Oil market shocks effects on Russian macroeconomic indicators: quantitative estimates with sign-identified SBVAR

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Abstract

This paper constructs and estimates a structural Bayesian VAR (SBVAR) model to quantify the effects of different oil market shocks identified in the vein of Baumeister and Hamilton (2015b) on three macroeconomic indicators in Russia.

The impulse response functions analysis yuilds the mixed results for the real monetary incomes and CPI inflation but undoubtedly indicates that two of three oil demand shocks under consideration positively affect the industrial production index.

The mean estimate of the forward error variance of explained by oil market shocks at one-year horizon is between 14 and 30% for real monetary incomes and between 15% and 25% for inflation depending on the prior distribution. The fraction of the forward error variance of industrial production explained by oil shocks at a one-year horizon is between 35% and 45%. These values seem to be surprisingly high even for an oil-dependent economy like Russia's and need to be examined using a sensitivity analysis.

JEL-Classification: C11, C32, E32, Q43
Keywords: oil market shocks, Bayesian SVAR, sign restrictions

1 Introduction

The influence of world oil market events on the Russian economy is regularly discussed in media and in popular economic literature. The evident reason of the interest is the large share of Russian exports that is attributable to crude oil and oil products. An oil price drop decreases the trade and the budget balance. Therefore, it may be surprising that quantitative estimates of oil price effects on macroeconomic indicators in Russia are extremely scarce. This paper fills that gap and aims at quantifying the effects of different oil market shocks on three key macroeconomic indicators in Russia. To reach the goal, in this paper I construct and estimate a structural Bayesian VAR model (SBVAR) and identify it with sign restrictions. The results are based on impulse response functions (IRF) analysis and forward error variance decomposition.

The shocks identification in the paper is realized as proposed by Baumeister and Hamilton (2015a). Baumeister and Hamilton (2015b) show how the oil shocks identified following the same algorithm affect oil market variables. However, no previous papers have shown how the shocks identified in the same way affect external variables with respect to the oil market. As empirical research, this paper is of one the rare examples of econometric analysis of oil market shocks on the Russian economy, and the first one that uses the SBVAR model.

2 Baseline Model

The vector of endogenous variables consists of two parts: the variables describing the world oil market and one variable being a Russian economy indicator. The first block of the variables identifies the oil shocks. I then measure how these identified shocks affect a Russian indicator of economic activity included in the model.

For the shocks identification, the model by Baumeister and Hamilton (2015b) is used. The model by Baumeister and Hamilton (2015b) is extended here to estimate the role of the oil market shocks as sources of business cycles. A feature of that model (in contrast to Kilian (2009), Kilian and Murphy (2012), Peersman and Van Robays (2009)) is including stocks in the vector of endogenous variables. It permits to obtain more reasonable estimates of demand and supply elasticities in the oil market. At the same time, using a variable that can be estimated with a measurement error only makes the estimation more tricky and requires some changes of the estimation algorithm with respect to the baseline model.

The oil stocks change if the quantities supplied and demanded are not equal:

$$Q_t^S - Q_t^D = \Delta I_t^*, \tag{1}$$

where Q_t^D is a quantity demanded of oil in period t, Q_t^S is a quantity of oil produced in period t, and ΔI_t^* is growth of world oil stocks. The star as the upper index means that the variable is observed with a measurement error. Let $q = 100 \ln(Q_t/Q_{t-1})$ be an observed monthly growth rate of oil production. Then monthly growth rate of the oil demand is written as $q_t - \Delta i_t^*$, where $\Delta i_t^* = 100\Delta I_t^*/Q_{t-1}$.

The model used for estimation is written as:

$$q_t = \alpha_{qp} p_t + b_1' x_{t-1} + u_{1t}^* \tag{2}$$
$$z_t = \alpha_{zp} p_t + b_2' x_{t-1} + u_{2t}^* \tag{3}$$
$$q_t = \beta_{qz} z_t + \beta_{qp} p_t + \chi^{-1} \Delta i_t + b_3' x_{t-1} + u_{3t}^* - \chi^{-1} e_t \tag{4}$$
$$\Delta i_t = \psi_1 q_t + \psi_2 z_t + \psi_3 p_t + b_4' x_{t-1} + \chi u_{4t}^* + e_t \tag{5}$$
$$\upsilon_t = \gamma_1 q_t + \gamma_2 z_t + \gamma_3 p_t + \gamma_4^* \Delta i_t^* + b_5' x_{t-1} + u_{5t}^*, \tag{6}$$

where q_t is the world monthly oil production rate, z_t is the world economic activity index, p_t is the monthly oil price growth rate, Δi_t is the measure of world stocks growth rate, υ_t is one of the main indicators of the Russian economy, the effect of oil market shocks on υ_t is measured, x_{t-1} represents all lags of endogenous variables: $(x_{t-1}' = (y_{t-1}', y_{t-2}', \ldots, y_{t-m}', 1)')$ and $y_t = (q_t, z_t, p_t, \Delta i_t, \upsilon_t)'$, u_{1t}^* is the oil supply shock, u_{2t}^*- economic activity shock, u_{3t}^* is the oil market specific demand shock, u_{4t}^* is the stocks demand shock that is often titled as speculative demand shock, u_{5t}^* is a internal economy non-oil market shock. Equation (2) is the oil supply curve. Equation (3) describes the economic activity factors. Equation (4) represents the inverse demand function, equation (5) describes the stocks dynamics and equation (6) describes the dynamics of the Russian times series. In the paper, three different Russian variables are used. They are real monetary income, industrial production, and CPI inflation.

Two last equations in the system above are written under assumption that only a part of the world oil shocks is measured:

$$\Delta i_t = \chi \Delta i_t^* + e_t, \tag{7}$$

where $\chi < 1$ is a parameter that represents the measurable part of world oil stocks.

3 Estimation

The system written above may be written in the matrix form as:

$$\tilde{A}y_t = \tilde{B}x_{t-1} + \tilde{u}_t, \tag{8}$$

$$y_t = (q_t, z_t, p_t, \Delta i_t, v_t)' \tag{9}$$

where the dimensions of the matrix $\tilde{A}$ are (5×5), and the matrix can be written as:

$$\tilde{A} = \begin{bmatrix} 1 & 0 & -\alpha_{qp} & 0 & 0 \\ 0 & 1 & -\alpha_{zp} & 0 & 0 \\ 1 & -\beta_{qz} & -\beta qp & -\chi^{-1} & 0 \\ -\psi_1 & -\psi_2 & -\psi 3 & 1 & 0 \\ -\gamma_1 & -\gamma_2^* & -\gamma 3 & -\gamma 4 & 1 \end{bmatrix} \tag{10}$$

and the shocks vector is as follows:

$$\tilde{u}_t = \begin{bmatrix} u_{1t}^* \\ u_{2t}^* \\ u_{3t}^* - \chi^{-1}e_t \\ \chi u_{4t}^* + e_t \\ u_{5t}^* - \gamma_4 e_t \end{bmatrix} \tag{11}$$

Due to the measurement error taken into account explicitly, the covariance matrix $D^* = cov(u_{it}, u_{jt})$ is not diagonal:

$$D^* = \begin{bmatrix} d_{11}^* & 0 & 0 & 0 & 0 \\ 0 & d_{22}^* & 0 & 0 & 0 \\ 0 & 0 & d_{33}^* + \chi^{-2}\sigma_e^2 & -\chi^{-1}\sigma_e^2 & \gamma_4\chi^{-1}\sigma_e^2 \\ 0 & 0 & -\chi^{-1}\sigma_e^2 & d_{44}^*\chi^{-2} + \sigma_e^2 & -\gamma_t\sigma_e^2 \\ 0 & 0 & \gamma_4\chi^{-1}\sigma_e^2 & -\gamma_t\sigma_e^2 & d_{55}^* + \gamma_4^2\sigma_e^2 \end{bmatrix} \tag{12}$$

To rewrite the model in its usual form with a diagonal covariance matrix of structural shocks, it is possible to multiply both sides of the equation (8) by an auxiliary matrix Γ given as:

$$\Gamma = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & 1 & 0 \\ 0 & 0 & \phi & \tau & 1, \end{bmatrix} \tag{13}$$

where $\rho = -\frac{D^*_{34}}{D^*_{33}}$, $\tau = \frac{D^*_{34} D_{35*} - D^*_{33} D^*_{45}}{D^*_{33} D^*_{44} - D^{*2}_{34}}$, $\phi = \frac{-D^*_{53} - D^*_{43}\tau}{D^*_{33}}$ and D^*_{ij} defines an element in the row i and column j of the matrix D^*. Defining $A = \Gamma\tilde{A}$, $B = \Gamma\tilde{B}$ and $u_t = \Gamma\tilde{u}_t$ permits to rewrite model (8) in the usual SVAR form:

$$Ay_t = Bx_{t-1} + u_t, \quad u_t \sim i.i.dN(0, D) \tag{14}$$

with a diagonal matrix $D = \Gamma\tilde{D}\Gamma'$.

The paper is estimated following the explicit sign restrictions algorithm proposed by Baumeister and Hamilton (2015a). It means that the restrictions are imposed on the parameters of contemporaneous interdependence (matrix A in (14)). Some of those parameters, as explained above, have clear economic meaning (as price elasticity of oil demand, for example), and must be either positive or negative. This feature is exploited in the estimation algorithm and priors in the form of the truncated Student distributions are imposed.

Contrary to Baumeister and Hamilton (2015b), in this paper the priors are imposed directly on the parameters of matrix A and not $\tilde{A}$. This is regarded as the only possible solution that makes using posteriors derived by Baumeister and Hamilton (2015a) still possible [1]. For all three datasets, the model is estimated with the RW-MCMC routine using $2 \cdot 10^5$ iterations, half of which is burned-in.

4 Empirical results

For all three datasets, impulse response functions, historical decompositions, and forecast error decompositions (FEVD) are calculated. All impulse response functions and historical decomposition of the oil price dynamics are given in the Appendix. The FEVD is presented here.

The Tables 1-3 contain the FEVD at the 12-month horizon. Table 1 shows the decomposition for the set with real money incomes added as an additional Russian variable, Table 2 shows the decomposition for the set with industrial production, and Table 3 shows the decomposition for the set including the CPI inflation.

Visual analysis of impulse response functions does not give any precise answer about the external shocks effects on real monetary incomes and inflation, as these effects vary from negative to positive on different iterations of the algorithm. However, the economic activity shock and consumption

[1] The problem is due to the measurement error in the stocks variable. It requires pre-multiplying the system by the auxiliary matrix. If prior distributions on the parameters of $\tilde{A}$ are imposed, the prior and posterior distributions refer to different matrices. This clearly contradicts the algorithm proposed by Baumeister and Hamilton (2015a).

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	60	4	38	5	4
Economic activity shock	7	83	12	5	3
Consumption demand shock	12	4	21	60	3
Inventory demand	19	5	24	28	4
Internal shock	2	4	5	2	86

Table 1: FEVD for a dataset with real monetary incomes in Russia, [1] - Oil production; [2] - World industrial production; [3] - Oil price; [4] - Stocks ; [5] - Real monetary incomes

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	60	5	39	5	7
Economic activity shock	8	84	14	5	16
Consumption demand shock	12	5	22	60	6
Inventory demand	17	4	23	27	5
Internal shock	3	2	2	2	66

Table 2: FEVD for a dataset with Russian industrial production index, [1] - [4] as above; [5] - Industrial production

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	58	4	41	5	3
Economic activity shock	8	85	13	5	4
Consumption demand shock	12	4	20	62	5
Inventory demand	20	4	24	25	4
Internal shock	2	2	2	2	85

Table 3: FEVD for a dataset with Russian CPI inflation, [1] - [4] - as above; [5] - CPI inflation

demand shock positively affect the industrial production index (the former shock affects the IP index immediately). According to the median point FEVD estimates, external shocks account for 14% of the mean squared error associated with the 12-month forecast of real incomes and 15 % of inflation with all four shocks explaining approximately the same fraction of the forecast error variance. The estimates show that external shocks account for a surprisingly large share of the MSE associated with a one year forecast of industrial production (about 34). However, the latter result might be upward biased due to the way how the world economic activity index is calculated and needs to be checked with a sensitivity analysis (that will be added shortly). Though the aim of the paper is to determine the role of oil price shocks for the dynamics of some Russian economy macroindicators,as a by-product it is also possible to draw conclusions about the oil price as well.

The FEVD analysis of oil price shows that the oil supply shock affects the price more strongly than other kinds of shocks, though all demand shocks taken together explain the greater part of the MSE than the supply shock does (60% against 40%) at one-year horizon. The historical decomposition graphs demonstrate that the drop of oil price in 2008 is attributed to all four shocks (at the very beginning of that drop, the inventory demand shock was crucial). This conclusion is in line with that of Baumeister and Hamilton (2015b), even though it was drawn on a much longer and less recent sample in their paper. However, unlike Baumeister and Hamilton (2015b), the historical decomposition shows that the economic activity shock did not play a significant role in the oil price decrease in 2014.

5 Prior modifications

5.1 Modification 1. No effect of the internal shocks on oil market variables

The baseline model laid above implicitly assumes that the covariance matrix $cov(B|A)$ is diagonal and its main diagonal consists of five equivalent blocs. It means that the prior variance of a parameter at a lag value of a variable depends on the number of the lag and the variable itself but not on the equation that contains the variable. For example, the prior variance of a parameter at p_{t-3} is the same in all equations. In many cases this assumption can be considered as plausible if a researcher does not have any special prior information that allows her to believe in different shrinkage in different equations. In this particular model a researcher probably has a such kind of information. Russia is a small open economy and its internal shocks can hardly affect oil market variables even with a lag. It seems plausible that a matrix of prior variances for lag coefficients can be written as follows:

$$V_{ij,p} = \begin{pmatrix} v_{1,1,p} & v_{1,2,p} & v_{1,3,p} & v_{1,4,p} & 0 \\ v_{2,1,p} & v_{2,2,p} & v_{2,3,p} & v_{2,4,p} & 0 \\ v_{3,1,p} & v_{3,2,p} & v_{3,3,p} & v_{3,4,p} & 0 \\ v_{4,1,p} & v_{4,2,p} & v_{4,3,p} & v_{4,4,p} & 0 \\ v_{5,1,p} & v_{5,2,p} & v_{5,3,p} & v_{5,4,p} & v_{5,5,p} \end{pmatrix},$$

where $v_{i,j,p}$ is a prior variance of an element $b_{i,j}$ in a lag matrix at a lag p (B_p).

Taken into account that all parameters $b_{i,5,p}$ have zero prior mean, the modification of the prior covariance matrix implies that any effect of the Russian indicator on oil markets variables is ruled out at any lag. Technically it means that a conjugate Normal - inverted Wishart distribution for $B|A$ and $D|A, B$ is replaced with independent Normal - inverted Wishart distribution.

Tables 4 - 6 contain the FEVD at a 12-month horizon for this prior distribution. They show the decomposition with the real money income, industrial production and the CPI inflation, respectively, included in the variable set. Zero values in the last rows of all tables is a consequence of the modification of the prior distribution. In all three cases the median ratio of forecast error variance explained by the oil market shocks taken together increases considerably in comparison with the baseline model. According to the median point FEVD, oil market shocks account for 30% of the mean squared error associated with a 12-month forecast of the real money incomes, 45% of industrial production and 25% of inflation.

The impulse response functions show that internal shock does not influence the variables of the identification block (the assumption embedded in the prior) but the effects of oil market shocks on the Russian indicators are close to those revealed in the baseline model. However, we can conclude that the most of the 95% of the IRF show that a negative supply shock and positive demand shock exert a positive effect on Russian real money incomes, at the same time positive inventory demand exerts a negative effect on real monetary incomes. The consumption demand shock and economic activity shock positively affect the industrial production. The negative supply shock probably increases the industrial production but the influence, if there is any, lasts a short period of time. The effects of oil market shocks on CPI inflation in Russia are uncertain as they vary from negative to positive on different iterations of the algorithm.

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	64	4	37	5	8
Economic activity shock	8	87	14	5	4
Consumption demand shock	11	4	23	62	8
Inventory demand	17	4	26	28	11
Internal shock	0	0	0	0	70

Table 4: FEVD for a dataset with real monetary incomes in Russia, prior modification 1, [1] - Oil production; [2] - World industrial production; [3] - Oil price; [4] - Stocks ; [5] - Real monetary incomes

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	68	4	33	5	8
Economic activity shock	8	86	14	5	19
Consumption demand shock	11	5	27	60	9
Inventory demand	13	4	26	30	9
Internal shock	0	0	0	0	55

Table 5: FEVD for a dataset with Russian industrial production index, prior modification 1, [1] - [4] as above; [5] - Industrial production

5.2 Modification 2. Softer prior in oil production and economic activity equations

A second prior modification replaces two exclusion restrictions in the contemporaneous structural parameter matrix A with softer restrictions determined in the form of Student distributions with zero means. This identification scheme implies the contemporaneous interdependence between the economic activity and oil production variables in two first equations of the system.

Therefore, the A-matrix is now written as:

$$\tilde{A} = \begin{bmatrix} 1 & -\alpha_{qy} & -\alpha_{qp} & 0 & 0 \\ -\alpha_{yq} & 1 & -\alpha_{yp} & 0 & 0 \\ 1 & -\beta_{qz} & -\beta qp & -\chi^{-1} & 0 \\ -\psi_1 & -\psi_2 & -\psi 3 & 1 & 0 \\ -\gamma_1 & -\gamma_2^* & -\gamma 3 & -\gamma 4 & 1 \end{bmatrix} \tag{15}$$

The main objective of this prior modification is to let data to speak for

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	60	5	41	5	5
Economic activity shock	8	87	14	5	5
Consumption demand shock	12	4	21	63	8
Inventory demand	20	4	24	27	8
Internal shock	0	0	0	0	75

Table 6: FEVD for a dataset with Russian CPI inflation, prior modification 1, [1] - [4] - as above; [5] - CPI inflation

themselves without imposing restrictions that may not be supported by the data. However, I do not assume the possibility of non-zero parameters at stocks variable in the first two equations for technical reasons. As world stocks are determined with a measurement error, an assumption that the stock variable is included in the first two equations deprives D^* matrix of all zero elements. Matrix Γ becomes lower triangular and contains 10 parameters. The solution is cumbersome.

Tables 7 - 9 show the FEVD at the 12-month horizon for this alternative prior modification. The tables contain the decomposition with the real money income, industrial production and the CPI inflation, respectively, included in the variable set.

The impulse response functions are similar to those of the baseline model.

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	41	12	51	6	5
Economic activity shock	19	75	19	6	8
Consumption demand shock	15	7	14	64	3
Inventory demand	25	7	17	24	3
Internal shock	0	0	0	0	80

Table 7: FEVD for a dataset with real monetary incomes in Russia, prior modifications 1 and 2, [1] - Oil production; [2] - World industrial production; [3] - Oil price; [4] - Stocks ; [5] - Real monetary incomes

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	29	57	13	5	20
Economic activity shock	24	28	65	7	16
Consumption demand shock	16	7	10	66	5
Inventory demand	31	8	12	22	6
Internal shock	0	0	0	0	53

Table 8: FEVD for a dataset with Russian industrial production index, prior modification 1 and 2, [1] - [4] as above; [5] - Industrial production

6 Conclusion

In the paper, I construct an SBVAR model to identify the contribution of oil market structural shocks into some Russian macroeconomic indicators dynamics. The main interest of this paper is the quantitative estimate of the impact of oil market shocks on macroeconomic volatility in Russia. The core of the model used in the paper is the model by Baumeister and Hamilton (2015b) extended by one equation describing the dynamics of a macroeconomic indicator in question. The model is general and can be applied to any economy.

The identified shocks give economically plausible results about their effects on the oil market and global activity, though the sign of some of these effects is predetermined by the sign restrictions embedded in the priors.

The main research question of the paper is answered differently for different indicators. The mean estimate of the forward error variance explained by oil market shocks at a one-year horizon is between 14% and 30% depending on the prior for real monetary incomes and between 15% and 25% for inflation.

	[1]	[2]	[3]	[4]	[5]
Oil supply shock	18	9	76	6	6
Economic activity shock	13	82	12	6	6
Consumption demand shock	21	4	7	70	6
Inventory demand	49	5	6	17	4
Internal shock	0	0	0	0	78

Table 9: FEVD for a dataset with Russian CPI inflation, prior modification 1 and 2, [1] - [4] - as above; [5] - CPI inflation

Conversely, the fraction of the forward error variance of industrial production explained by oil shocks at one year horizon is between 35% and 45% depending on the prior. These values seem to be surprisingly high, even for an oil-dependent economy like Russia's, and need to be examined using a sensitivity analysis.

The empirical results of the estimation allow drawing a conclusion about the oil price dynamics as well. The estimation results show that the oil supply shock affects the price dynamics more strongly than any of the demand shocks. However, all three demand shocks in total drive the oil price dynamics more strongly than the supply shock. As in the paper by Baumeister and Hamilton (2015b), I show here that the oil price drop in 2008 was triggered by all four shocks considered. At the very beginning of that drop, the inventory demand shock played the most significant role. Contrary to their results, the historical variance decomposition of the shocks in this paper shows that the economic activity shock was not a significant driver of the oil price decrease in 2014.

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Appendices

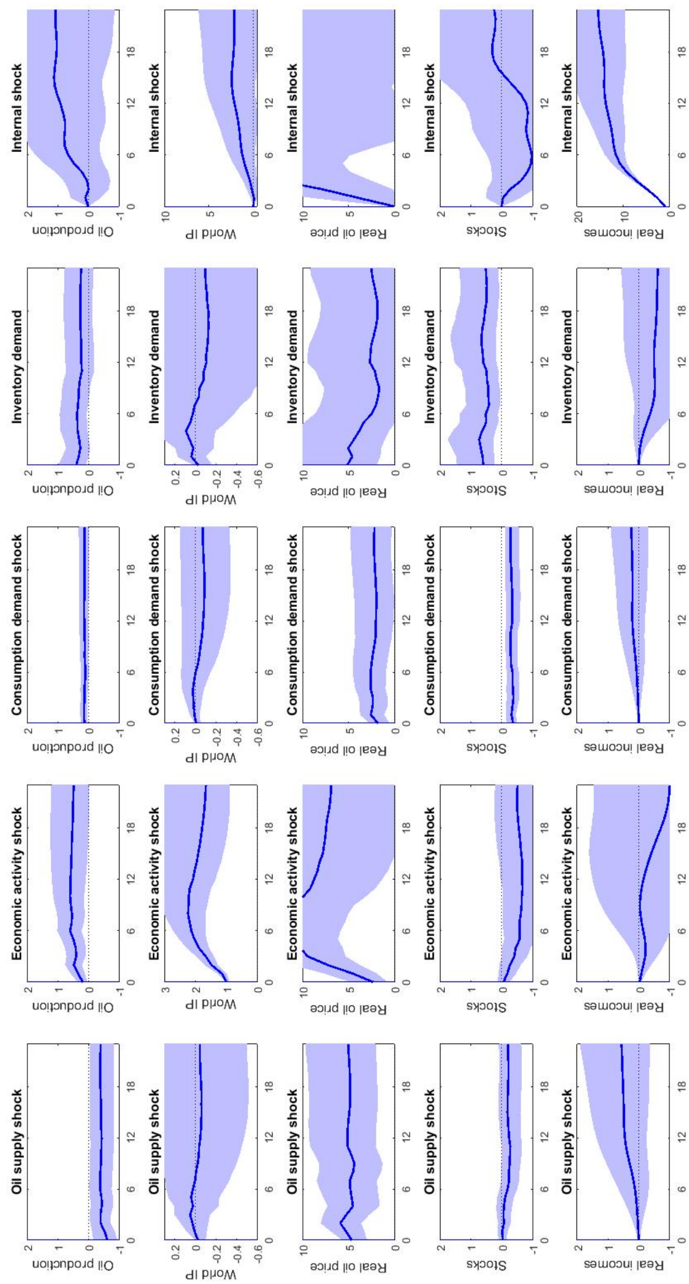

Figure 1: Impulse response functions for all five variables with real money incomes as Russian macroindicator

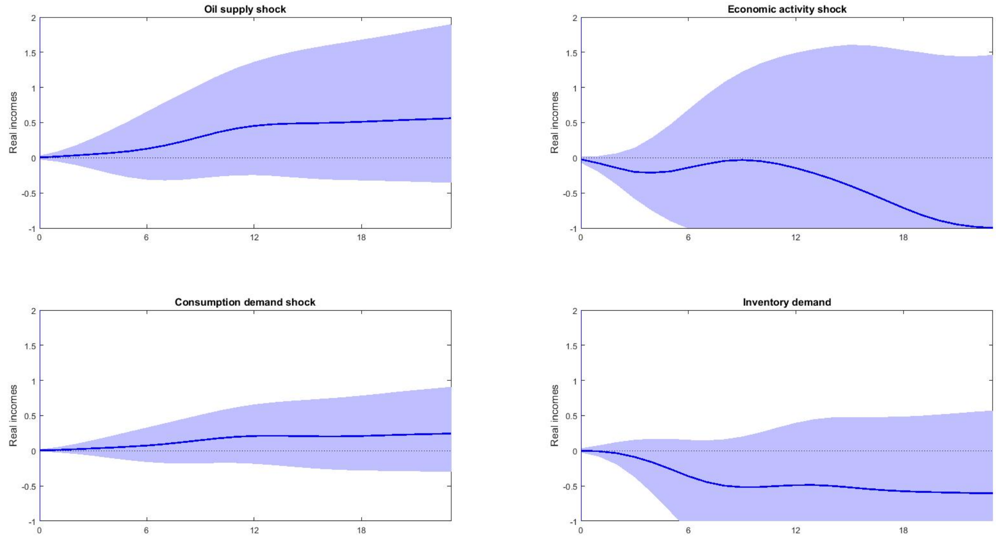

Figure 2: Impulse response functions for real money incomes hit by oil market shocks (the same as shown in last row of Figure 1

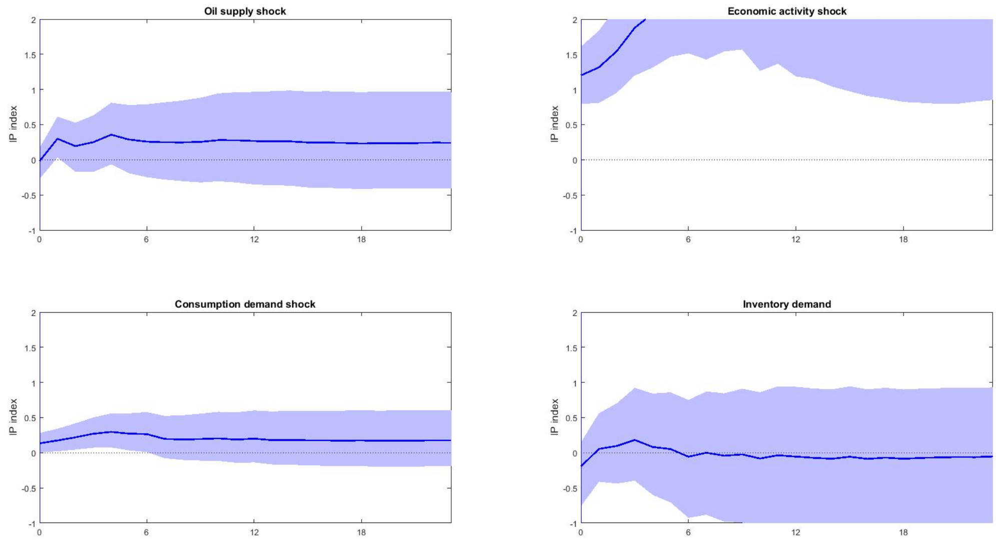

Figure 3: Impulse response functions for industrial production index

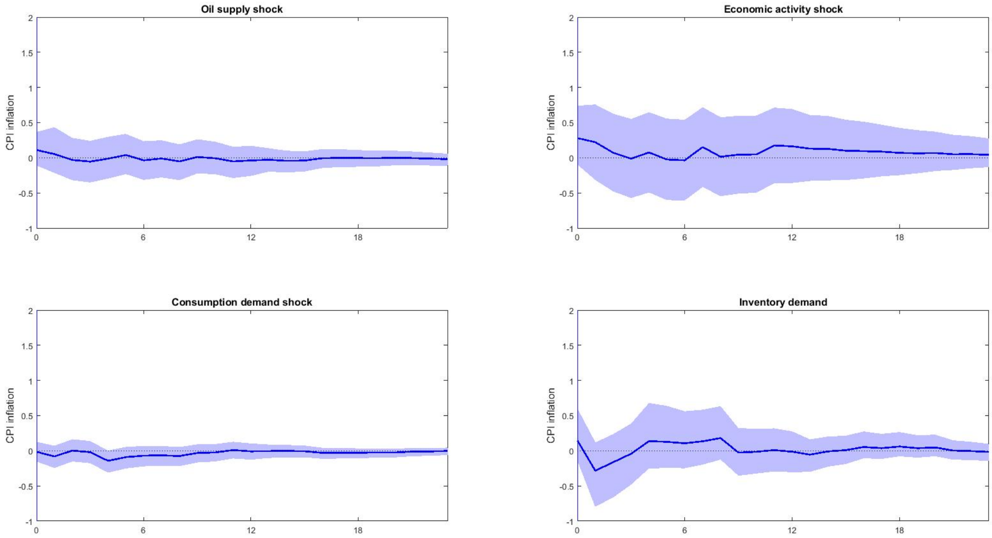

Figure 4: Impulse response functions for CPI inflation

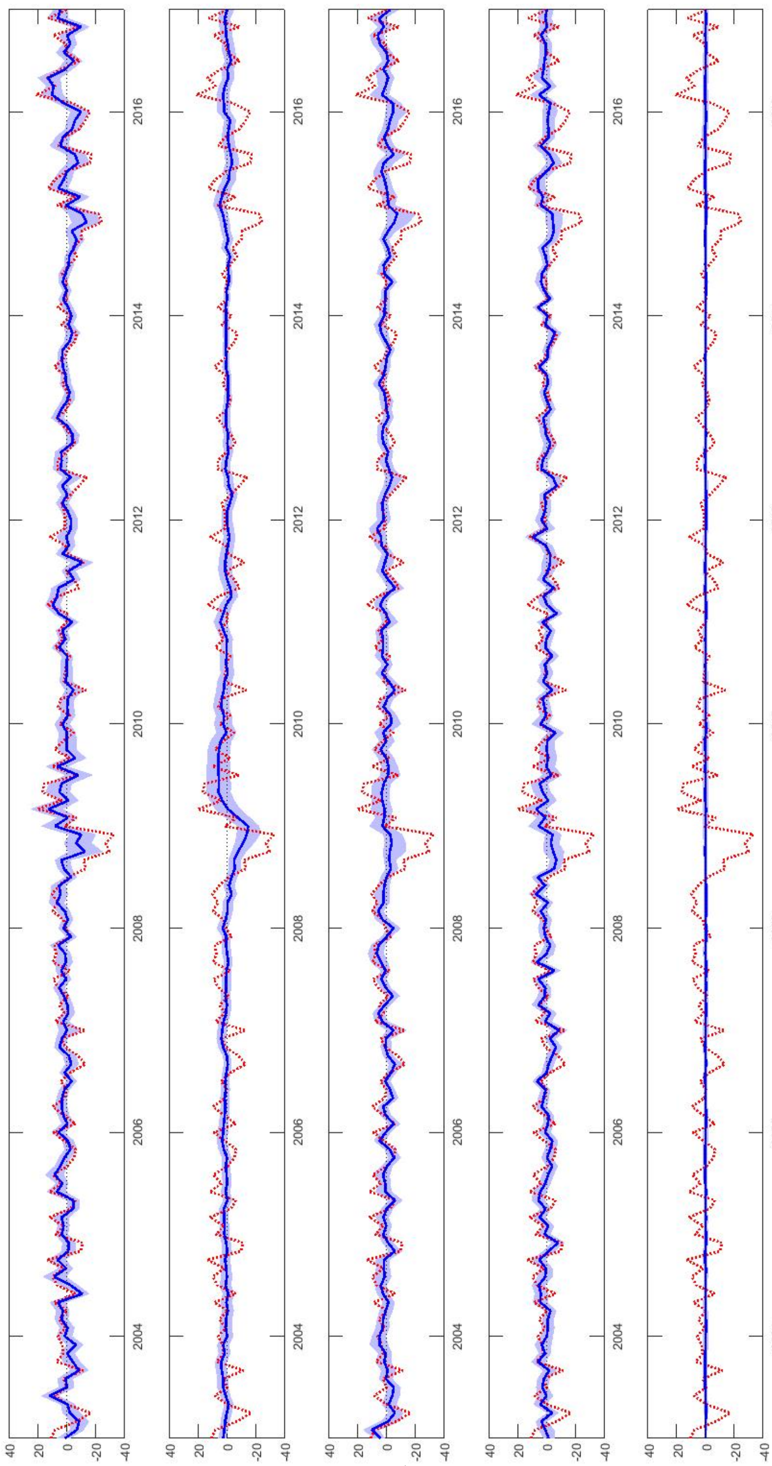

Figure 5: Historical decomposition of oil price dynamics

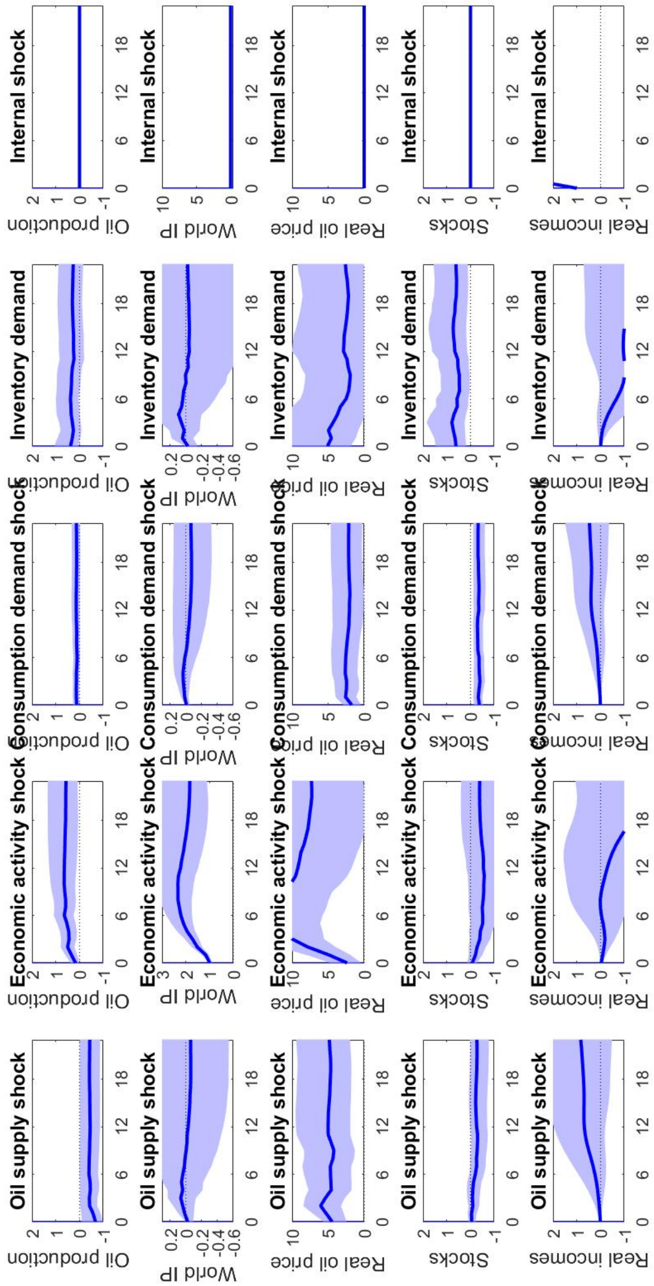

Figure 6: Impulse response functions for all five variables with real money incomes as Russian macroindicator

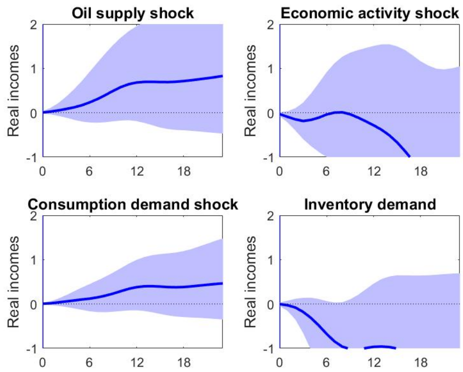

Figure 7: Impulse response functions for real money incomes hit by oil market shocks (the same as shown in last row of Figure 6), prior modification 1

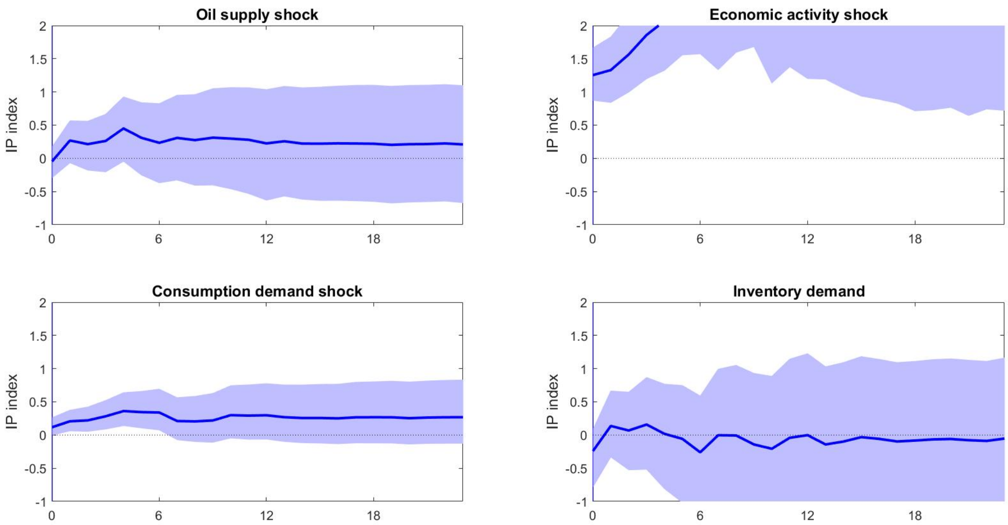

Figure 8: Impulse response functions for industrial production index, prior modification 1

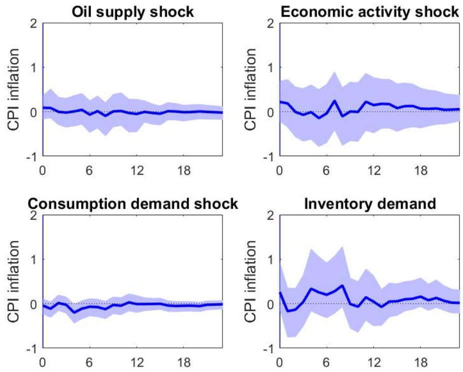

Figure 9: Impulse response functions for CPI inflation, prior modification 1

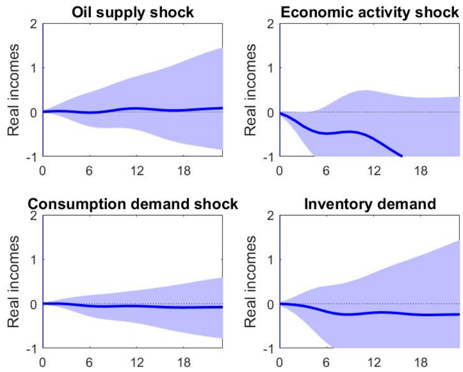

Figure 10: Impulse response functions for real money incomes hit by oil market shocks, prior modification 1 and 2

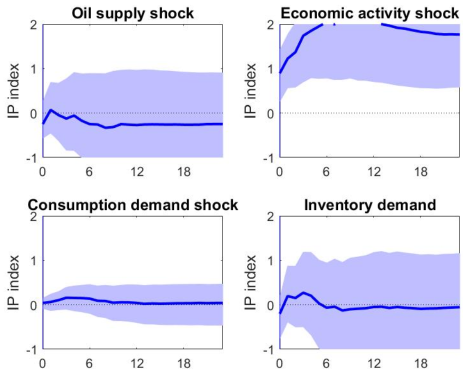

Figure 11: Impulse response functions for industrial production index, prior modification 1 and 2

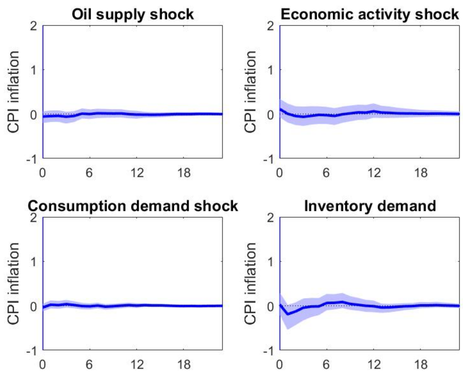

Figure 12: Impulse response functions for CPI inflation, prior modification 1 and 2