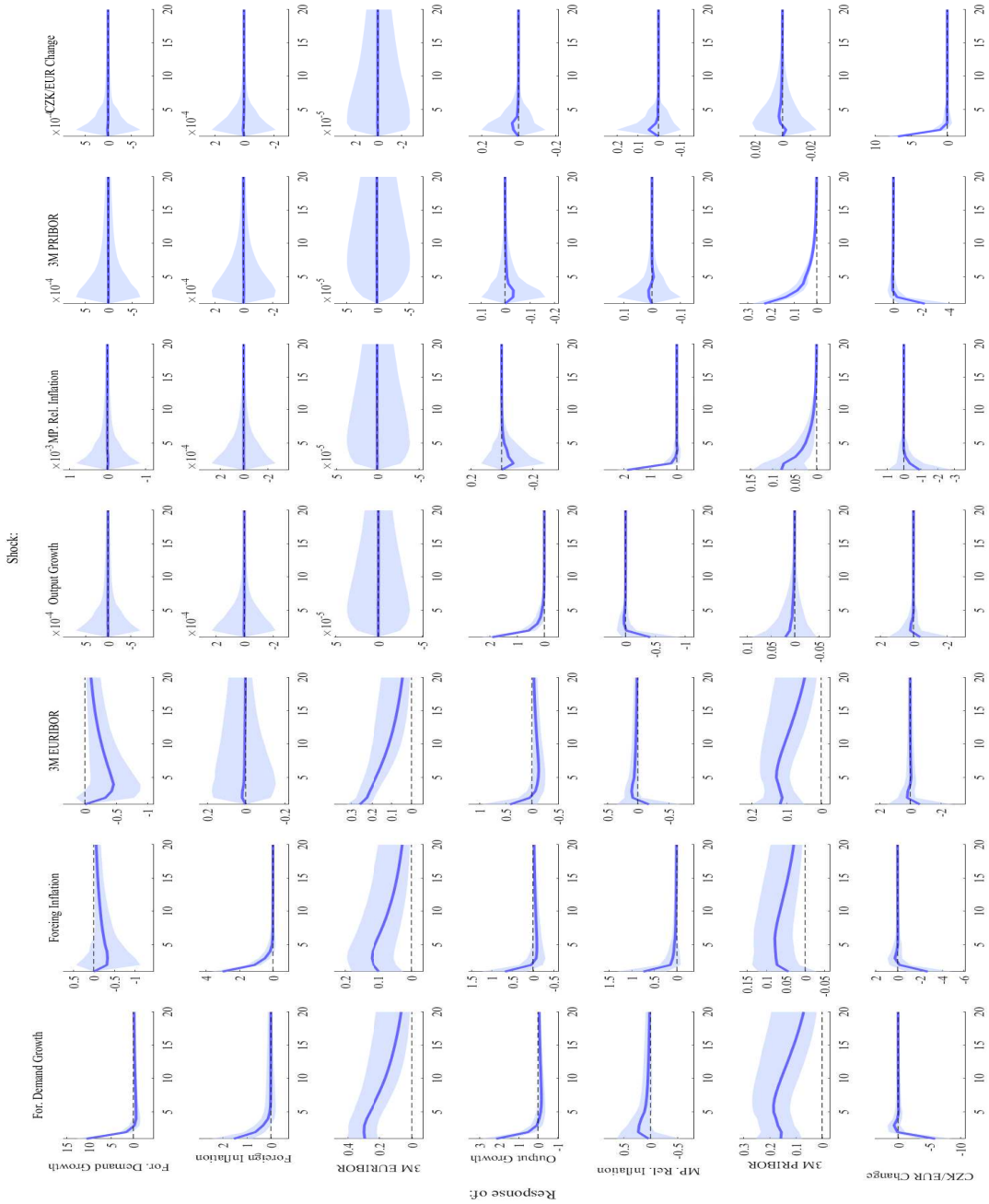
Figure D1: YoY Changes Model - Sequential Prior and Posterior Median of Steady State Over Time.



Note: The specification with growth data in annualized y-o-y terms is considered; the horizontal axis denotes the quarter in which the forecast is made.

Appendix E: Impulse Response Functions

Figure E1: Impulse Response Functions - Baseline Model in 2016q4

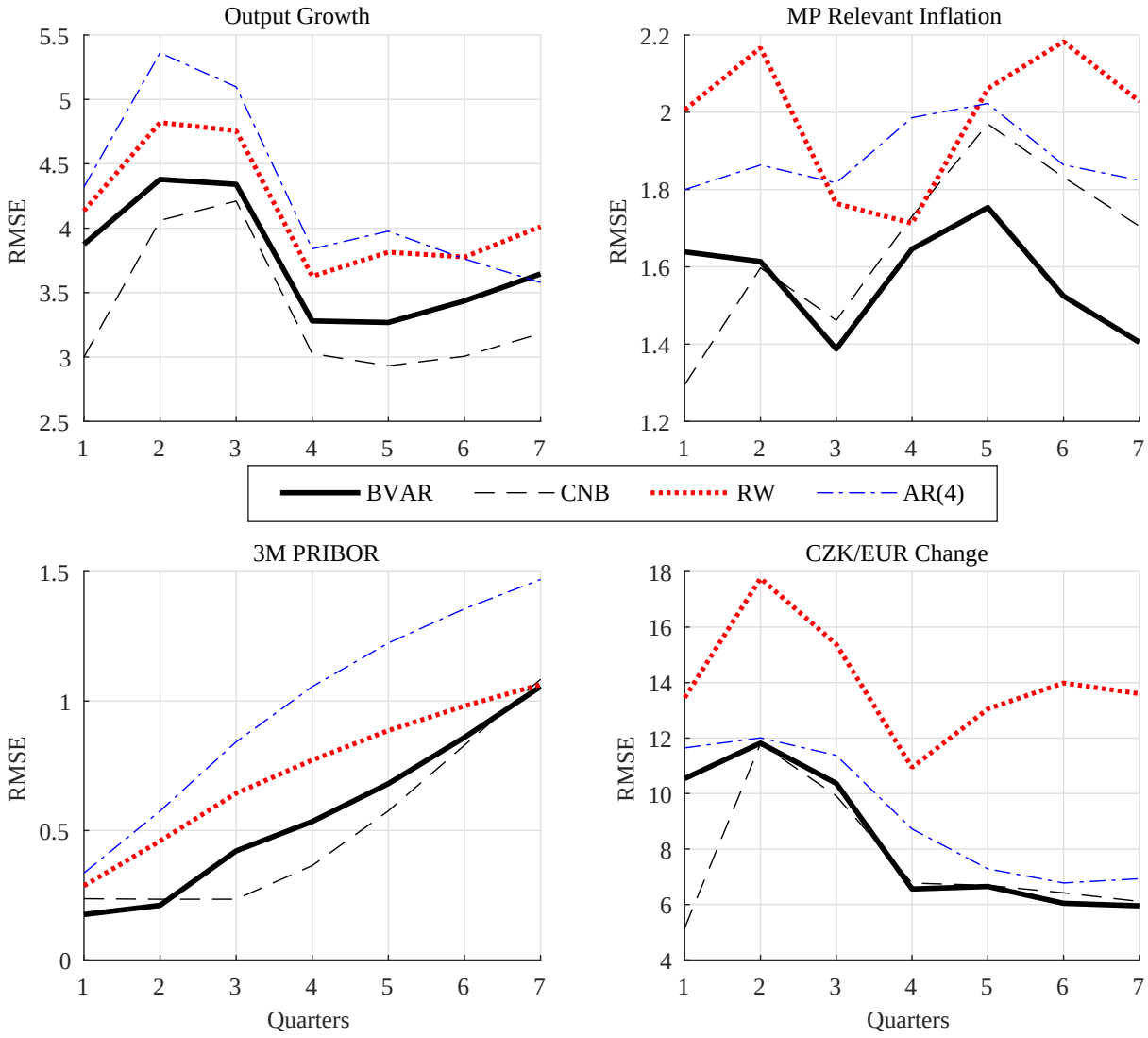


Note: The specification with growth data in q-o-q changes is employed. The model is estimated on the full sample.

Appendix F: RMSE Evaluated Using the Vintage after Two Years

Here, the forecasts are compared with the vintage released two years after the forecast was constructed. The specification with data in q-o-q changes is employed. Figure F1 shows that the qualitative conclusions relating to the forecasting performance do not change when the most recent data vintage is used to evaluate forecast performance.

Figure F1: RMSE - Forecasts Evaluated with Respect to the Vintage After Two Years



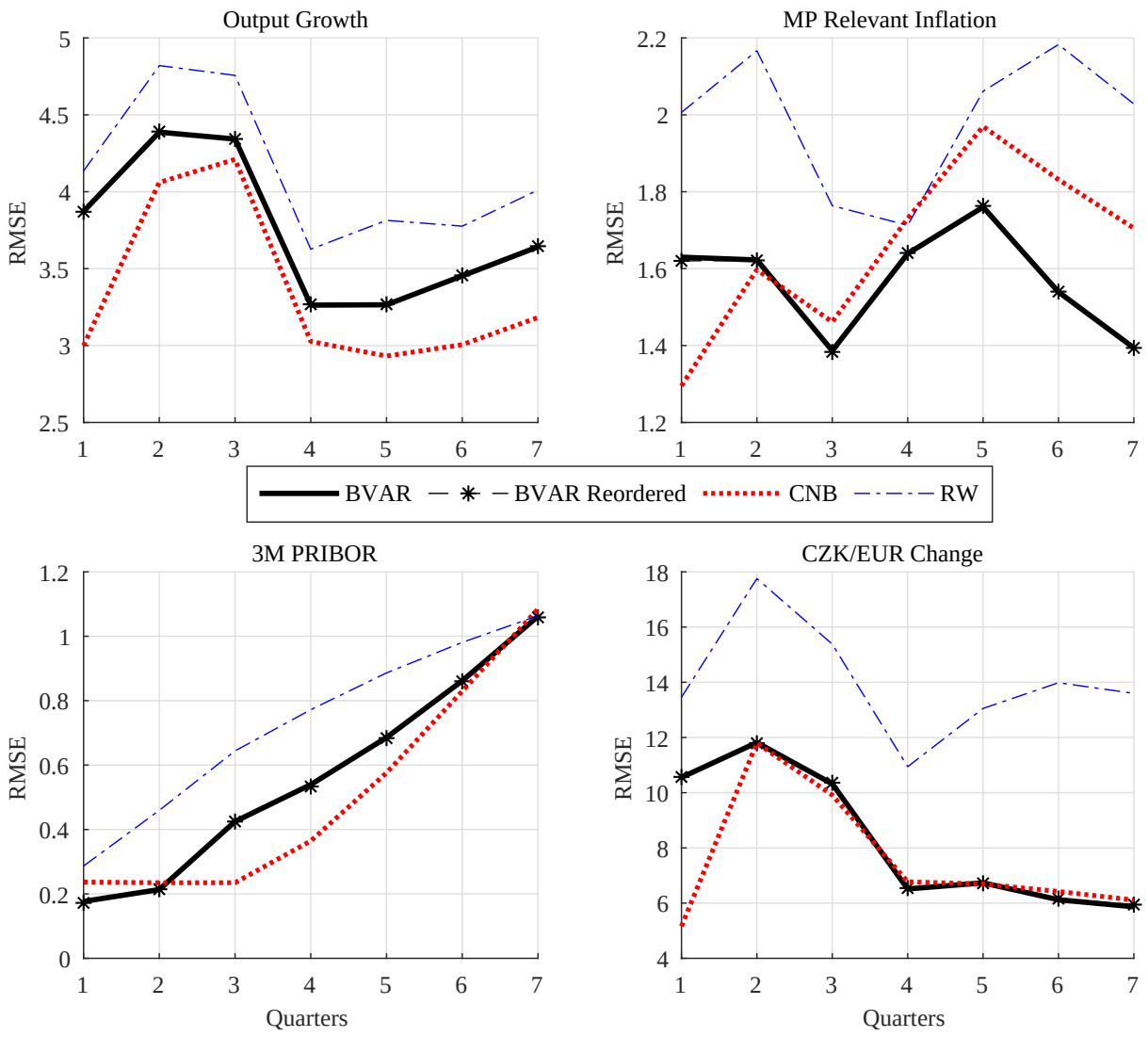
Appendix G: Robustness Checks – Different Ordering of Variables

Recursive identification draws on the assumption that some variables do not contemporaneously react to other variables. This strong assumption is often debated. The zero contemporaneous reaction of interest rates to an unexpected change in the exchange rate is frequently questioned, especially if quarterly data are employed (e.g. Vonnák (2010)).

To examine the effect of the ordering of variables, the following figure presents the RMSEs for the specification where exchange rate growth replaces the interest rate and the interest rate is ordered last in the vector of endogenous variables. The ordering of the rest of the variables is the same as in the benchmark specification.

Figure G1 suggests that the effects of this particular change in the ordering of the variables are minimal.

Figure G1: RMSE - Different Ordering of Endogenous Variables



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