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A BVAR Model for Forecasting Ukrainian Inflation

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Abstract

In this paper, I examine the forecasting performance of a Bayesian Vector Autoregression (BVAR) model with steady-state prior and compare the accuracy of the forecasts against the forecasts of QPM model and official NBU forecasts over the period 2016q1–2020q1.

My findings suggest that inflation forecasts produced by the BVAR model are more accurate than those of the QPM model two quarters ahead and are competitive for the longer horizon. For GDP growth, the forecasts of the BVAR outperform those of the QPM for the whole forecast horizon. For inflation they also outperform the official NBU forecasts over the monetary policy horizon, whereas the opposite is true for the forecasts of the GDP growth.

JEL Codes: C30, C53, E37.

Keywords: BVAR, forecast evaluation, inflation forecasting.

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Contents

1.Introduction

In 2016 the National Bank of Ukraine moved de facto to an inflation targeting regime. One of the required preconditions for successful implementation of an inflation targeting regime is the development of models capable of producing accurate and well-grounded forecasts. In this framework forecasting inflation becomes an essential task.

Regular medium-term macroeconomic forecasts and monetary policy recommendations at the National Bank of Ukraine (NBU) are mostly based on a Quarterly Projection Model (QPM[1]), which is the main element of the Forecasting and Policy Analysis System (FPAS). The QPM is a semi-structural, forward-looking New-Keynesian model of a small open economy. Owing to the fact that the main role of the QPM is to produce story-telling and to incorporate some expert judgments, the issue of the forecasts' accuracy may fade into the background. For that reason, it is worth having an additional empirical model producing more accurate forecasts.

The aim of this research is to develop a Bayesian Vector Autoregression (BVAR) model for forecasting inflation in Ukraine, to examine the forecasting performance of the model, and to compare the accuracy of the forecasts against the forecasts of the QPM model and official NBU forecasts.

The forecasting evaluation exercise uses quarterly data for the period of 2016q1–2020q1. During this period the QPM was the main forecasting model; and official NBU forecasts were systematically documented. This allows the forecasts based on BVAR models to be compared with both QPM and official NBU forecasts.

A Bayesian approach to estimation was chosen given that Ukrainian data is short and dimensionality problems may arise with the large number of parameters present in the model. The imposition of priors not only solves the dimensionality problem but supplements the information contained in the data with the personal judgments contained in the prior. Hopefully, the use of different sources of information will sharpen macroeconomic analysis.
I employ a BVAR model with an informative steady- state prior as in Villani (2009), because this type of priors is widely used for inflation forecasting in countries which adopted an inflation targeting regime, as it explicitly uses information about the inflation target and other equilibrium values.

The paper is organized as follows. Section 2 contains a literature review. The theoretical framework and some issues regarding the forecast conditioning procedure can be found in Section 3. Section 4 presents an overview of inflation dynamics in the Ukraine during the past 15 years. Section 5 describes the data and presents some correlation analysis. Section 6 presents empirical specifications of the models and the priors. Section 7 describes the results and the forecasting performance. Finally, Section 8 offers some concluding remarks. Additional information and results can be found in the Appendices A-D.

[1] Detailed information regarding the QPM model can be found in Grui and Vdovychenko (2019)

2. Literature review

The recent forecasting literature points out that among empirical models, BVARs have superior abilities when it comes to forecast output and inflation. In this section an overview of recent empirical papers using BVAR models for forecasting purposes is provided. The attention is focused on the papers which are using BVARs with steady state priors.

Villani (2009) was the first who imposed prior directly on the steady state of the model. He argued that this form of prior can be very important, especially for long term horizon forecasts. Indeed, prior beliefs regarding the steady state are often available in relatively strong form and seems to improve forecasting ability of the models.
Iversen et al. (2016) compared forecasts made with a DSGE model and with a BVAR model against judgmental forecasts published by the Riksbank and found that BVAR model forecasts for inflation and the repo rate have outperformed DSGE model forecasts and the Riksbank's published forecasts. They also evaluated the usefulness of conditioning information for the model-based forecasts (forecasts were conditioned on the international forecast and the short-term forecast) and found that the difference between conditional and unconditional forecasts is rather small for the BVAR forecasts. However, for DSGE-based forecasts, conditioning information was helpful.
Brázdik and Franta (2017) also came to the conclusion that over the monetary policy horizon the BVAR approach provides a more precise inflation forecast than official ones published by the Czech National Bank. In their study, they considered BVAR forecasts, conditioning on the foreign outlook and, for the period of the exchange rate floor, also on the officially announced exchange rate and interest rate commitments.
Beechey and Österholm (2010) emphasized that for the inflation targeting countries such as Australia, Canada, New Zealand and Sweden the out-of-sample forecasts of the mean-adjusted autoregressive model are superior to those of the traditional specification, often by non-trivial amounts.
Clark (2011) showed that a BVAR model with a steady-state prior and stochastic volatility improves the real-time accuracy of density forecasts and modestly improves the accuracy of point forecasts. As he is dealing with forecasting of US indicators, his model is specified for a closed economy. The endogenous variables are GDP growth, the unemployment rate, inflation and federal funds rate, and the nominal exchange rate. One of the specifications also includes as an endogenous variable the long-term inflation expectation from the Blue Chip Consensus, which is used to measure trend inflation.

The model for the Swedish economy used in Villani (2009) and Iversen et al. (2016) has also foreign indicators and the endogenous variables of the model are foreign GDP growth, foreign inflation, foreign interest rate, domestic GDP growth, domestic inflation, domestic interest rate, and the real exchange rate. The model considered in Iversen et al. (2016) also has nominal wages, hours worked, and the trade-weighted nominal exchange rate instead of real exchange rate.
The model of Brazdik and Franta (2017) for Czech economy is similar to the Villani (2009), however it also has nominal exchange rate instead of real exchange rate.

To select the specification of a BVAR model for Ukrainian economy it is worth starting from the specifications used in the above-mentioned papers. To the best of my knowledge, I am first to use a BVAR model with a steady-state prior for forecasting Ukrainian inflation.

3. The theoretical framework

3.1 A BVAR model with steady state prior

Villani (2009) proposes to use a VAR model in a mean adjusted form:

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

where $t = 1..T$, y_t is an $n \times 1$ vector of endogenous variables, x_t is an $m \times 1$ vector of exogenous variables, ε_t is i.i.d. $N(0, \Sigma)$, $A(L) = I - A_1 L - A_2 L^2 - \cdots A_p L^p$ is a p lag polynomial, $A_1 \ldots A_p$ are $n \times n$ matrices , F is $n \times m$ matrix of coefficients for the m endogenous variables.
Taking expectations on both sides of equation and rearranging the equation one has:

$$E(y_t) = Fx_t \tag{2}$$

That is, the long-run value of the variables of the VAR is determined by the exogenous component of the model and Fx_t represents an unconditional mean of y_t. When the exogenous component includes only constant terms, Fx_t reduces to a vector of constants so that $E(y_t) = \mu$. Thus, the steady-state values for the data are μ.
To proceed, (1) can be rearranged into VAR in standard form adding additional lagged values of exogenous variables:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + Fx_t - A_1 F x_{t-1} - A_p F x_{t-p} \quad + \varepsilon_t \tag{3}$$

After rewriting (3) into transposed form, stacking observations and gathering the regressors into matrices we get:

$$\begin{pmatrix} y_1' \\ y_2' \\ \vdots \\ y_T' \end{pmatrix} = \begin{pmatrix} y_0' \; y_{-1}' \cdots y_{1-p}' \\ y_1' \; y_0' \cdots y_{2-p}' \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ y_{T-1}' \; y_{T-2}' \cdots y_{T-p}' \end{pmatrix} \begin{pmatrix} A_1' \\ A_2' \\ \vdots \\ A_p' \end{pmatrix} + \begin{pmatrix} x_1' \; -x_0' \cdots -x_{1-p}' \\ x_2' \; -x_1' \cdots -x_{2-p}' \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ x_T' \; -x_{T-1}' \cdots -x_{T-p}' \end{pmatrix} \begin{pmatrix} F' \\ F'A_1' \\ \vdots \\ F'A_p' \end{pmatrix} + \begin{pmatrix} \varepsilon_1' \\ \varepsilon_2' \\ \vdots \\ \varepsilon_T' \end{pmatrix} \tag{4}$$ [1]

Or in compact notation:

$$Y = XB + Z\Delta + E \tag{5}$$

where

$$Y = \begin{pmatrix} y_1' \\ y_2' \\ \vdots \\ y_T' \end{pmatrix}, X = \begin{pmatrix} y_0' \; y_{-1}' \cdots y_{1-p}' \\ y_1' \; y_0' \cdots y_{2-p}' \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ y_{T-1}' \; y_{T-2}' \cdots y_{T-p}' \end{pmatrix}, B = \begin{pmatrix} A_1' \\ A_2' \\ \vdots \\ A_p' \end{pmatrix}, Z = \begin{pmatrix} x_1' \; -x_0' \cdots -x_{1-p}' \\ x_2' \; -x_1' \cdots -x_{2-p}' \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ x_T' \; -x_{T-1}' \cdots -x_{T-p}' \end{pmatrix},$$

$$\Delta = \begin{pmatrix} F' \\ F'A_1' \\ \vdots \\ F'A_p' \end{pmatrix}, E = \begin{pmatrix} \varepsilon_1' \\ \varepsilon_2' \\ \vdots \\ \varepsilon_T' \end{pmatrix}$$

Vectorizing (4) and compactly rewriting it we obtain:

$$y = \bar{X}\beta + \bar{Z}\delta + \epsilon \tag{6}$$

where $y = vec(Y),\ \bar{X} = I_n \otimes X, \beta = vec(B),\ \bar{Z} = I_n \otimes Z,\ \delta = \mathrm{vec}(\Delta), \epsilon = vec(E)$. Let:

$$vec(\Delta') = vec\big(F\ A_1 F \dots A_p F\big) = \begin{pmatrix} I_{nm} \\ I_m \otimes A_1 \\ \vdots \\ I_m \otimes A_p \end{pmatrix} vec(F) = U\psi \tag{7}$$

where $\psi = vec(F),\ U = \begin{pmatrix} I_{nm} \\ I_m \otimes A_1 \\ \vdots \\ I_m \otimes A_p \end{pmatrix}$ (8 and 9)

Note that there are now three blocks to estimate – β, which corresponds to the coefficients on the endogenous variables y_t; ψ, which corresponds to coefficients on the exogenous variables x_t and Σ- residual variance-covariance matrix.

A diffuse prior for the error covariance matrix is assumed, while the prior on the other two sets of coefficients is normal.

$$p(\Sigma) \propto |\Sigma|^{-(n+1)/2} \tag{10}$$

$$\beta \sim \mathrm{N}(\beta_0, \Omega_0) \tag{11}$$

$$\psi \sim \mathrm{N}(\psi_0, \Lambda_0) \tag{12}$$

Dieppe et al. (2016) argue that one can't set a flat prior for ψ as in the Minnesota scheme~~,~~ because the very purpose of this type of prior is to add an information about means into the estimation process. It is recommended to specify a subjective 95% probability interval for the prior values. Using the properties of the normal distribution, the prior mean of the distribution is determined as the mode of the specified subjective 95% probability interval, while the variance is obtained by the fact that the bounds of a subjective 95% probability interval are located at 1.96 standard deviations from the mean.

Villani (2009) shows the complete derivation of the posterior distribution. The steps of a Gibbs sampling algorithm for BVAR with steady-state prior can be found in the Appendix A.

3.2 Hyperparameter values

To find the values of hyperparameters for the model, a grid search similar to the procedure used by Giannone et al. (2012) is applied.
First, a range for each hyperparameter is specified together with a step size defining the size of the increment within the range. Then the marginal likelihood is estimated for each model with every possible combination of hyperparameter values. The optimal combination, which is the one that maximizes the marginal likelihood is kept.

3.3 Forecasting

Iterated BVAR forecasts for up to 6 quarters are simulated in the form of a posterior predictive distribution. The root mean squared error (RMSE) is used to evaluate the accuracy of the BVAR point predictions and to compare its accuracy against the QPM model and the official forecasts of the NBU. Also, a simple AR model is constructed to serve as a benchmark (the lag length of AR model is selected minimizing the RMSE within the forecasting exercise period).

Together with unconditional forecasts, I compute forecasts conditioning on foreign indicators. I do so for a number of reasons. First, almost all medium-term forecasts at the NBU are based on some assumptions concerning either external or internal factors (e.g., conditioning on the interest rate, as it serves as a main instrument of monetary policy; or on external variables, as more precise forecasts of external indicators are available). Hence, conditioning allows forecasts to be more realistic. Moreover, it makes the interpretation of forecasts and story building-around it easier. Second, conditioning on the same variables used in the QPM makes the comparison of the models more meaningful. Finally, I expect the conditional inflation forecast to be more precise and I am going to examine this hypothesis.

There are several options in the literature on how to incorporate external information into the forecasts of BVAR. The hard conditioning option was developed by Waggoner and Zha (1999), who derived a Gibbs sampling algorithm to construct the posterior predictive distribution of the conditional forecast.
A more efficient solution was suggested by Jarocinski (2010). In this framework shocks are divided into constructive and non-constructive. Constructive shocks are the shocks on which a condition is imposed. However, conditioning may not be unique, meaning the same condition may be imposed on different shocks. Thus, the researcher should carefully select the shocks generating the constraint, in order to produce sensible economic results.
In contrast to hard conditioning where future values of variables are fixed at single points, soft conditioning is more flexible and deals with conditions that only restrict the future values within a certain range. Soft conditioning was also introduced by Waggoner and Zha (1999). However, an alternative methodology (entropic tilting) initially proposed by Robertson et al. (2005) and further developed by Krüger et al. (2017), allows to incorporate external information into model-based forecasts.
Comparing the soft conditioning by Waggoner and Zha (1999) with entropic tilting, Dieppe et al. (2016) argue that one of the main advantages of entropic tilting is its high flexibility. This is because the method of Waggoner and Zha (1999) only allows to set the center of the predictive distribution, whereas the entropic tilting method allows any moment associated with the distribution to be determined, along with quantile values.

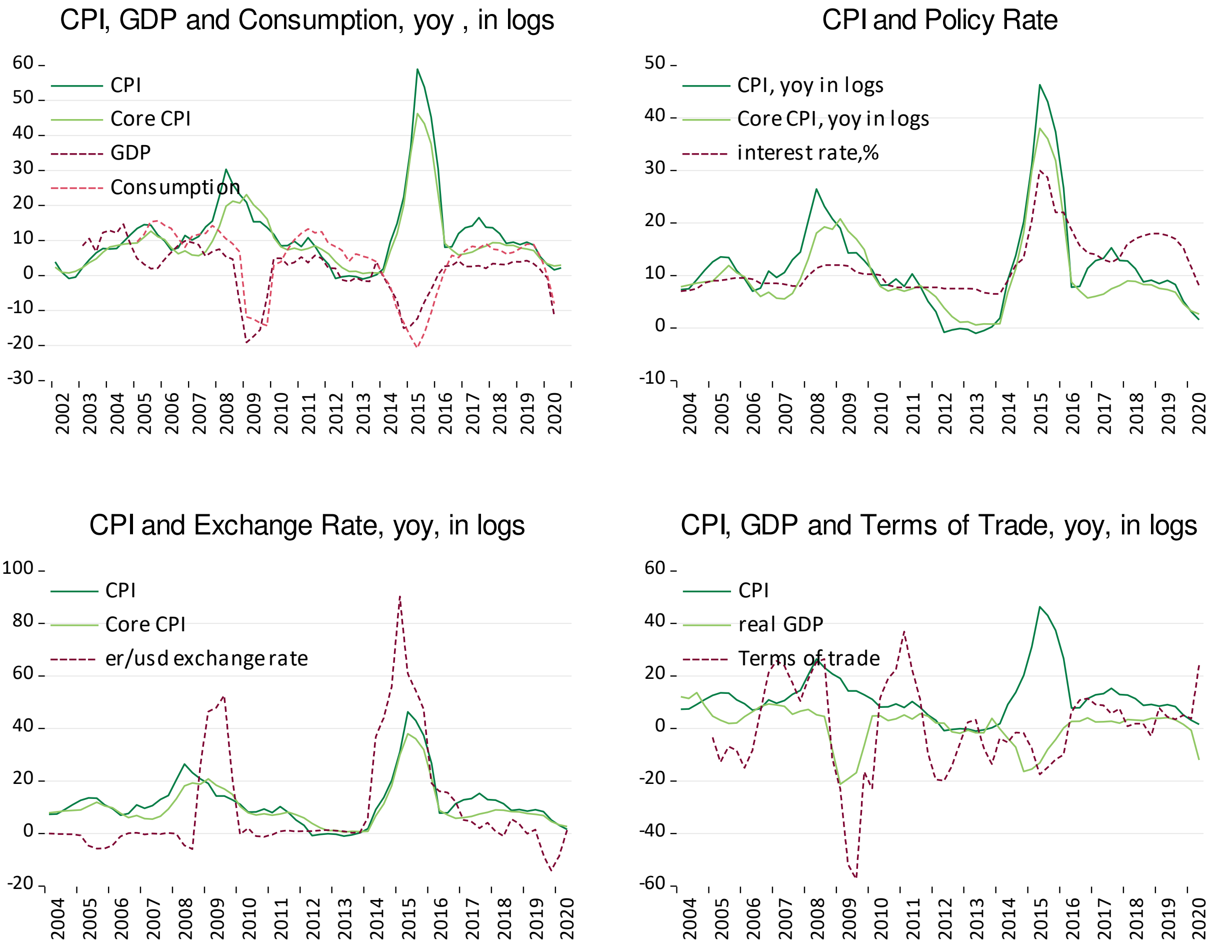
The main idea of the entropy tilting method is to change the initial predictive distribution of the unconditional forecast to a new one that satisfies specified moment conditions, to minimize the

distortions in the other properties of the new distribution. In other words, to get new distribution one minimizes the relative entropy between the two distributions, subject to the restriction that the new distribution satisfies the specified moment conditions. So, by construction conditional forecasts obtained through entropic tilting are as close to the initial distribution of unconditional forecast as possible. Further details on technical implementation of entropic tilting can be found in Dieppe et al. (2016).
In this paper I use entropic tilting, presuming that it will produce more accurate forecasts.

4. Inflation in Ukraine, an overview

In the last two decades, inflation in Ukraine has been relatively high, the average year-over-year growth in the price level being around 10%. Since 2005 Ukraine has had two episodes with inflation exceeding 20%. In 2008, at the beginning of the World Financial Crisis, the Ukrainian economy was overheated. Despite the slowdown in GDP growth during the crisis, consumption growth together with a substantial increase in minimum wages pushed prices upward.

Figure 1. Main economic indicators



During the Great Recession Ukraine was hit by a sharp terms-of-trade shock: the prices of steel declined substantially (in 2008 steel represented about 40% of exports and 15% of GDP), while energy import prices remained high due to phasing out of Russia's gas subsidies. The materialization of the terms of trade shocks had a considerable impact on the real sector.-In addition, major strains were building up in the banking system following a system-wide run on deposits. A loss of confidence domestically led to a capital flight out of the hryvnia into foreign exchange cash. Altogether, this led to a massive devaluation of the currency, fall in real GDP and a shrinking of the current account deficit in 2009.

In 2010-2011 the economy started recovering, inflation went down to single digit, exchange rate was stabilized, and growth rebounded. In 2012-2013 inflation approached zero level due to weak economic activity (the annual GDP growth was 0.2% in 2012 and 0.0% in 2013). Keeping the exchange rate stable led to the accumulation of huge imbalances in the economy. In 2014 these imbalances along with the military conflict in the east of the country led to a severe economic crisis with the real GDP falling by 10% in 2015, with sharp depreciation of the hryvnia and inflation reaching its peak of almost 60% year-over-year in the spring of 2015.

It is worth noting that the nature of two high inflation episodes (2008 and 2015) is different: the second inflationary spike was caused by the pass-through of the hryvnia devaluation, whereas in 2008 rising inflation was a sign that the economy had been overheating.

In August 2015 the NBU declared a transition to the inflation targeting regime in order to break the upward inflationary trend and stabilize the economy. De facto it moved to the inflation targeting regime in 2016. The NBU announced the medium-term inflation target (year-over-year CPI growth) to be set at 5% and to be achieved gradually with the following stages:

- 12% +/- 3 ppts as of the end of 2016;
- 8% ± 2 ppts as of the end of 2017;
- 6% ± 2 ppts as of the end of 2018;
- 5% ± 1 ppt as of the end of 2019 and further on.

It is well known that the inflation targeting regime uses the policy rate as a main instrument. To bring inflation down to the target the NBU should increase the interest rate to moderate demand and slow down inflationary pressure. Thus, the gradual strategy of bringing inflation to its target was chosen deliberately in order to minimize the costs of disinflation for economic growth.

In general, the process of disinflation which started in 2016 went well and in 2019 consumer price inflation gradually declined to a six-year low of 4.1%. Thus, the NBU finally achieved its target of 5% ± 1 ppt. The average GDP growth was 2,8% in 2016-2019.

2020 brought a new challenge: the COVID-19 pandemic may be a shock of unprecedented severity affecting all areas of the economy. In this situation swift and reasonable policy measures are of great importance. In the near future policy makers will need to find the balance between supporting the economy using an accommodative policy and maintaining price stability.

To summarize, the recent economic developments in Ukraine show that along with domestic conditions, external ones are another important driver of inflation and should be used to forecast Ukrainian inflation.

5. Data description and correlations analysis

I use quarterly foreign data, national accounts data, prices and exchange rates over the period of 2004q1–2020q1 (see Table B.1, Appendix B). Alternative measures of different variables are employed in order to find the one with the highest predictive power for inflation:

- In addition to weighted CPI, PPI is used for foreign price levels;
- CPI and PPI deflator-based REER[2] are used for the real exchange rate;
- Overnight or 3-month LIBOR is used as the foreign interest rate;
- Various commodity prices are employed as an alternative for foreign price levels;
- I use 2 measures of terms of trade, constructed as the ratio between the index of export prices and the index of import prices for (1) goods, (2) most important groups of raw commodities;
- Monetary aggregate M2, nominal and real wage are used to reflect domestic factors.

All the data except interest rates are measured in natural logarithms. Growth variables in annualized quarter-over quarter terms are used. To choose the variable to be used in the forecasting exercise I employ a simple correlation analysis. The figures as well as the correlation coefficients between Ukrainian CPI, GDP and other variables are presented in Table B.2, Appendix B.

The CPI is significantly correlated with both inflation differential of trading partners and NEER. However, there is no significant correlation of CPI with weighted GDP of trading partners and various commodity prices, as these indicators may be more important for domestic production rather than consumption. CPI has very weak negative correlation with the lagged policy rate, whereas the contemporaneous correlation has a positive sign. This can be explained by the fact that the interest rate hadn't been used as an instrument-prior to 2016 (before the implementation of inflation targeting), so the monetary transmission mechanism didn't work as it was supposed to.

In addition to unconditional correlations, correlations conditioned on the policy rate were analyzed. However, no serious differences with unconditional correlations were found (see Figure B.1, Appendix B). Domestic GDP is significantly correlated with foreign GDP, which means that for such a small open economy as the Ukraine, external demand is an important factor of GDP growth. The positive correlation of GDP with terms of trade and commodity prices reflects the fact that these indicators drive Ukrainian business cycle, Ukraine being a commodity exporter.
For the same reason as with CPI, the correlation of GDP with policy rate is weak. The correlation with monetary aggregates and wages suggest not to include them into the model.

Taking into account the results of the correlation analysis together with the stylized facts from the Section 3 and the models described in the literature review, the following indicators were chosen for the BVAR model for Ukrainian economy: weighted[3] GDP of trading partners, weighted inflation differential of trading partners, domestic GDP, domestic CPI, domestic policy rate, nominal effective exchange rate (NEER), terms of trade, constructed as the ratio of most important groups of raw commodities and non-energy commodity price index.

6. Empirical model specifications and the priors

[2] To construct a weighted measure of foreign indicators, 3 sets of countries-trading partners were used. The first one contains 5 countries: Euro Area, United States, Russian Federation, China and Turkey. The second index consists only of Euro Area, United States, Russian Federation to simplify the assumptions on the external sector behavior. The third one, has data for 40 countries. However, only weighted real GDP and CPI are available for this broader set of countries.

[3] Aggregated foreign indicators for 40 countries were chosen

The benchmark BVAR specification (MB) for Ukraine is the following:

$$y_t = (\Delta gdp_t^f, \pi_t^f, \Delta gdp_t, \pi_t, i_t, neer_t)' \tag{13}$$

y_t includes foreign GDP growth (Δgdp^f), foreign inflation (π^f), domestic GDP growth (Δgdp), domestic inflation (π), domestic interest rate (i), and the NEER ($neer$).

In order to find the best possible set of variables, two additional specifications are considered (MA_p and MA_tot):

$$y_t = (\Delta gdp_t^f, wbnonen_t, \Delta gdp_t, \pi_t, i_t, neer_t)' \tag{14}$$

y_t includes non-energy commodity price index ($wbnonen$) instead of foreign inflation (π^f).

$$y_t = (\Delta gdp_t^f, \pi_t^f, \Delta gdp_t, \pi_t, i_t, neer_t, tot_t)' \tag{15}$$

in addition to the variables from the benchmark model, y_t includes terms of trade (tot).

In order to take into account that Ukraine is a small open economy, foreign variables and terms of trade are treated as block exogeneous. Namely, the block submatrices in A(L) corresponding to the effects of domestic variables on foreign ones are set to zero.

Standard lag length criterions were used to select the lag length (see Table C.1, Appendix C). Different criterions suggest the use of lags from 1 up to 5. In general, specifications with, larger lag length were preferred. As a robustness check, more parsimonious specifications with two lags were also estimated and the results didn't significantly differ.

The hyperparameters for the models are set according to the results of grid search procedure (information regarding grid search is in Table C.2, Appendix C). The values of hyperparameters used as well as the information regarding number of lags and the number of iterations is presented in Table 1.

Table 1. Hyperparameters and lags

	MB	MA_P	MA_TOT
Autoregressive coefficient	0.5	0.4	0.4
Overall tightness (λ_1)	0.2	0.2	0.2
Cross-variable weighting (λ_2)	1	0.9	1
Lag decay (λ_3)	1	1	1
block exogeneity shrinkage λ_5:	0.001	0.001	0.001
total number of iterations:	10000	10000	10000
burn-in iterations:	5000	5000	5000
Lag length	3	4	5

The priors on the steady states are normally distributed. In order to account for changes in monetary policy regime (the move to inflation targeting in 2016) two different sets of priors are employed. The first regime covers the period from 2004q1 up to 2015q4 and the second regime starts at 2016q1.

To specify the moments of the prior distribution values Dieppe et al (2016) recommend first to set a subjective 95% probability interval and then calculate mean and variance for each variable. Brazdik and Franta (2017), on the contrary, suggest to calculate 95% probability interval based on the mean and variance.

I follow Brazdik and Franta (2017). The means of the priors are taken from the trends estimated in the QPM model. Variances are set using the information from other studies keeping in mind that tighter interval would imply smaller prior variance and hence greater confidence that the steady-state value corresponds to the specified prior mean. On the other hand, a wider interval would imply larger prior variance and more weight given to the data.

Table 2. Steady state prior distributions

	regime 1: 2004q1 2015q4				regime 2: 2016q1 2020q1			
	mean	var	95% Interval		mean	var	95% Interval	
GDPW	4.0	0.5	3.0	5.0	3.0	0.5	2.0	4.0
CPIW	6.0	0.5	5.0	7.0	3.5	0.5	2.5	4.5
GDPUA	1.0	1.0	-1.0	3.0	2.0	0.5	1.0	3.0
CPIUA	11.0	2.0	7.1	14.9	8.0	1.0	6.0	10.0
IUA	12.5	0.7	11.1	13.9	11.0	0.6	9.8	12.2
NEER	-6.8	2.0	-10.7	-2.9	-2.5	1.0	-4.5	-0.5
TOT	-2.0	1.0	-4.0	0.0	3.0	0.5	2.0	4.0
PNONEN	6.0	1.0	4.0	8.0	1.0	0.5	0.0	2.0

The CPI prior for the 2nd regime is set in a different manner. Since in the inflation targeting regime both target and the bounds for inflation are known, the bounds are used directly to set the values for 95% interval. The means and variances from Villani (2009) and Brazdik and Franta (2017) are in Tables C.3 and C.4, Appendix C. Steady state priors for Ukrainian model are presented in Table 2. In general, priors for Ukrainian model are looser than those for Swedish model and tighter than those for Czech model.

7. Estimation results and Forecasting performance

7.1. Estimation results

The priors and posterior estimates of the steady state[4] for BVAR models are presented in Table 3. Specifically, priors are reported for the 2nd regime, while posterior estimates are presented for 2020q1 (which corresponds to the end of the sample, so that the full data set was used for the estimation).
There are some differences between the prior and posterior medians of the steady state for 2020q1 as well as differences in the values of the posterior medians of three BVAR models which are worth discussing.

Table 3. Priors and posterior estimates for 2020q1

[4] The estimates of the steady states are based on the reduced-form VAR, hence structural shock identification does not play any role. Impulse responses based on recursive identification can be found in Figures D.1-D.3, Appendix D.

	Prior, 2016q1 2020q1			Posterior, MB			Posterior, MA_P			Posterior, MA_TOT		
	median	95% Interval		median	95% Interval		median	95% Interval		median	95% Interval	
GDPW	2.0	3.0	4.0	2.7	1.9	3.7	1.8	2.7	3.6	1.8	2.7	3.6
CPIW	2.5	3.5	4.5	3.4	2.6	4.2				2.5	3.3	4.0
GDPUA	1.0	2.0	3.0	2.0	1.1	3.0	1.0	2.0	3.0	1.1	2.1	3.0
CPIUA	6.0	8.0	10.0	7.8	5.9	9.7	5.6	7.5	9.5	5.7	7.7	9.6
IUA	9.8	11.0	12.2	11.8	10.7	13.0	10.7	11.9	13.0	10.7	11.9	13.0
NEER	-4.5	-2.5	-0.5	-2.3	-4.2	-0.3	-4.4	-2.4	-0.4	-4.4	-2.3	-0.4
TOT	2.0	3.0	4.0							2.0	3.0	4.0
PNONEN	0.0	1.0	2.0				0.1	1.1	2.0			

All three models have lower posterior medians for foreign GDP and CPI than the prior median value. However, for the MB model this difference is more pronounced. The reason for the difference may be the fact that in contrast to MB model, both MA_P and MA_TOT models contain additional information on dynamics of commodity prices, which may influence steady state values of foreign variables.
Lower steady state values of external demand in MB model, in turn, affect domestic GDP growth. Hence, the posterior medians for the domestic variables of MB model, suggest lower steady-state value of GDP growth, inflation, policy rate and more pronounced NEER depreciation trend.

7.2 Forecasting performance

In this subsection, the forecasting performance of the BVAR models is examined. The RMSE is employed as the measure of forecasting performance. In addition to RMSE, the equal forecasting accuracy of the models is statistically evaluated using the Diebold-Mariano test. The comparison is split into 4 stages. During the first stage, the unconditional forecasts of MB, MA_P and MA_TOT are compared to the forecasts of the AR1 model.
Then, during the second stage, the forecasts of the BVAR model with the most accurate unconditional forecasts are compared with the forecasts of the same model, conditioned on the external sector indicators to examine whether conditioning improves forecasting accuracy.
At the following stage, the conditional forecasts of the best model from the second stage are compared with the conditional forecasts of the QPM model.
Finally, at a fourth stage, conditional forecasts of the best BVAR model are transformed from annualized quarter-over-quarter indicators into year-over-year indicators and compared with official NBU forecasts. The data transformation is necessary because NBU forecasts are only available on the year-over-year basis.
Because the forecasting performance for inflation at the monetary policy horizon is of most interest, I focus attention on the forecast horizons from 4 to 6 quarters.

Table 4. RMSEs for unconditional forecasts relative to the AR1 model

	CPI			GDP		
period	MB	MA_P	MA_TOT	MB	MA_P	MA_TOT
1	1.05	1.02	1.05	0.89	0.99	0.89
2	1.02	1.02	0.93	0.51*	0.44*	0.48*
3	1.11	1.15	1.11	0.51*	0.50*	0.52*
4	1.04	1.02	0.97	0.67*	0.59*	0.60*
5	0.73*	0.75*	0.64*	0.74*	0.67*	0.73*
6	0.72*	0.69*	0.67*	0.83*	0.75*	0.82*

Note: Asterisks indicate that according to the Diebold-Mariano test difference in forecasting performance relative to the AR1 model is statistically significant at 15% level.

The forecast accuracy of the unconditional BVAR forecasts with different variable specifications is reported in Table 4. Plots of the forecasts can be found in Figure D.4, Appendix D. RMSE values are shown relative to those of an AR1 model in order to facilitate the comparison. Thus, for the given model a value below unity means better than the AR1 model's precision.

Regarding CPI, the BVAR model which includes terms of trade (MA_TOT) seems to have the best forecasting accuracy and outperforms AR1 at the horizon of interest. It is worth noting that in the short run AR1 forecasts are more accurate, however the difference is not statistically significant.
Regarding GDP, the BVAR models outperform the AR1 model from 2nd to 6th quarters and the differences are statistically significant. The added prior information may be the reason for superior performance of the BVAR models at the longer horizons.
Since the BVAR model which includes terms of trade (MA_TOT) has lower RMSE for inflation it will be used in further comparison.

The value of incorporating external conditioning information can be judged by comparing the RMSE for the conditional and the unconditional BVAR forecasts (see Table 5).
Regarding CPI, on average, conditional forecasts are more accurate than unconditional ones, but the difference is rather small. For GDP, unconditional forecasts perform better than the conditional ones, still the difference is not significant.
Hence, I may conclude that adding external information probably does not play an important role in improving forecasting accuracy of inflation and GDP.

Table 5. RMSEs for unconditional and conditional forecasts of MA_TOT relative to the AR1 model

	CPI		GDP	
q	MA_TOT(cond)	MA_TOT	MA_TOT(cond)	MA_TOT
1	1.07	1.05	0.89	0.89
2	0.83*	0.93	0.79*	0.48*
3	1.02	1.11	0.72*	0.52*
4	0.83*	0.97	0.83	0.60*
5	0.78*	0.64*	0.91	0.73*
6	0.66*	0.67*	0.82*	0.82*

Note: Asterisks indicate that according to the Diebold-Mariano test difference in forecasting performance relative to the AR1 model is statistically significant at 15% level.

Table 6 shows the results of the third stage (see also Figure D.5, Appendix D). For CPI inflation, the BVAR forecasts are superior for 4th and 6th quarters, while RMSE of the QPM forecasts for 5th quarter is lower than that of the BVAR. Also, for the 1st quarter both the BVAR and the QPM are inferior to the AR1.

Table 6. RMSEs of conditional forecasts relative to the AR1 model

	CPI		GDP	
q	MA_TOT(cond)	QPM	MA_TOT(cond)	QPM
1	1.07	1.17*	0.89	1.04
2	0.83*	1.18	0.79*	0.84*
3	1.02	0.95	0.72*	0.97
4	0.83*	0.89	0.83	0.89
5	0.78*	0.74*	0.91	0.95
6	0.66*	0.69*	0.82*	0.88

Note: Asterisks indicate that according to the Diebold-Mariano test difference in forecasting performance relative to the AR1 model is statistically significant at 15% level.

The results are better for GDP. Both the BVAR and the QPM forecasts beat AR1 forecasts starting from 2nd quarter, although not all differences are statistically significant. For the whole horizon, GDP forecasts of the BVAR model are more accurate than those of the QPM model.

Thus, in general, for both inflation and GDP growth the BVAR model forecasts are, at least, competitive if not better than QPM forecasts.

The forecasting performance of the BVAR and official NBU forecasts for year-over year indicators is compared in Table 7. Plots of the forecasts can be found in Figure D.6, Appendix D.

Table 7. RMSE of the forecasts for the indicators on year-over-year basis

	CPI		GDP	
q	MA_TOT(cond)	NBU	MA_TOT(cond)	NBU
1	1.07	0.99	0.89	1.02
2	0.95	0.85	0.74*	0.87
3	0.90	0.90	0.59*	0.68*
4	0.82*	0.88	0.52*	0.60*
5	0.64*	0.92	0.62*	0.36*
6	0.55*	0.85	0.66*	0.52*

Note: Asterisks indicate that according to the Diebold-Mariano test difference in forecasting performance relative to the AR1 model is statistically significant at 15% level.

Regarding CPI, the BVAR forecasts outperform the official NBU forecasts at the horizon of interest. However, in the short run the official NBU forecasts are the most accurate: they beat both the BVAR and AR1 forecasts. This finding could be a consequence of the fact that the NBU is considering a broader information set during the forecasting process and different types of models specifically designed for short run forecasting. Moreover, CPI is forecasted at the disaggregated level and for some groups of prices (e.g. administrative prices) expert judgments are included.

Regarding GDP, NBU forecasts have better performance than BVAR forecasts at the horizon of interest probably because GDP components are treated separately and expert knowledge is included (for example, the BVAR model doesn't explicitly have variables reflecting fiscal policy stance).

To conclude, the BVAR forecasts of inflation outperform the official NBU forecasts at the horizon of interest, whereas the opposite is true for the forecasts of the GDP growth.

An interesting perspective can be added if we look at the forecast bias. The forecast bias is measured as the average forecast error at a certain horizon. In turn, the forecast error is calculated as the difference between the actual value and forecasted one. A non-zero bias indicates a possible persistent difference between the forecasts and the observed values.

Table 8. Forecast bias. CPI

	CPI					
q	MB	MA_P	MA_TOT	MA_TOT(cond)	QPM	AR1
1	0.39	1.54	0.16	0.04	0.30	-0.53
2	1.78	2.57	1.52	1.41	0.38	-0.80
3	2.81	3.27*	2.44	2.19	1.44	-0.94
4	2.84	2.93*	2.13	1.91	1.65	-1.69
5	1.17	1.06	0.41	0.89	1.12	-3.57*
6	0.41	0.06	-0.53	-0.64	0.75	-4.49*

Note: Based on the results of a simple unbiasedness test[5], asterisks indicate that the null hypothesis of unbiasedness is rejected.

Table 8 and 9 present the values of CPI and GDP forecast bias for quarter-over-quarter indicators. Regarding CPI, the hypothesis of unbiasedness is rejected only for some forecast horizons for the MA_P and AR1 models. Also except for the AR1 forecasts, a positive forecast bias is observed almost within the whole forecast horizon, meaning that the models on average underpredict inflation. As during the period of forecasting exercise the disinflation occurred, lower forecasting values may mean that models are assuming faster convergence to the steady state then it happened in real life. Moreover, the forecasts at the horizon of interest are less biased. In the 5th and 6th quarters the forecast bias of the models is decreasing, and for MA_TOT model, it even becomes slightly negative in 6th quarter.

Regarding GDP, the conditional forecasts of the BVAR have the smallest bias in absolute terms. However, contrary to other models, the errors of BVAR conditional forecasts have negative sign, meaning overprediction of GDP. Such a difference in the biases between conditional and unconditional forecasts may indicate the importance of conditioning for GDP forecasts.

Taking into consideration that official NBU forecasts are available only on a year-over-year basis, it is not possible to include them in to the above comparison. However, if we look at Figure D.6, Appendix D, official forecasts of the NBU on the year-over-year basis seem to be biased towards under-forecast. There may be several reasons that contribute to this. First, under the inflation targeting regime the NBU may have tried to anchor inflation expectations by approaching forecasts to the target which was lower than the actual inflation. Second, for both conditional BVAR forecasts and QPM forecasts, the observed values of external sector indicators are used. Whereas during the real forecasting process these values are unknown and values which are assumed may differ from actual ones.

Table 9. Forecast bias. GDP

[5] Unbiasedness test for the forecast error e_{t+h} for forecast horizon h implemented with a t-test in the following regression: $\mathrm{e}_{t+h} = y_{t+h} - y^{f}_{t+ht} = \tau_h + \varepsilon_t$, where the null hypothesis is $\tau_h = 0$

	GDP					
q	MB	MA_P	MA_TOT	MA_TOT(cond)	QPM	AR1
1	0.35	0.35	0.42	-0.23	0.99	1.99*
2	0.09	0.32	0.33	-0.64	0.79	2.59*
3	0.25	0.66	0.71	-0.29	0.50	2.97*
4	0.16	0.66	0.69	-0.13	0.31	2.84*
5	-0.14	0.24	0.29	-0.60	-0.52	2.37*
6	-0.34	0.11	0.03	-0.22	-0.75	2.08*

Note: Based on the results of a simple unbiasedness test, asterisks indicate that the null hypothesis of unbiasedness is rejected.

Finally, I would like to address an issue that has received much attention lately. As the estimation period ends in 2020q1, the forecasting accuracy of the BVAR during COVID-19 cannot be analyzed. However, the issue of dealing with Covid-19 outliers remains of key interest at the NBU because the developed BVAR model is going to be used for forecasting inflation and GDP in the years to come. There are several papers offering some solutions to the problem which are applicable to the model I consider.
Foroni et al. (2020) consider simple methods to improve growth nowcasts and forecasts. Specifically, they combine forecasts across various specifications for the same model or across different models, extend the model specification by adding MA terms, adjust the forecasts to put them back on track by a specific form of intercept correction etc. They find, that among all these methods, adjusting the original forecasts by an amount similar to the forecast errors made during the financial crisis and following recovery seems to produce the best results for the US, notwithstanding the different source and characteristics of the financial and the COVID crisis.
Lenza and Primiceri (2020) show how to handle a problem with COVID-19 outliers when estimating VAR models. Their solution consists of explicitly modeling the large change in shock volatility during the pandemic.

8. Conclusions

In this paper, I examined the forecasting performance of a Bayesian Vector Autoregression model with a steady-state prior for Ukrainian economy and compared the accuracy of the forecasts against the forecasts of the QPM model and official NBU forecasts. The RMSE is employed as the measure of forecasting performance. As the forecasting performance for inflation at the monetary policy horizon is of most interest, I focus on horizon from 4 to 6 quarters.

The BVAR model was estimated using both data for Ukrainian economy and foreign indicators. In addition to the benchmark specification of the model, models which include data on commodity prices and terms of trade were included in the alternative specifications to take into account the peculiarities of Ukrainian economy. The model containing terms of trade indicator happened to have the most accurate unconditional forecasts of inflation and GDP growth and outperformed the AR1 model at the horizon of interest. For this reason, it was further used to produce conditional forecasts.

The conditional forecasts of the BVAR model were compared to the forecasts of the QPM model. In general, for both inflation and GDP growth the BVAR model forecasts are competitive with the QPM forecasts.

As the NBU forecasts are only available on the year-over-year basis, the conditional BVAR forecasts were transformed from annualized quarter-over-quarter indicators into year-over-year indicators to compare the forecast accuracy. The BVAR forecasts of inflation outperform the official NBU forecasts at the horizon of interest, whereas the opposite is true for the forecasts of the GDP growth. In the short run NBU forecasts dominate probably because NBU is considering a broader information set during the forecasting process and different types of models specifically designed for short run forecasting.
It should be noted that due to the very short period used for forecasting evaluation exercise, the findings of the paper should be treated with caution and might be subject to change as the data accumulates.

In general, BVAR models with steady-state prior can be viewed as an effective tool to improve the forecasting accuracy of standard models as they explicitly use information about the inflation target and other equilibrium values. Future research may deal with estimation issues brought about by COVID-19.

References

1. Beechey M., Österholm P., (2010). Forecasting inflation in an inflation-targeting regime: A role for informative steady-state priors, International Journal of Forecasting, Elsevier, vol. 26(2), pages 248-264, April.
2. Brazdik F., Franta M., (2017). A BVAR Model for Forecasting of Czech Inflation, Working Papers 2017/7, Czech National Bank.
3. Clark, T. E. (2011). Real-Time Density Forecasts from Bayesian Vector Autoregressions with Stochastic Volatility, Journal of Business and Economics Statistics 29 (3): 327–341.
4. Dieppe A., Legrand R., van Roye B., (2016). The BEAR toolbox., Working Paper Series #1934, European Central Bank
5. Foron F., Marcellino M., Stevanović D., (2020). Forecasting the Covid-19 recession and recovery: lessons from the financial crisis., Working Paper Series #2468, European Central Bank.
6. Giannone D., Lenza M., Primiceri G., (2012). Prior selection for vector autoregressions., Working Paper Series #1494, European Central Bank.
7. Grui A., Vdovychenko A., (2019). Quarterly Projection Model for Ukraine, NBU Working Papers, 3/2019. Kyiv: National Bank of Ukraine.
8. Iversen, J., Laseen, S., Lundvall, H. and Söderström. U. (2016). Real-Time Forecasting for Monetary Policy Analysis: The Case of Sveriges Riksbank. CEPR Discussion Papers 11203, C.E.P.R. Discussion Papers.
9. Jarocinski M., (2010). Conditional forecasts and uncertainty about forecast revisions in vector autoregressions, Economics Letters, 108(3):257–259.
10. Krüger F., Clark T. E., Ravazzolo F., (2017). Using Entropic Tilting to Combine BVAR Forecasts With External Nowcasts, Journal of Business & Economic Statistics, 35(3):470–485.
11. Lenza M., Primiceri G., (2020). How to estimate a VAR after March 2020, Working Paper Series #2461, European Central Bank.
12. Robertson J. C., Tallman E. W., Whiteman C. H. (2005). Forecasting Using Relative Entropy. Journal of Money, Credit and Banking, 37(3):383–401.
13. Villani M., (2009). Steady-state priors for vector autoregressions, Journal of Applied Econometrics, John Wiley & Sons, Ltd., vol. 24(4), pages 630-650.
14. Waggoner D. F., Zha T., (1999). Conditional Forecasts In Dynamic Multivariate Models, The Review of Economics and Statistics, 81(4):639–651.

Appendix A.

Gibbs sampling algorithm for BVAR with steady-state prior

1. Define the number of iterations It of the algorithm, and the burn-in sample Bu .
2. Define initial values $\beta_{0,}$ B_0, Σ_0 for the algorithm. Obtain the initial value for U from $\beta_{0,}$
3. At iteration n, draw $\psi_{(n)}$, conditional on $\beta_{(n-1),} and\ \Sigma_{(n-1)}$. Draw $\psi_{(n)}$, from a multivariate normal:

$\pi(\psi|\beta_{(n-1)}\Sigma_{(n-1)}, y) \sim \mathrm{N}(\bar{\psi}, \bar{\Lambda})$

$$\bar{\Lambda} = \left[\Lambda_0{}^{-1} + U'\left(Z'Z \otimes \Sigma_{(n-1)}^{-1}\right)U\right]^{-1},\ \bar{\psi} = \bar{\Lambda}\left[\Lambda_0{}^{-1}\psi_0 + U' vec(\Sigma_{(n-1)}^{-1}(Y - XB'_{(n-1)})Z\right]$$

Reshape $\psi_{(n)}$, to obtain $F_{(n)}$, .
4. Use $F_{(n)}$ to obtain $\hat{Y}, \hat{X}$ and $\hat{y}$.
5. Draw the value $\Sigma_{(n)}$, conditional on $\mathrm{B}_{(n-1)}$ and $\psi_{(n)}$. Draw $\Sigma_{(n)}$, from an inverse Wishart distribution with scale matrix $\tilde{S}$ and degrees of freedom T:

$\pi(\Sigma_{(n)}|B_{(n-1)}\psi_{(n)}\ \ , y) \sim IW(\tilde{S}, T)$

$$\tilde{S} = \left(\hat{Y} - \hat{X}B_{(n-1)}\right)'\left(\hat{Y} - \hat{X}B_{(n-1)}\right)$$

6. Finally, draw $\beta_{(n)}$ conditional on $\Sigma_{(n)}$ and $\psi_{(n)}$, and reshape into $B_{(n)}$. Draw $\beta_{(n),}$ from a multivariate normal distribution with $\bar{\beta}$ mean and covariance matrix $\bar{\Omega}$:

$\pi(\beta_{(n)}\ |\Sigma_{(n)}\psi_{(n)}, y) \sim \mathrm{N}(\bar{\beta}, \bar{\Omega})$

$$\bar{\Omega} = \left[\Omega_0{}^{-1} + \Sigma_{(n)}^{-1} \otimes \hat{X}'\hat{X}\right]^{-1},\ \bar{\beta} = \left[\Omega_0{}^{-1}\beta_0 + \left(\Sigma_{(n)}^{-1} \otimes \hat{X}'\right)\hat{y}\right]$$

Update U from $B_{(n)}$.
7. Repeat until It iterations are realized, then discard the first Bu iterations.

Note that $\hat{y_t}$.is a demeaned data vector $\hat{y}_t = y_t - Fx_t$. and $A(L)\hat{y}_t = \varepsilon_t$ is a VAR in standard form conditional on F. Therefore, the conditional posterior distributions for $\beta_, and\ \ \Sigma$ a obtained with normal diffuse prior.

Appendix B.

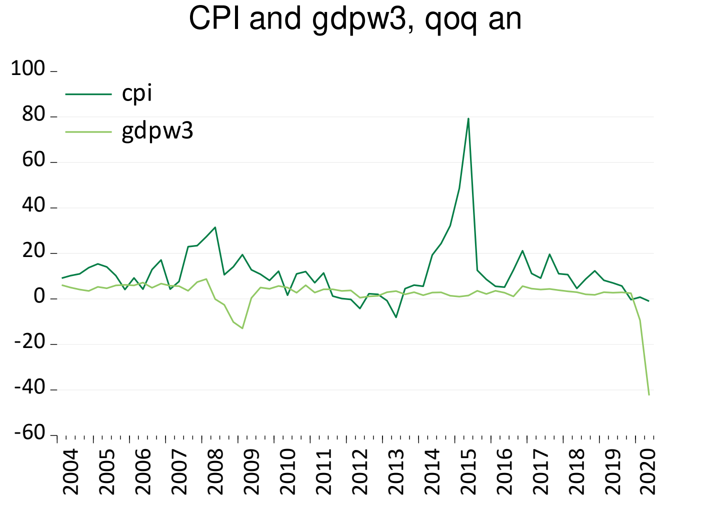
Table B.1. Data used for the research

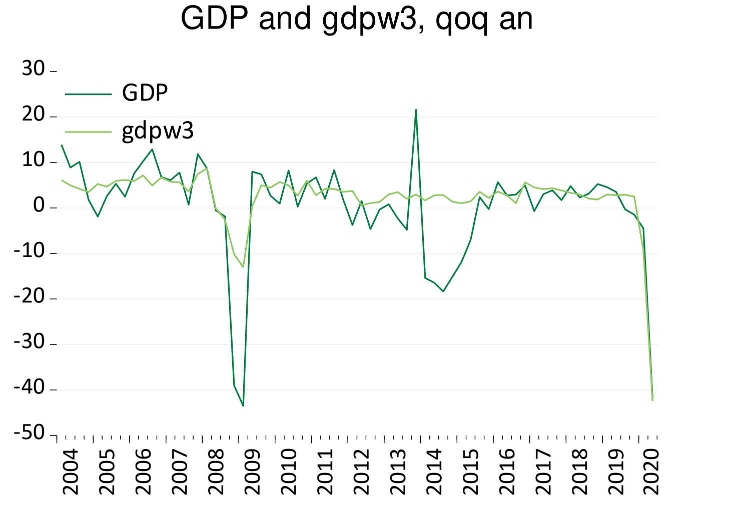
Series	Name	Definition	Source
Foreign output	gdpw1 gdpw2 gdpw3	Trade-weighted index of real GDP of major trading partners (3,5 and 40* countries)	NBU staff calculations, based on the data from national statistics committees (NSC)
Foreign price level	cpineerw1 cpineerw2 cpineerw3	Trade-weighted index of CPI of major trading partners (3*, 5 and 40 countries)	NBU staff calculations, based on the data from NSC
	ppineerw1 ppineerw2	Trade-weighted index of PPI of major trading partners (3 and 5 countries)	NBU staff calculations, based on the data from NSC
Commodity prices on foreign markets	wbnonen wben fao psteel pgrains	Non-energy commodities price index Energy commodities price index FAO price index Export price of steel Export price of grains	World bank commodity prices, FAO database, export and import prices from SSSU
Foreign interest rate	iw1 iw2	1-month LIBOR Rate* overnight LIBOR Rate	Thomson Reuters Datastream
Domestic output	gdpua	Ukrainian GDP at constant prices*	State Statistics Service of Ukraine (SSSU)
Domestic price level	cpiua	CPI*	SSSU
Domestic interest rate	iua	NBU policy rate*	NBU
Nominal effective exchange rate (+ means an appreciation)	neer1 neer2 neer3	Real effective exchange rate deflated by CPI (3*, 5 and 40 countries)	NBU staff calculations, based on the data from national statistics committees, Bloomberg, NBU data
Real effective exchange rate (+means an appreciation)	reercpiw1 reercpiw2 reercpiw3	Real effective exchange rate deflated by CPI (3 and 5 countries) (3,5 and 40* countries)	NBU staff calculations, based on the data from national statistics committees, Bloomberg, NBU data
	reerppiw1 reerppiw2	Real effective exchange rate deflated by PPI (3 and 5 countries)	
Terms of trade	totw1	Commodity terms of trade, based on IMF methodology	NBU staff calculations, based on the SSSU data
	totw2	Ratio between the index of export prices for grains and metals and the index of import prices for oil and gas*	NBU staff calculations, based on the SSSU data
Wage	nwage rwage	Average nominal wage Average real wage*	SSSU
Monetary aggregate	m2	M2	NBU

Note: the time series entering QPM model marked with asterisk

Table B.2. Figures and correlation tables

CPI, GDP and series chosen for models. Correlations and figures.



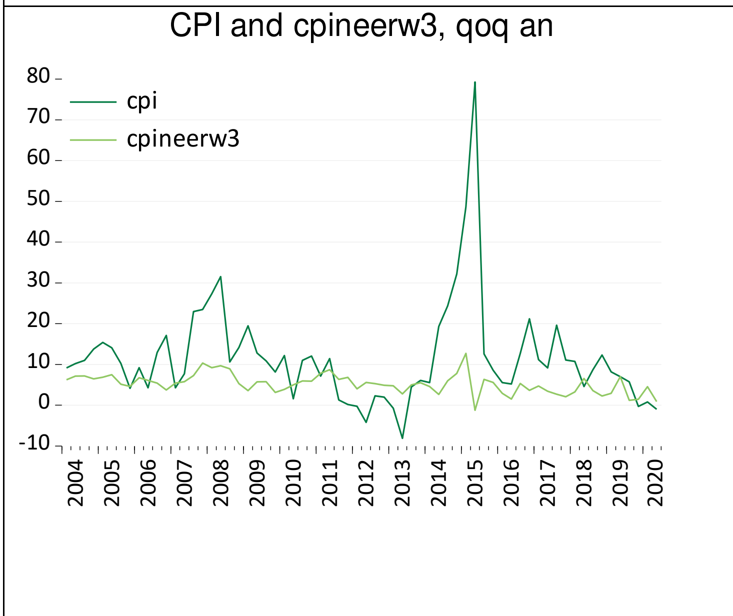


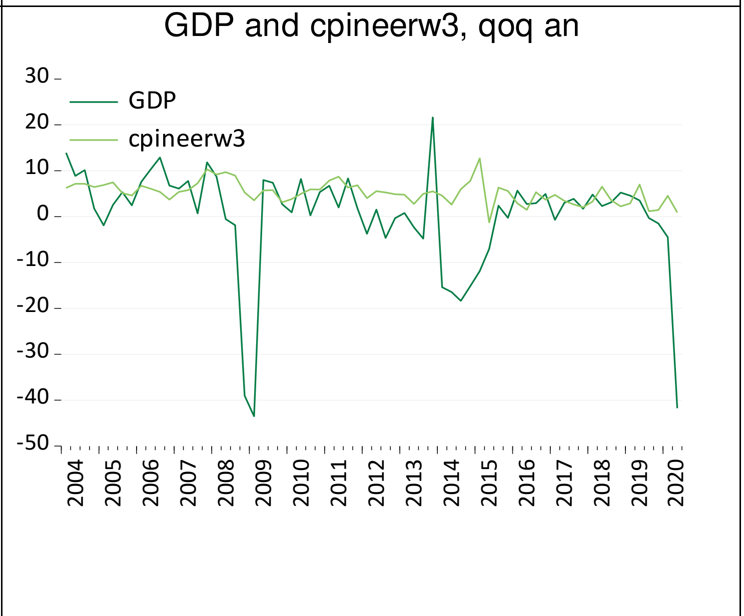
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LGDPW3-L...	CPIUA4Q,4*(LGDPW3-L...	i	lag	lead
		0	-0.0510	-0.0510
		1	-0.0779	0.0194
		2	-0.0094	-0.1052
		3	0.0296	-0.1785
		4	0.0595	-0.1614

Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LGDPW3-...	GDPUA4Q,4*(LGDPW3-...	i	lag	lead
		0	0.7340	0.7340
		1	0.4201	0.4817
		2	0.1937	0.1529
		3	0.0149	0.0107
		4	-0.1293	-0.1153



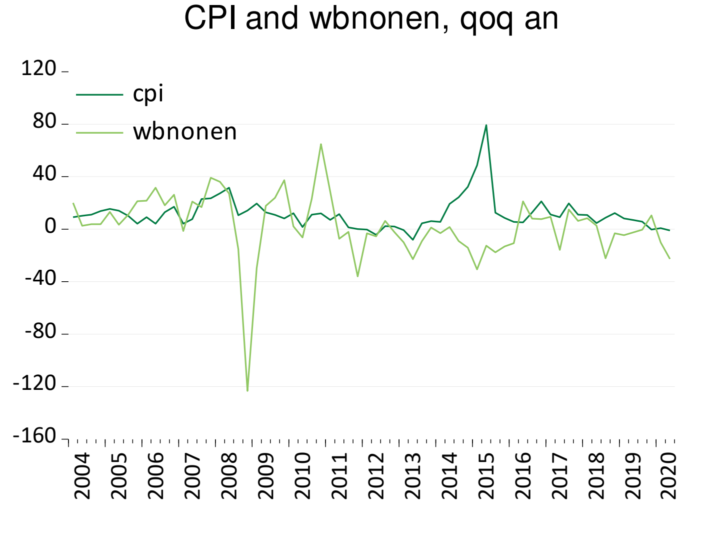


Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LCPINEER...	CPIUA4Q,4*(LCPINEER...	i	lag	lead
		0	0.1091	0.1091
		1	0.4565	0.1873
		2	0.1799	0.1459
		3	-0.0163	-0.0624
		4	-0.1258	-0.2036

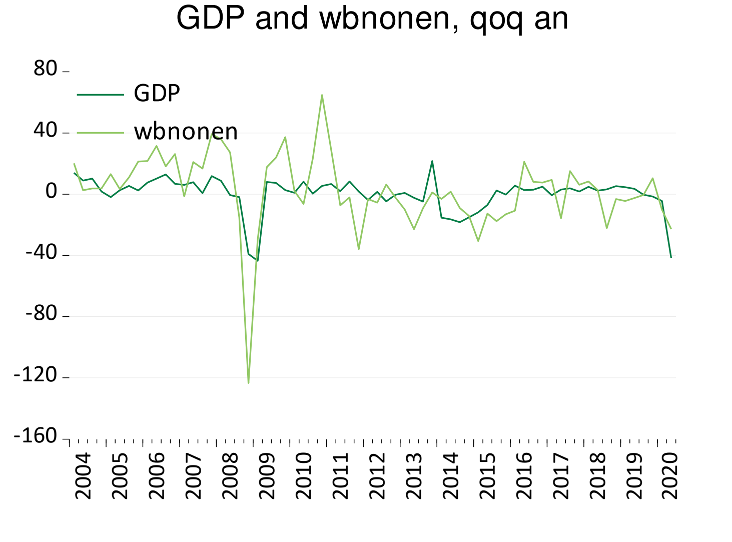
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LCPINEE...	GDPUA4Q,4*(LCPINEE...	i	lag	lead
		0	0.1086	0.1086
		1	-0.0752	0.0539
		2	-0.2167	-0.0505
		3	-0.2093	0.1188
		4	-0.1486	0.2097



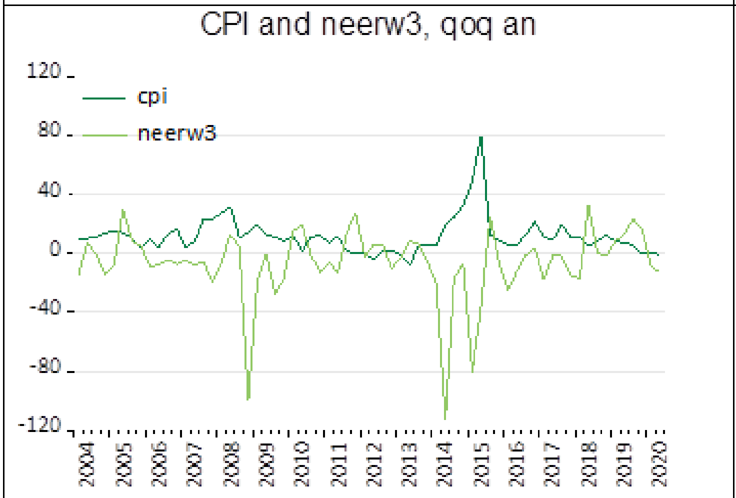
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LWBNONEN...	CPIUA4Q,4*(LWBNONEN...	i	lag	lead
		0	-0.0152	-0.0152
		1	-0.0945	-0.0539
		2	0.0080	-0.2525
		3	0.0035	-0.2045
		4	0.0422	-0.0515



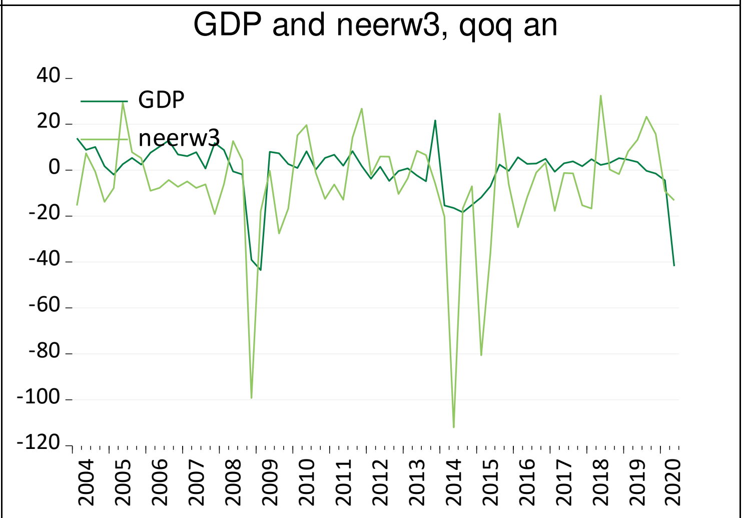
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LWBNON...	GDPUA4Q,4*(LWBNON...	i	lag	lead
		0	0.6217	0.6217
		1	0.5386	0.2659
		2	0.0430	0.1232
		3	-0.0933	-0.0552
		4	-0.0744	-0.0454



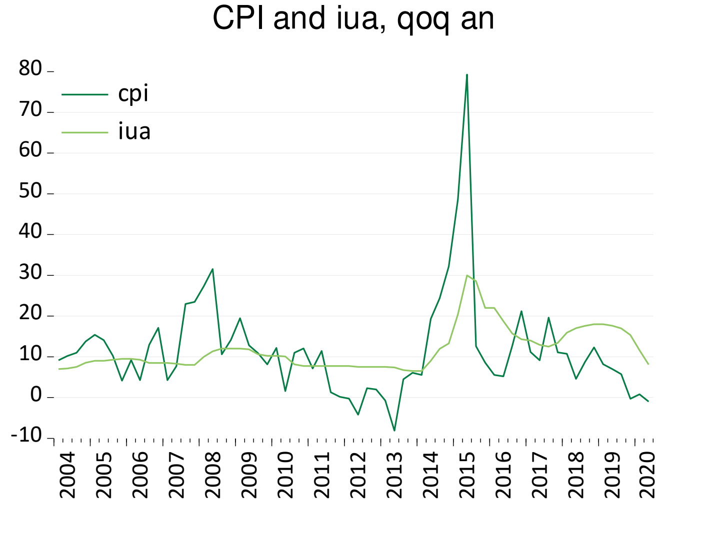
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

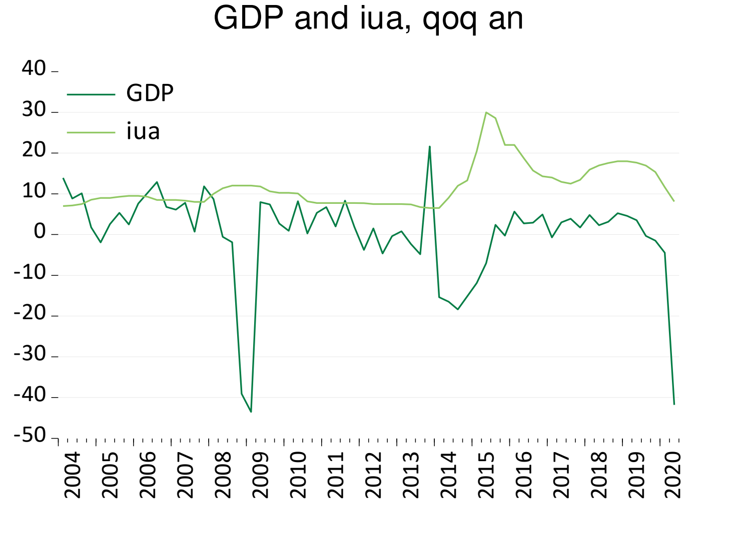
CPIUA4Q,4*(LNEERW3-...	CPIUA4Q,4*(LNEERW3-...	i	lag	lead
		0	-0.3955	-0.3955
		1	-0.4926	-0.0532
		2	-0.2706	-0.1109
		3	-0.3049	-0.1175
		4	-0.3953	0.0075



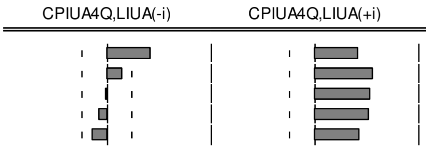
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LNEERW3...	GDPUA4Q,4*(LNEERW3...	i	lag	lead
		0	0.4784	0.4784
		1	0.4067	0.2452
		2	0.0145	0.0685
		3	0.0081	0.2364
		4	0.0619	0.0796



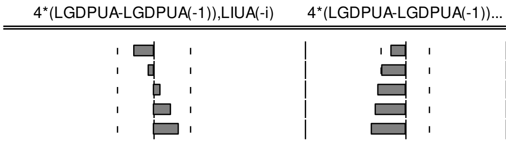


Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

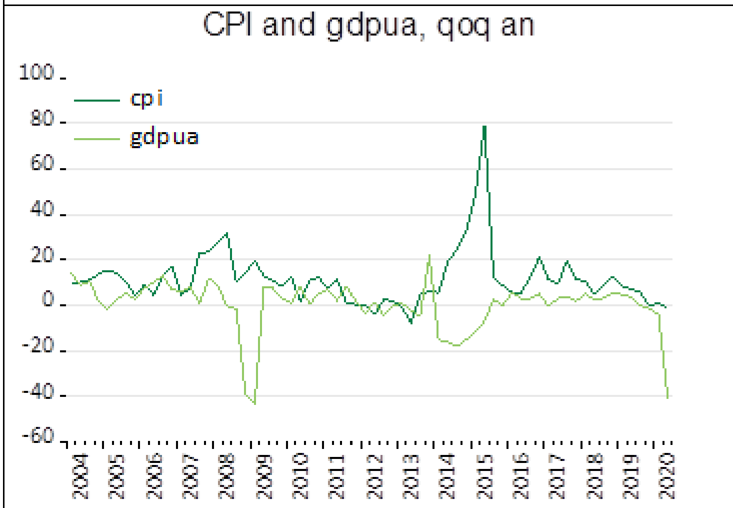


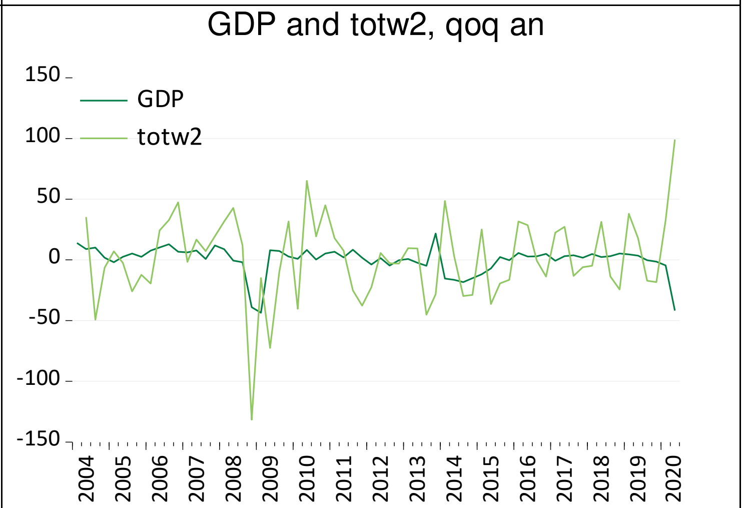
i	lag	lead
0	0.4354	0.4354
1	0.1559	0.5847
2	-0.0128	0.5604
3	-0.0783	0.5425
4	-0.1319	0.4476

Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

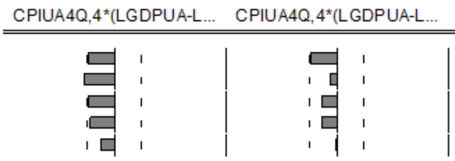


i	lag	lead
0	-0.1324	-0.1324
1	-0.0343	-0.2307
2	0.0484	-0.2781
3	0.1188	-0.3096
4	0.1646	-0.3449





Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations



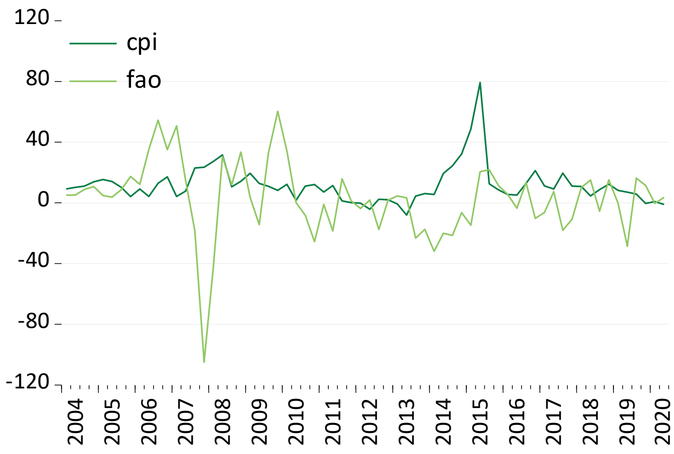
i	lag	lead
0	-0.2441	-0.2441
1	-0.2859	-0.0646
2	-0.2448	-0.1450
3	-0.2206	-0.1374
4	-0.1237	-0.0055

Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

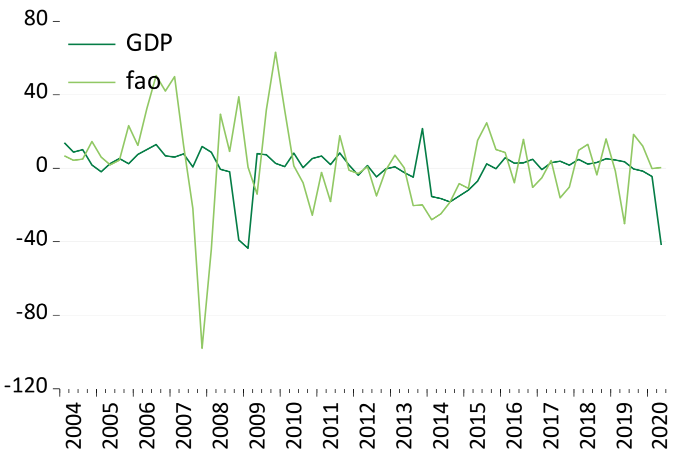
i	lag	lead
0	0.3264	0.3264
1	0.2466	0.3878
2	-0.0362	0.3099
3	-0.1467	-0.0182

Correlation with the rest of the variables

CPI and fao, qoq an



GDP and fao, qoq an



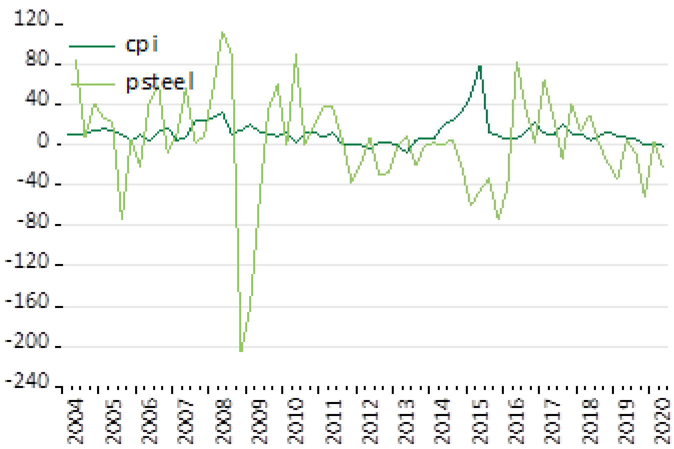
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LFAO-LFAO(...	CPIUA4Q,4*(LFAO-LFAO(...	i	lag	lead
		0	-0.1068	-0.1068
		1	-0.2542	0.0549
		2	-0.2247	0.2072
		3	-0.1223	0.2297
		4	-0.0710	0.1098

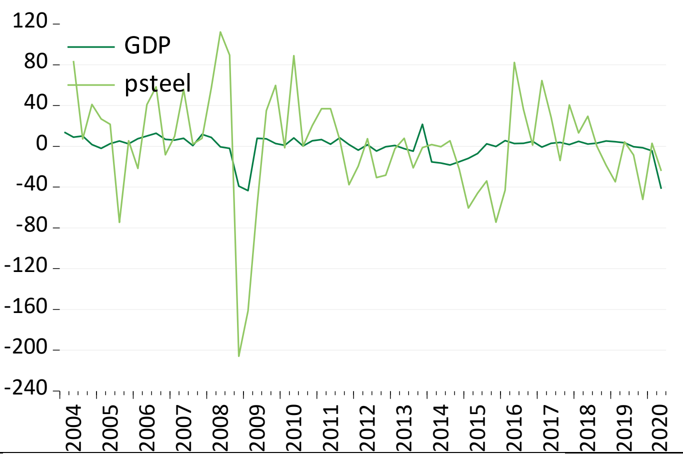
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LFAO-LFAO...	GDPUA4Q,4*(LFAO-LFAO...	i	lag	lead
		0	0.0106	0.0106
		1	-0.0077	0.1681
		2	0.1506	0.0498
		3	0.3301	-0.2253
		4	0.5711	-0.2825

CPI and psteel, qoq an



GDP and psteel, qoq an



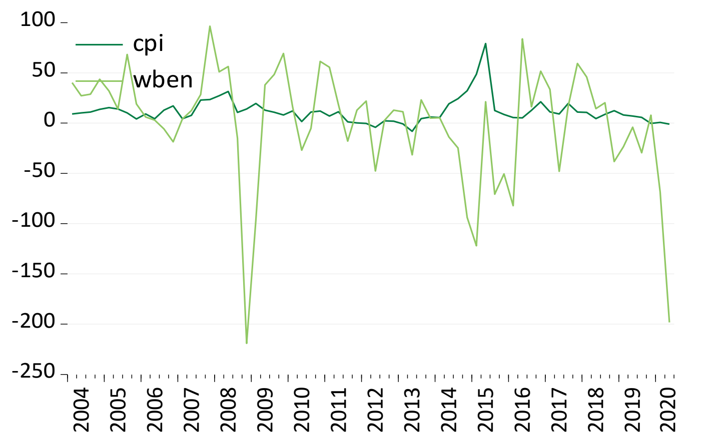
Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LPSTEEL-L...	CPIUA4Q,4*(LPSTEEL-L...	i	lag	lead
		0	-0.1140	-0.1140
		1	-0.0143	-0.0149
		2	0.0719	-0.1930
		3	0.0583	-0.2706
		4	0.0658	-0.0949

Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LPSTEEL-...	GDPUA4Q,4*(LPSTEEL-...	i	lag	lead
		0	0.5845	0.5845
		1	0.1881	0.4710
		2	-0.2412	0.2712
		3	-0.1864	0.0677
		4	-0.0536	-0.0145

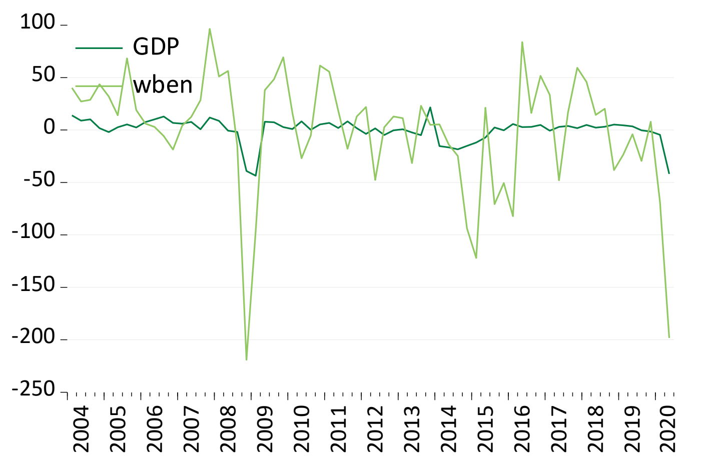
CPI and wben, qoq an



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LWBEN-LW...	CPIUA4Q,4*(LWBEN-LW...	i	lag	lead
		0	-0.0435	-0.0435
		1	-0.2790	-0.1064
		2	-0.1283	-0.2735
		3	-0.0457	-0.3386

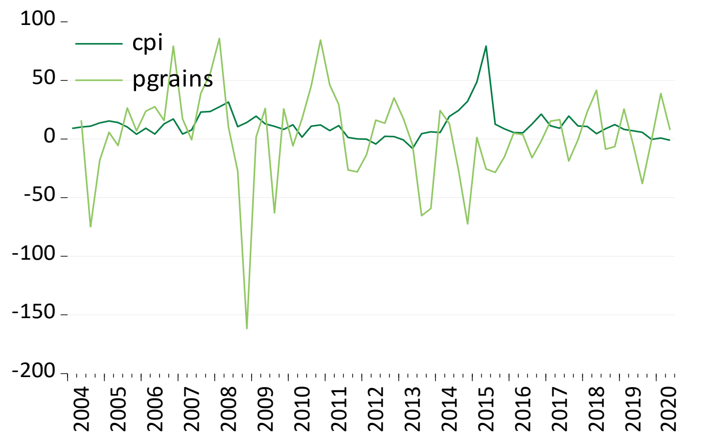
GDP and wben, qoq an



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LWBEN-L...	GDPUA4Q,4*(LWBEN-L...	i	lag	lead
		0	0.5927	0.5927
		1	0.4605	0.3475
		2	-0.0412	0.1477
		3	-0.1178	0.0132
		4	-0.1109	-0.0490

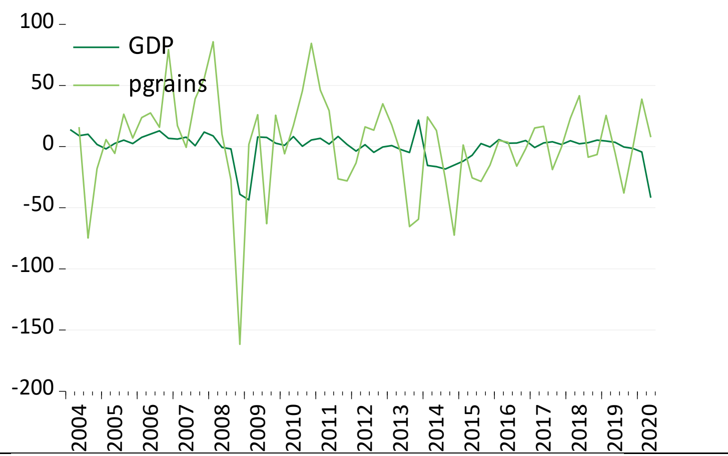
CPI and pgrains, qoq an



Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LPGRAINS-...	CPIUA4Q,4*(LPGRAINS-...	i	lag	lead
		0	-0.0577	-0.0577
		1	-0.0617	-0.0666
		2	-0.1692	-0.2170
		3	-0.0441	-0.1645
		4	-0.0197	-0.1075

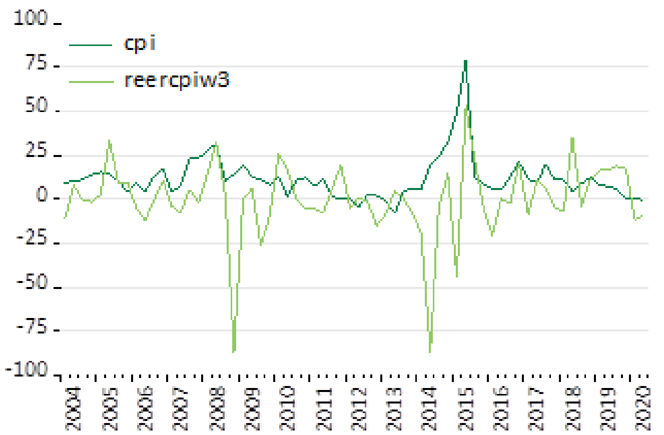
GDP and pgrains, qoq an



Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LPGRAINS...	GDPUA4Q,4*(LPGRAINS...	i	lag	lead
		0	0.3543	0.3543
		1	0.4598	0.1708
		2	0.1847	0.2680
		3	-0.0867	0.1445
		4	-0.0871	0.0205

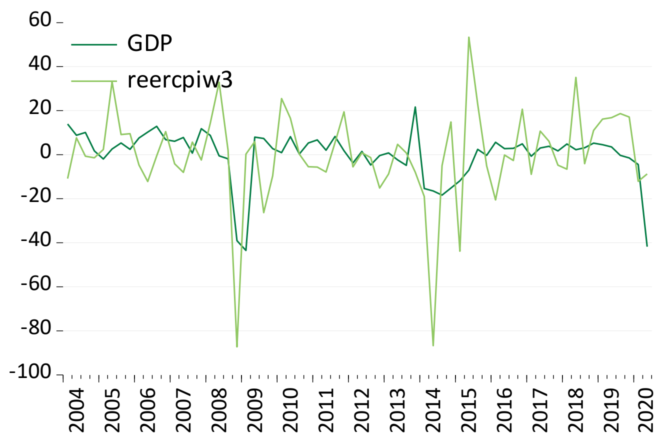
CPI and reercpiw3, qoq an



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LREERCPI...	CPIUA4Q,4*(LREERCPI...	i	lag	lead
		0	0.1352	0.1352
		1	-0.2726	0.2448
		2	-0.1435	0.0380
		3	-0.2429	-0.0233
		4	-0.4032	0.0581

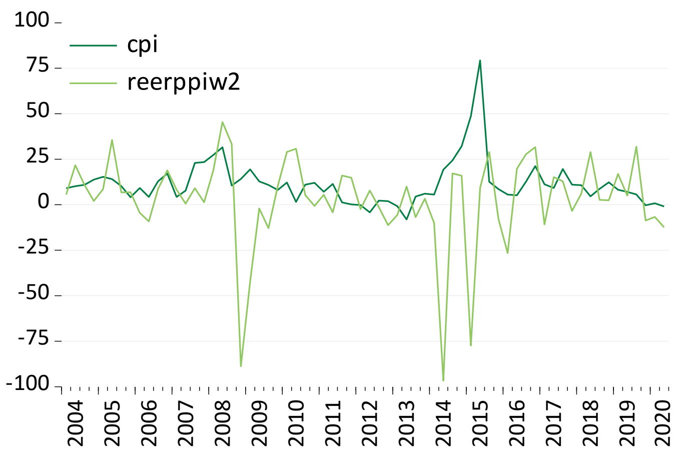
GDP and reercpiw3, qoq an



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LREERCP...	GDPUA4Q,4*(LREERCP...	i	lag	lead
		0	0.3603	0.3603
		1	0.4178	0.0990
		2	-0.0055	-0.0227
		3	-0.0516	0.1202
		4	0.0584	-0.0252

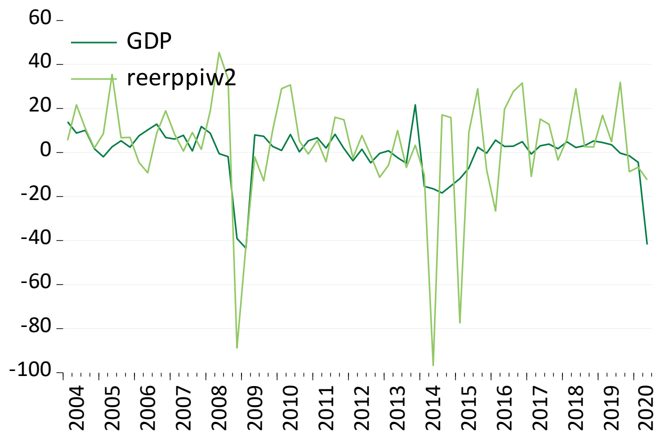
CPI and reerppiw2, qoq an



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LREERPPI...	CPIUA4Q,4*(LREERPPI...	i	lag	lead
		0	-0.1043	-0.1043
		1	-0.3147	0.1319
		2	-0.0708	-0.0403
		3	-0.1250	-0.1374
		4	-0.3237	0.0473

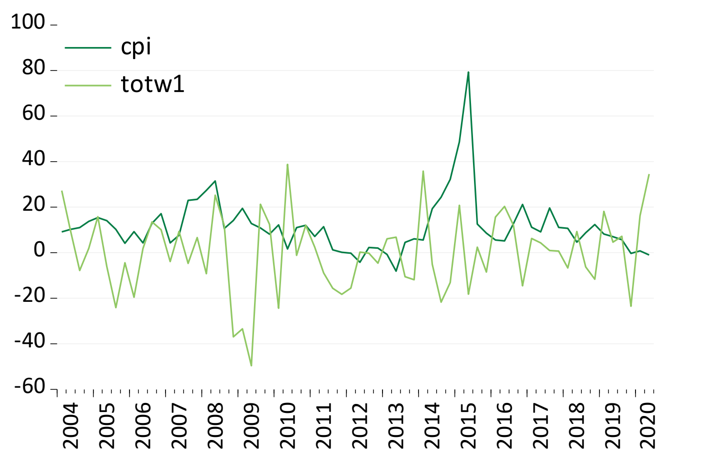
GDP and reerppiw2, qoq an



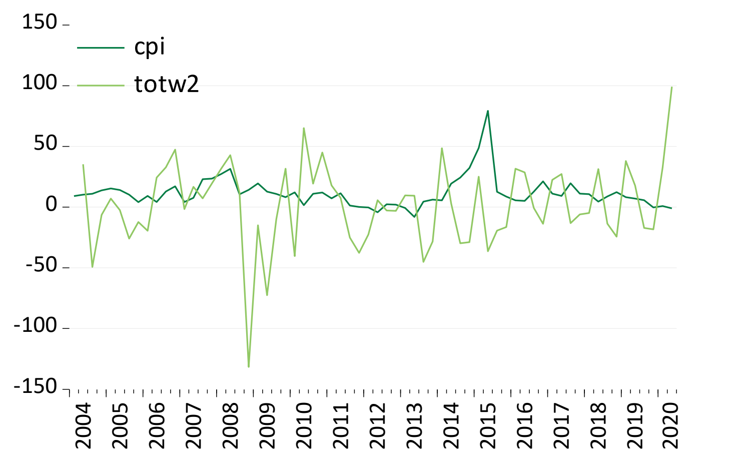
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LREERPP...	GDPUA4Q,4*(LREERPP...	i	lag	lead
		0	0.5374	0.5374
		1	0.2965	0.3359
		2	-0.1087	0.0928
		3	-0.0618	0.2015

CPI and totw1, qoq an



CPI and totw2, qoq an



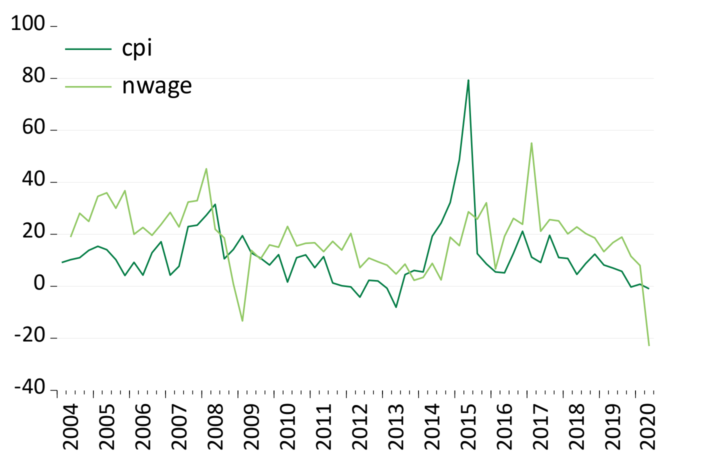
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LTOTW1-L...	CPIUA4Q,4*(LTOTW1-L...	i	lag	lead
		0	-0.1115	-0.1115
		1	0.1321	0.0019
		2	-0.0065	-0.0658
		3	-0.0668	-0.0320
		4	0.1733	-0.0552

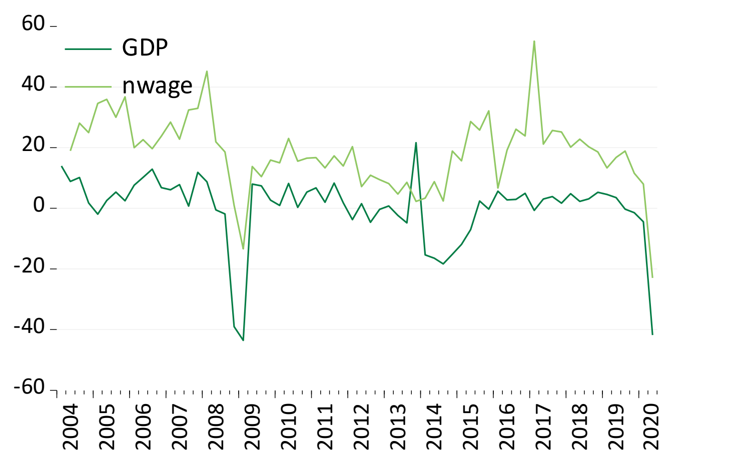
Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LTOTW2-L...	CPIUA4Q,4*(LTOTW2-L...	i	lag	lead
		0	-0.0884	-0.0884
		1	0.0936	-0.0378
		2	-0.0150	-0.1631
		3	-0.0242	-0.0707
		4	0.1257	-0.1035

CPI and nwage, qoq an



GDP and nwage, qoq an

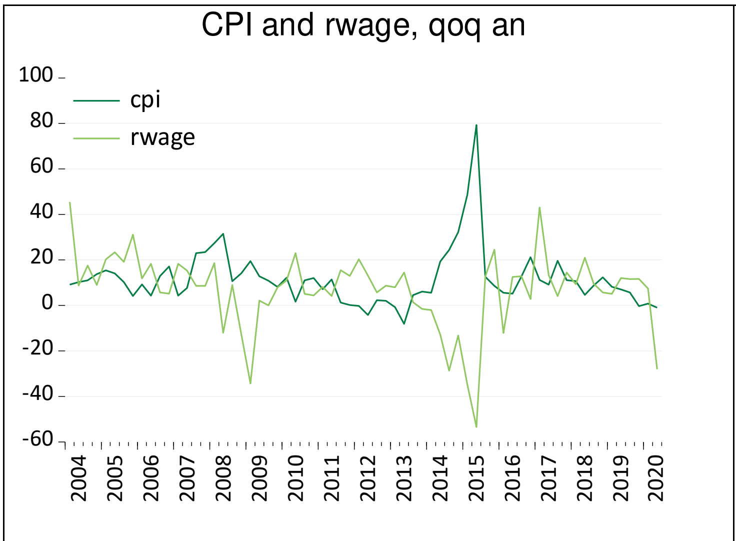


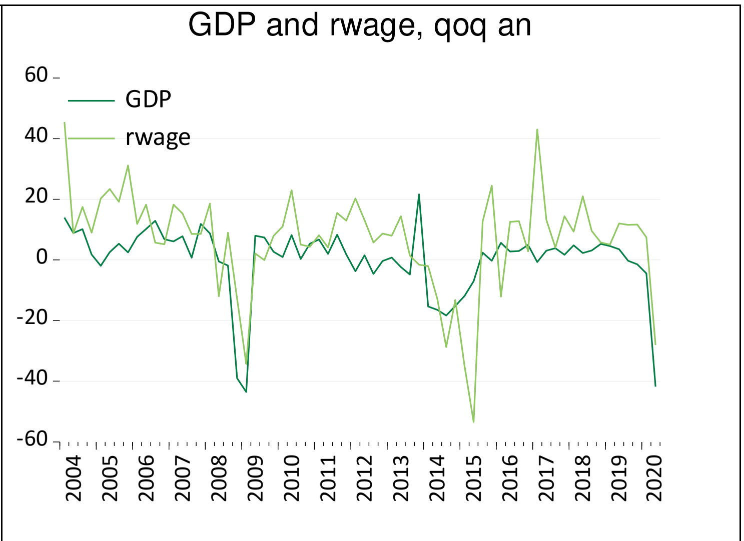
Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LNWAGE-L...	CPIUA4Q,4*(LNWAGE-L...	i	lag	lead
		0	0.2271	0.2271
		1	0.0963	0.3217
		2	0.0193	0.2910
		3	-0.1215	0.0214
		4	-0.0687	0.0272

Sample: 2004Q1 2020Q1
Included observations: 64
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LNWAGE-...	GDPUA4Q,4*(LNWAGE-...	i	lag	lead
		0	0.4493	0.4493
		1	0.3175	0.3683
		2	0.1529	0.1834
		3	0.0706	0.0883
		4	0.0337	0.0807



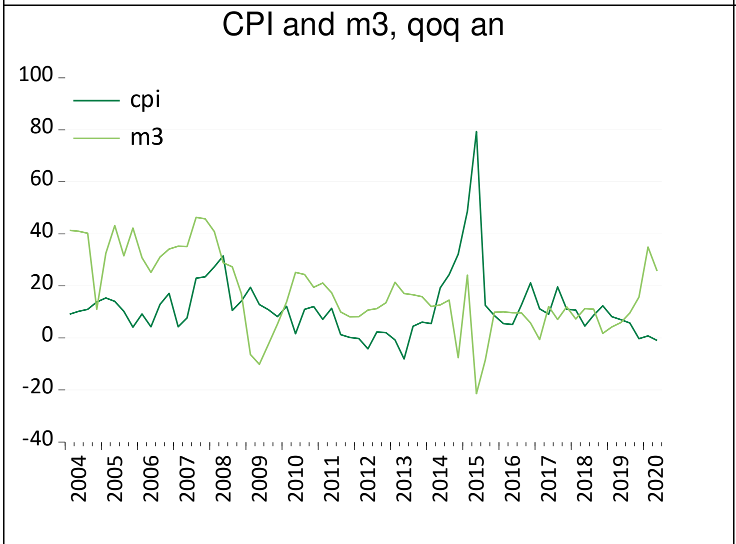


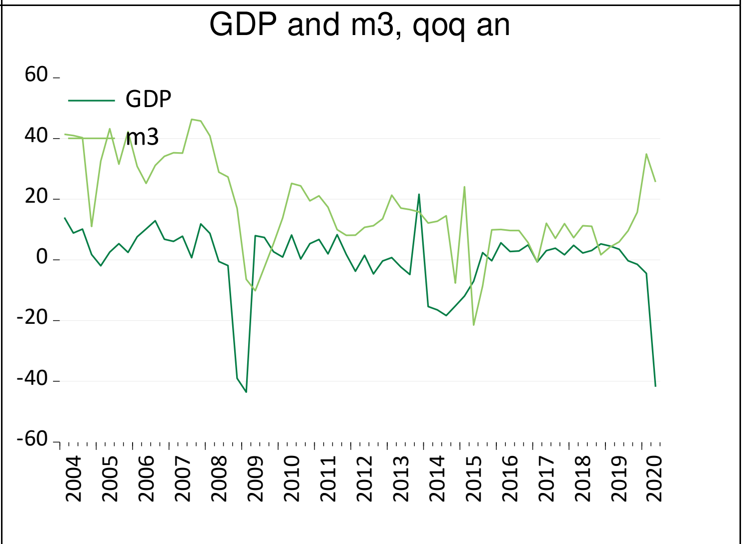
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LRWAGE-L...	CPIUA4Q,4*(LRWAGE-L...	i	lag	lead
		0	-0.6575	-0.6575
		1	-0.4103	-0.2464
		2	-0.2686	-0.0518
		3	-0.2771	-0.1953
		4	-0.0738	-0.0341

Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LRWAGE-...	GDPUA4Q,4*(LRWAGE-...	i	lag	lead
		0	0.5569	0.5569
		1	0.2899	0.4828
		2	0.2600	0.3264
		3	0.1590	0.2400
		4	0.0243	0.1592



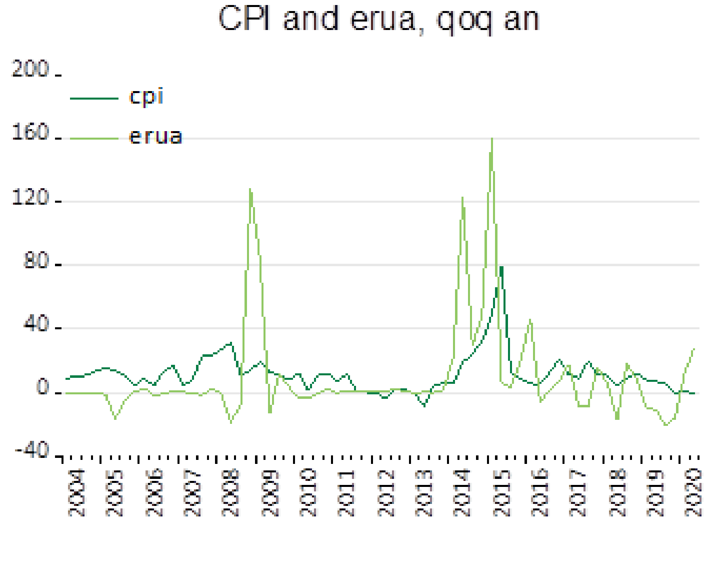


Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LM3-LM3(-1)...	CPIUA4Q,4*(LM3-LM3(-1)...	i	lag	lead
		0	-0.1595	-0.1595
		1	0.1179	-0.2252
		2	0.0326	-0.1563
		3	0.1842	-0.1482
		4	0.1560	-0.1802

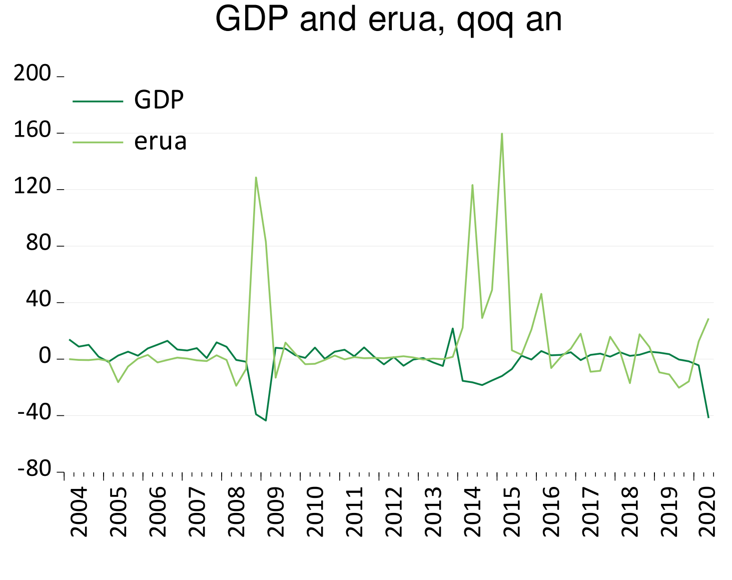
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LM3-LM3(-...	GDPUA4Q,4*(LM3-LM3(-...	i	lag	lead
		0	0.3108	0.3108
		1	0.1286	0.4316
		2	0.0464	0.4433
		3	-0.0494	0.4073
		4	-0.1282	0.2772



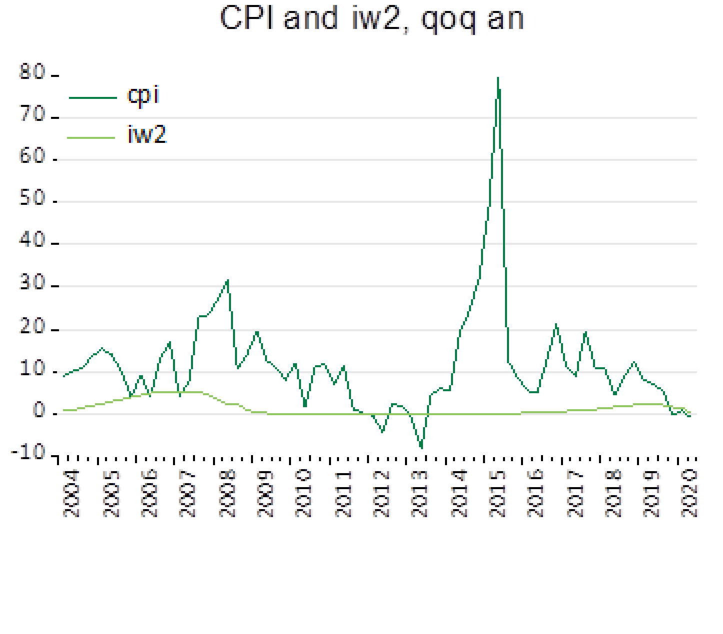
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

CPIUA4Q,4*(LERUA-LE...	CPIUA4Q,4*(LERUA-LE...	i	lag	lead
		0	0.3415	0.3415
		1	0.6037	0.1174
		2	0.2818	0.1803
		3	0.2424	0.2333
		4	0.3010	0.0019



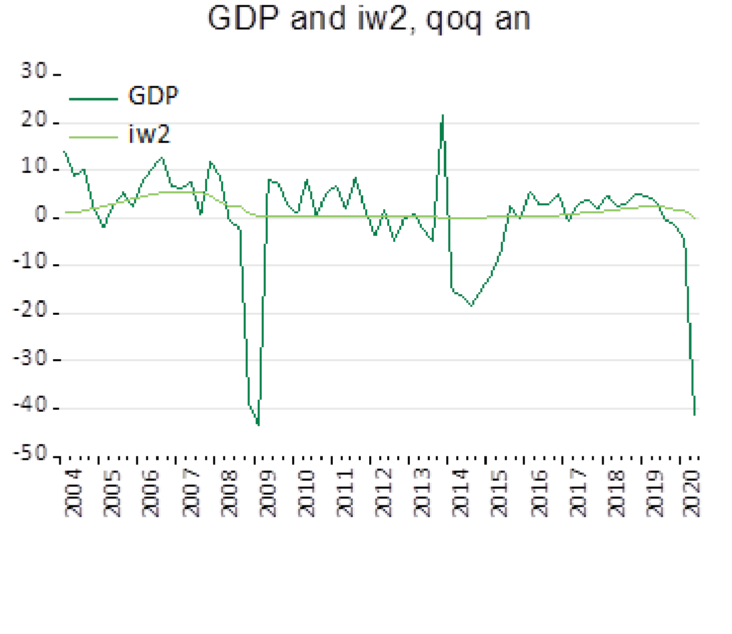
Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

GDPUA4Q,4*(LERUA-LE...	GDPUA4Q,4*(LERUA-LE...	i	lag	lead
		0	-0.6700	-0.6700
		1	-0.4367	-0.4086
		2	0.0050	-0.1332
		3	0.0054	-0.2173
		4	-0.0173	-0.0669



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

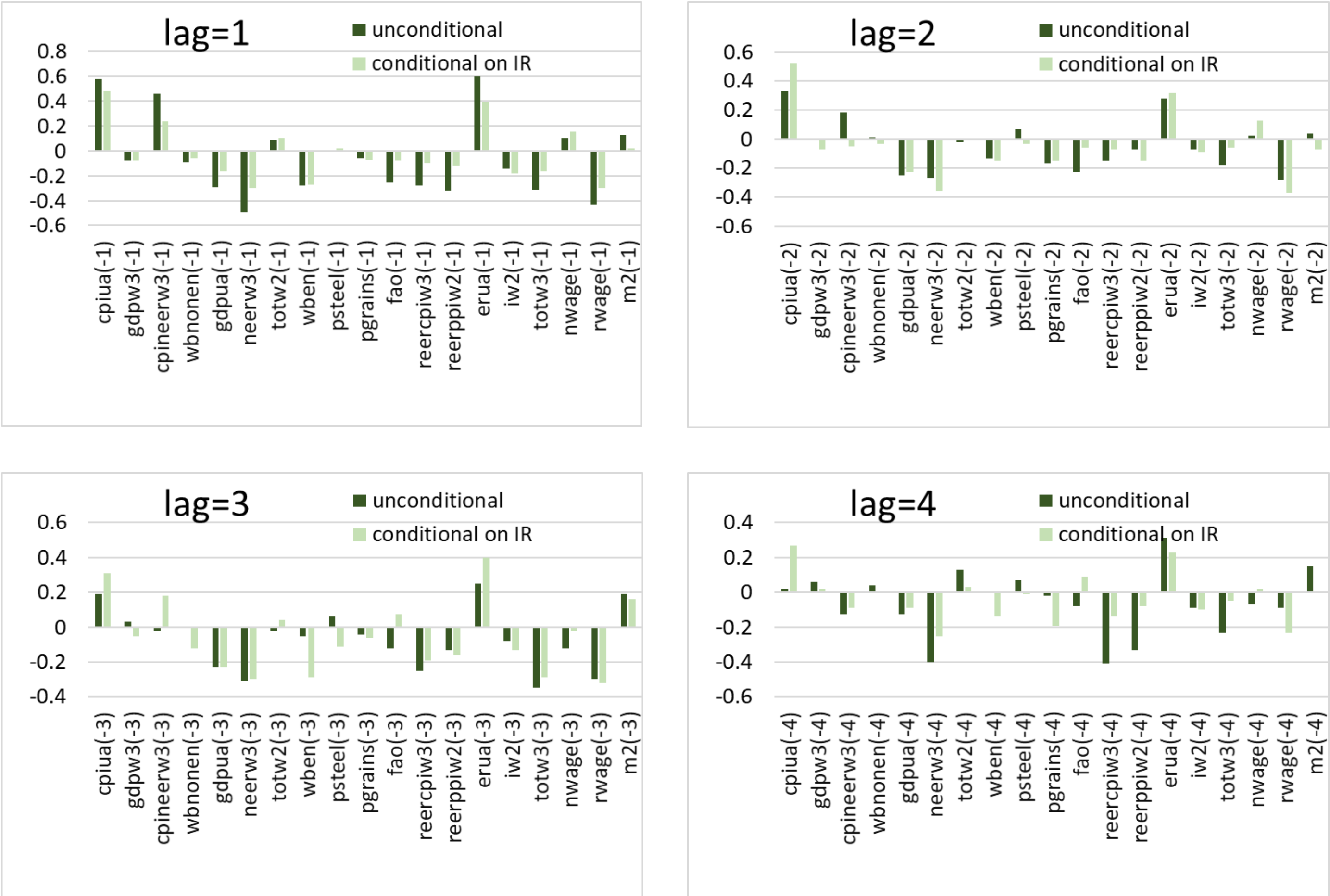
4*(LCPIUA1-LCPIUA1(-1)...	4*(LCPIUA1-LCPIUA1(-1)...	i	lag	lead
		0	-0.0795	-0.0795
		1	-0.0286	-0.1124
		2	0.0277	-0.1401
		3	0.0633	-0.1442
		4	0.1066	-0.1403



Sample: 2004Q1 2020Q1
Included observations: 65
Correlations are asymptotically consistent approximations

4*(LGDPUA-LGDPUA(-1))...	4*(LGDPUA-LGDPUA(-1))...	i	lag	lead
		0	0.3162	0.3162
		1	0.2290	0.3448
		2	0.1586	0.3543
		3	0.1144	0.3537
		4	0.0063	0.3313

Figure B.1. Conditional and unconditional correlations



Appendix C.

Table C.1. Lag length criterions

	LR	FPE	AIC	SC	HQ
MB	3	2	5	1	1
MA_P	4	4	5	1	1
MA_TOT	2	2	5	1	1

Note: numbers in the Table 1 indicate lag order selected by the criterion:
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table C.2. Grid search for hyperparameters

	Min value	Max value	Step size
Autoregressive coefficient	0.2	1	0.1
Overall tightness (λ_1)	0.05	0.2	0.01
Cross-variable weighting (λ_2)	0.1	1	0.1
Lag decay (λ_3)	1	2	0.2

Table C.3. Steady state prior distributions (Villani)

	regime 1: 1980q1 1992q4				regime 2: 1993q1 2005q4			
	mean	var	95% Interval		mean	var	95% Interval	
GDPw	2.5	0.8	1.0	4.0	2.5	0.3	2.0	3.0
CPIw	4.0	0.5	3.0	5.0	2.0	0.3	1.5	2.5
irw	7.0	0.5	6.0	8.0	5.0	0.3	4.5	5.5
GDP	2.3	0.6	1.0	3.5	2.3	0.1	2.0	2.5
CPI	7.0	0.5	6.0	8.0	2.0	0.2	1.7	2.3
ir	8.5	0.8	7.0	10.0	4.3	0.1	4.0	4.5
REER	3.9	0.3	3.4	4.5	3.9	0.0	3.9	4.0

Note: the time series entering QPM model marked with asterisk

Table C.4. Steady state prior distributions (Brazdik and Franta)

	regime 1: 2008q3 2010q1				regime 1: 2010q2 2013q3				regime 1: 2013q4 2016q4			
	mean	var	95% Interval		mean	var	95% Interval		mean	var	95% Interval	
GDPw	9.4	3.1	3.4	15.4	8.9	2.0	4.9	12.9	7.2	1.0	5.2	9.2
CPIw	2.0	1.5	-1.0	5.0	2.0	1.0	0.0	4.0	2.0	0.5	1.0	3.0
Euribor 3m	4.0	1.5	1.0	7.0	4.0	1.0	2.0	6.0	3.5	0.5	2.5	4.5
GDP	5.0	1.5	2.0	8.0	4.0	1.0	2.0	6.0	3.0	0.5	2.0	4.0
CPI	3.0	1.0	1.0	5.0	2.0	0.5	1.0	3.0	2.0	0.3	1.5	2.5
Pribor 3m	3.0	4.1	-0.5	15.4	3.0	1.3	0.5	5.5	3.0	0.8	1.5	4.5
CZK/EURO	-2.4	3.1	-8.4	3.6	-2.4	2.0	-6.4	1.6	-1.5	1.0	-3.5	0.5

Appendix D.

Figure D.1. Impulse response functions, MB model

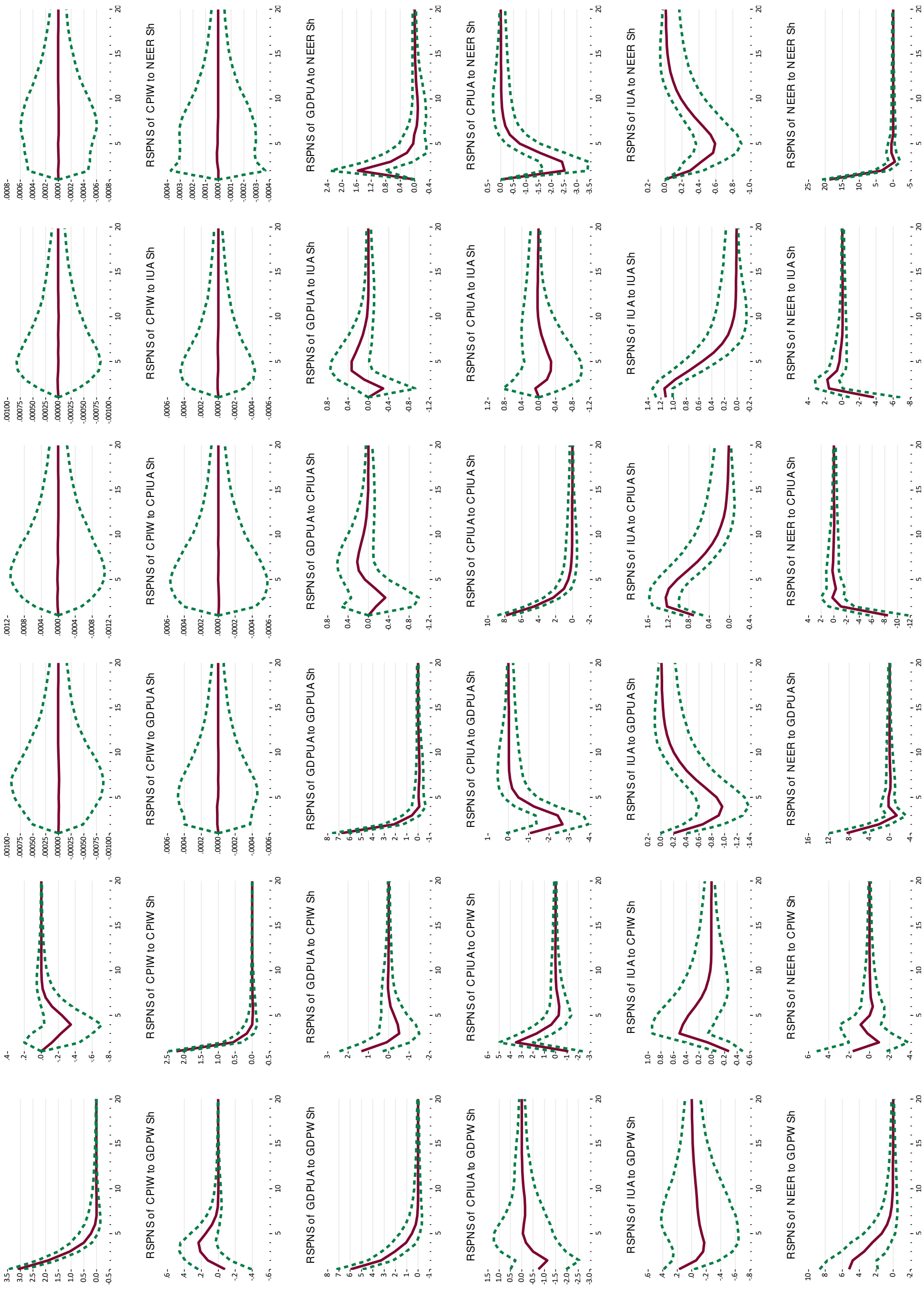


Figure D.2. Impulse response functions, MA_P model

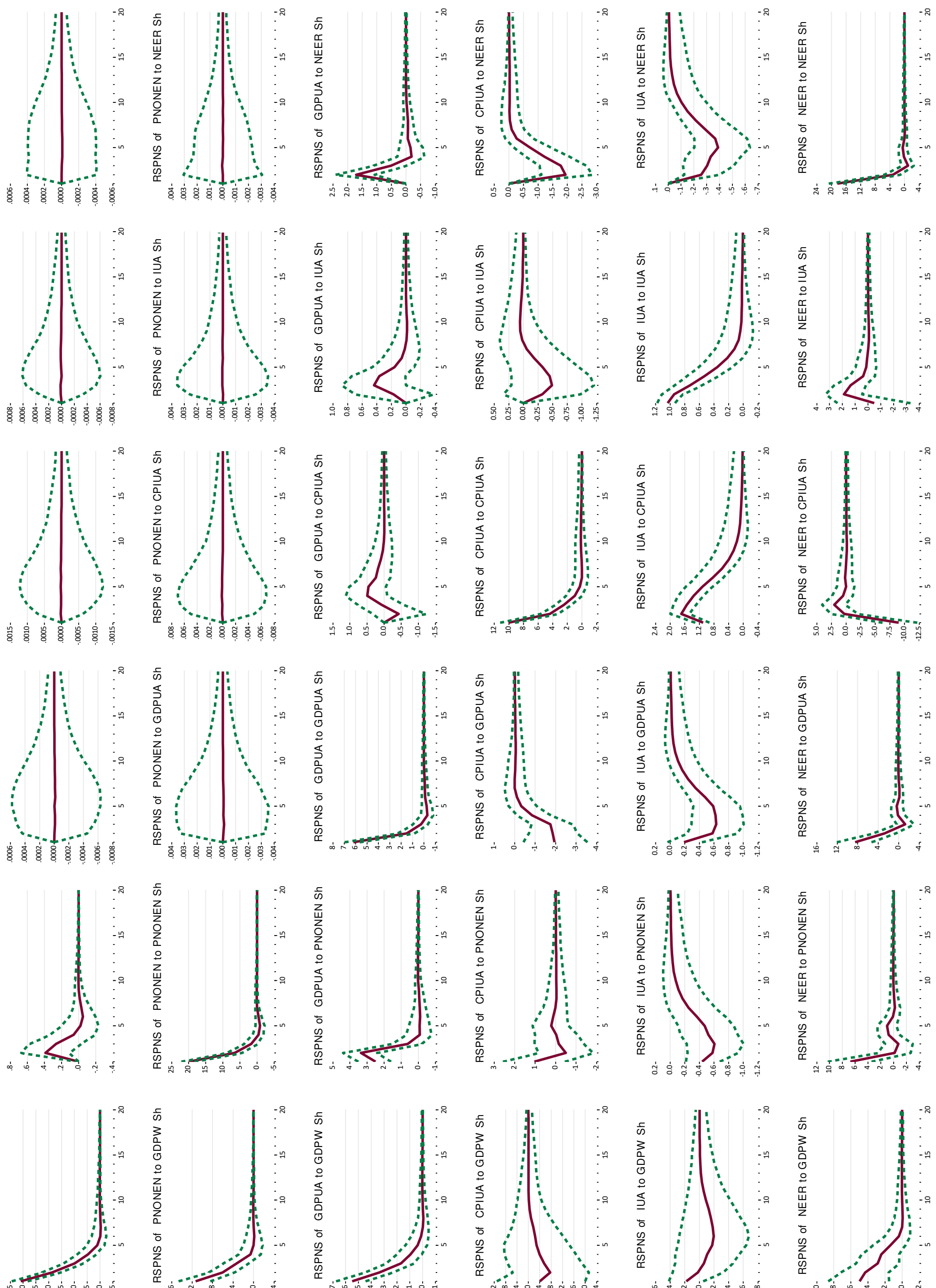


Figure D.3. Impulse response functions, MA_TOT model

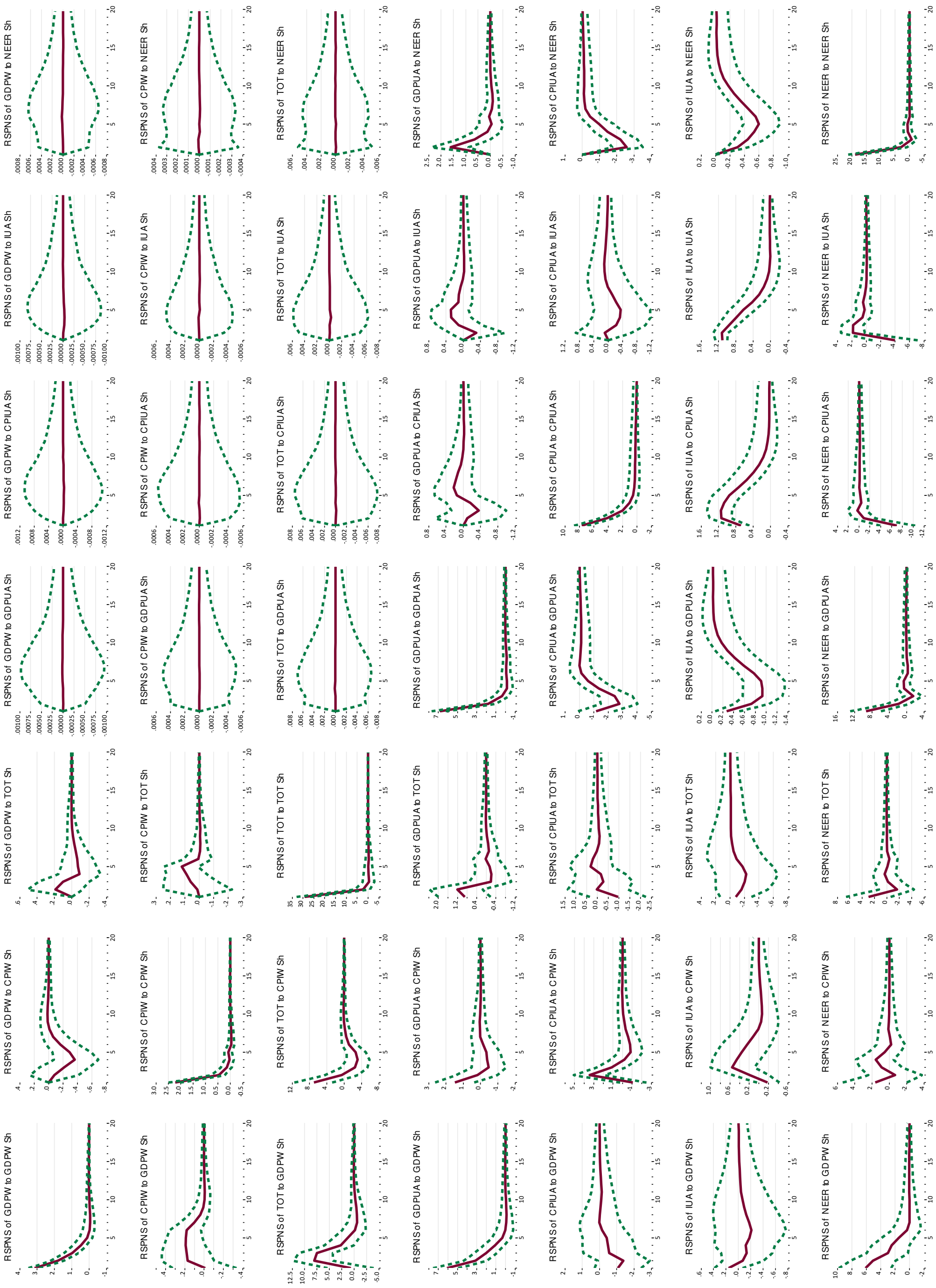


Figure D.4. Unconditional BVAR and AR1 forecasts

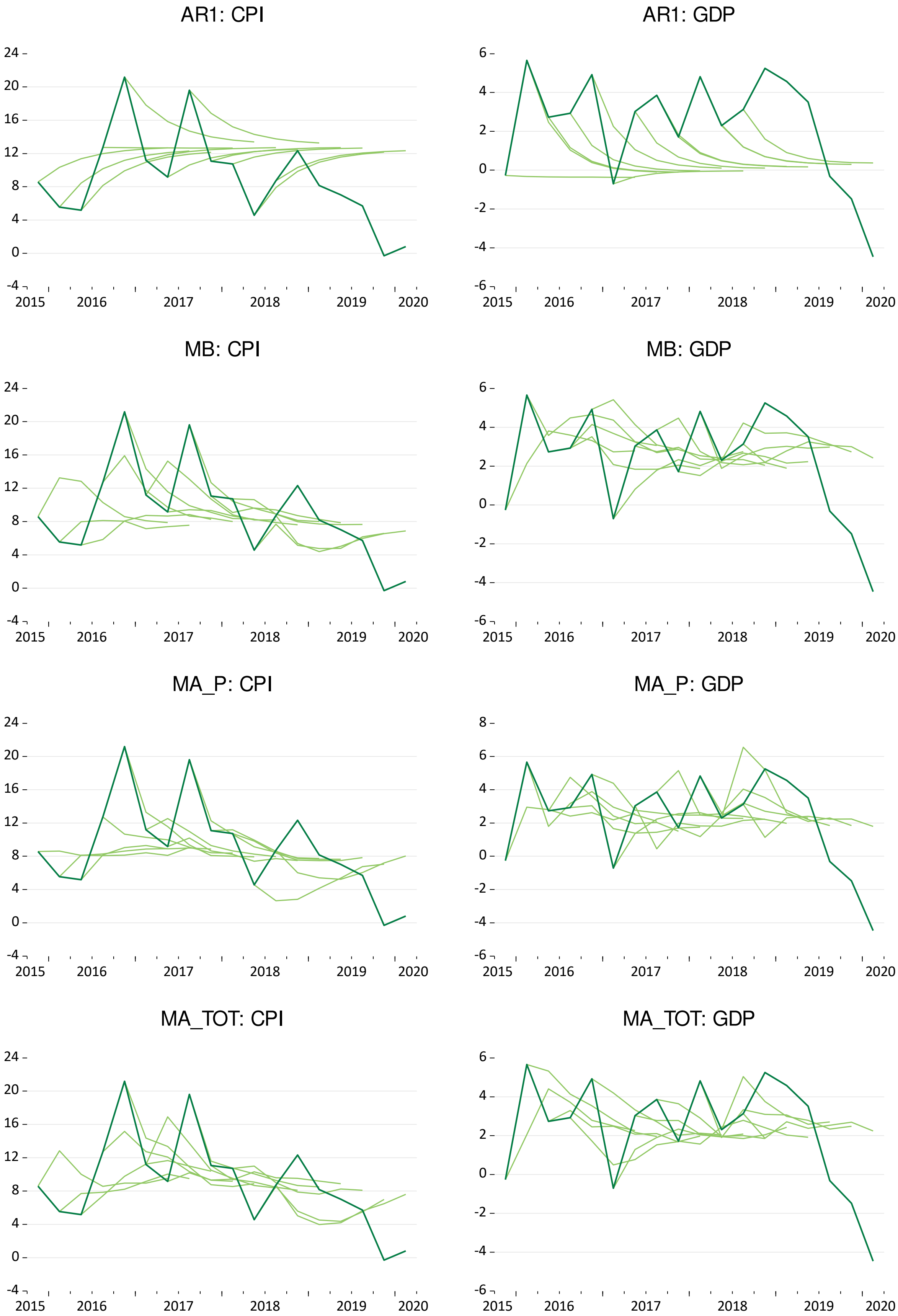


Figure D.5. Conditional BVAR and QPM forecasts

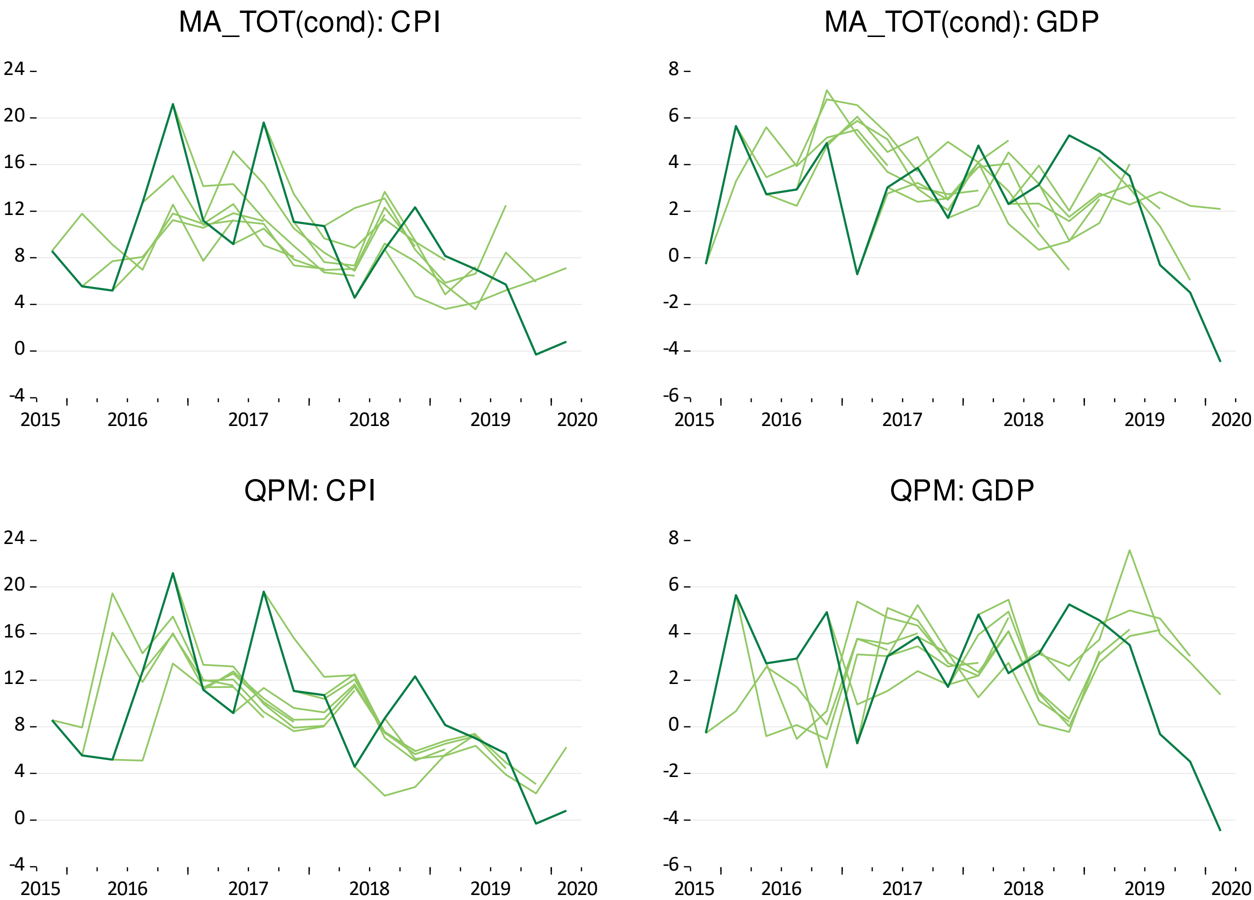


Figure D.6. Conditional BVAR and official NBU forecasts for the indicators on year-over-year basis