A Bivariate Forecasting Model For Russian GDP Under Structural Changes In Monetary Policy and Long-Term Growth

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Abstract

This paper estimates a bivariate econometric model to describe Russia's real GDP while taking account of the Russian economy's high dependence on oil prices, monetary policy regime change, and economic growth slowdown. We follow the theory of long-run neutrality of monetary policy and assume that the Bank of Russia's monetary policy regime change in late 2014 has influenced only the short-run relationship between Russia's GDP and oil prices, but long-run multiplier is invariant to monetary policy. The paper also attempts to take account of the economic growth slowdown in last decade. The model has demonstrated good forecasting performance.

Introduction

The paper presents a forecasting model for Russian GDP, incorporates the high dependence on terms of trade, slowdown of economic growth in Russia after the global financial crisis, and the change in the monetary policy regime in the fourth quarter of 2014. Forecasting macroeconomic indicators is essential in economic analysis. When developing measures of monetary and fiscal policies, regulators make decisions based on their own forecast models. This applies to the Bank of Russia and the Ministry of Economic Development of Russia, as well as other authorities in the economic and social areas. Besides, almost all Russian research centers and economic policy authorities have their own forecasting models. The Russian economic literature describes a considerable number of such forecasting models, including ARIMA models (Turuntseva et al., 2015), VAR models (Turuntseva et al., 2005), large macroeconometric models (Mikhailenko, 2005; Uzyakov et

al., 2009; Ayvazyan et al., 2013), factor models (Styrin, Potapova, 2009; Astafieva, Turuntseva, 2014; Porshakov et al., 2015), BVAR models (Demeshev, Malakhovskaya, 2015; Deryugina, Ponomarenko, 2015; Pestova, Mamonov, 2016b) and DSGE models (Ivaschenko, 2013; Malakhovskaya, 2016; Kreptsev, Seleznev, 2018). Some authors as Turuntseva (2011), and Pestova, Mamonov (2016a) provide extensive reviews of the Russian forecast models. However, the implications of the transition to the inflation targeting regime for the Russian GDP have not yet been studied in depth. Therefore there is a need new type of forecasting model which take into account the changes that entails the transition to the new monetary policy regime.

The paper has a following structure: In the first section, we briefly describe the overview of the Russian economy over the period under consideration, describe the importance of the terms of trade and monetary policy. In the section "Specification of the model" we construct the ARX and ECM models and take into account the factors mentioned in the section earlier. In the section "Estimation of the model", we present the results of models estimation and analyze the influence of the oil prices on Russian GDP in different monetary policy regimes based on impulse response analysis. In the forecasting section, we test the ARX and ECM out of sample forecasting performance.

Overview of the Russian economy

Crude oil prices are the most important indicator of foreign economic conditions and a salient determinant of the key macroeconomic indicators in Russia's economy. Exports of crude oil, natural gas, and refined petroleum products make up the majority of Russia's exports; therefore, oil prices can be used as a proxy variable for terms of trade. Oil prices tumbled during the 2008–2009 and 2014–2015 financial crises. Russia lost 7.8% of its GDP (in constant prices) in 2009, compared with a 2.8% contraction in 2015. Oil prices were definitely not the only negative determinant of the 2009 drop in output. However, many experts predicted, based on historical data analysis, that Russia would plunge into a deep

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economic recession in 2015 and face a 5–9% decline in GDP. A soft decline in production during the most recent financial crisis can be accounted for by the Bank of Russia's monetary policy change from a managed float to a floating exchange rate and inflation targeting regimes.

From a theoretical point of view, a floating exchange rate regime is more conducive than is a managed float to stabilizing business activity in emerging economies (Devereux et al. 2006; Friedmanm 1953; Gertler et al. 2007). If foreign economic conditions change under the floating exchange rate regime, the real exchange rate can quickly adjust to its long-run equilibrium through change in the nominal exchange rate. Under the managed float regime, by contrast, the real exchange rate adjustment would require prices of goods to be changed; therefore, when price flexibility is not absolute, extended periods of time may elapse before the adjustment to the equilibrium takes place. Consequently, long periods of real exchange rate misalignment and a wide gap between domestic goods' demand and the effective level of demand can be seen under a managed ruble exchange rate. Broda (2004) and Edwards and Yeyati (2005) provided empirical evidence suggesting that a floating exchange rate has a stabilizing effect on output under the influence of terms-of-trade shocks. Figure 1 presents the Russian real GDP in 2011 constant prices from Rosstat and the real Brent oil prices, which we get by deflating nominal oil prices (U.S. Energy Information Administration) by the dollar CPI (FRED Economic Data). Quarterly oil prices are getting by averaging of monthly nominal prices. At final, we have all data in quarterly expression from 1999Q1 to 2018Q4.

[Figure 1 near here]

The Bank of Russia's move to the inflation targeting and floating exchange rate regimes can, therefore, be regarded as a positive economic policy aimed at stabilizing business activity. However, a change in the MP (monetary policy) regime leads to a change in the cross-correlation relationship between macroeconomic indicators, meaning that a structural change in the parameters of regression equations can be seen due to the MP regime change.

The presence of structural changes, in turn, can substantially impair the forecasting performance of macroeconomic models as a result of misspecification (Clements and Hendry 2006; Pesaran et al. 2006).

The Bank of Russia shifted to the floating exchange rate regime late in 2014; therefore, the number of observations for estimating the model parameters under this new regime is very small. Making use of the preceding monetary policy regime's information about system parameters, which are stable in time, is a promising approach in this context. The key underlying premise of the model developed in this paper rests on the hypothesis that monetary policy is neutral in the long term and that monetary policy regimes influence only the short-run dynamics of the economic system adjustment to the long-run equilibrium. The MP regime change is assumed to involve only a change in the nature of adjustment of real macroeconomic indicators to the long-run equilibrium, while the long-run multipliers of the real macroeconomic indicators with respect to fundamental shocks remain invariant to the MP regime.

We built econometric models—based on the works of (Beck et al., 2007; Kuboniwa, 2014; Rautava, 2004)—under the premise of long-run relationship between Russian real GDP and oil prices (a proxy for terms of trade). Accordingly, we assumed that the long-run elasticity of GDP with respect to oil prices is invariant to the MP regime. We decided upon pair regressions between GDP and oil prices, given the small number of observations at hand. We considered two specifications—either with or without cointegration between them—to ensure robust results. The second specification allows for no cointegration, because other skipped nonstationary factors of Russian GDP could possibly be at play.

The long-run dependence of an oil producing economy on oil prices can be explained through the capital formation channel. Esfahani et al. (2014) relied on an extended Solow model (Solow, 1956) to substantiate the cointegration relation for some oil producing economies by supposing that some oil export earnings are saved in the form of fixed

investment. Positive dependence of the oil producing economy's output level on the level of oil prices is substantiated within the context of the premises laid out by the authors: a permanent rise in oil prices implies an increase in investment and, therefore, in the volume of physical capital, which represents the factor of production of goods and services, thereby resulting in a permanent increase in output in the long term. In Ramsey's multisector models of optimal growth, a rise in oil prices and an improvement in terms of trade brings about higher returns on investment in both the export-led sectors and the nontradable sectors (prices of nontradables increase due to higher demand), thereby boosting the volume of capital in the economy, output, fixed capital per worker, and worker's labor productivity (Idrisov et al., 2015).

We also assume that the long-run growth rate of Russia's economy remained unchanged when the floating exchange rate regime was established. Figure 1, however, shows a distinct break in the long-run growth trend around the 2008–2009 crisis. Russian GDP demonstrated very high growth rates until 2008–2009, which can be interpreted through recovery growth after the transformation downturn. However, the growth rate slowed considerably afterwards, possibly because the rapid growth via the channel of imitation of technologies had lost its potential against the backdrop of a considerably narrowing labor productivity gap between domestic and foreign economies. Based on a cointegrated regression model, Polbin and Skrobotov (2016) provided formal statistical evidence supporting this change in the trend slope, and identified a change in 2007Q3, shortly before the 2008–2009 financial crisis. In this paper, we also consider this structural change.

Specification of the model

We assume that a stochastic process for the Russian real GDP y_t is given by the equation

$$\ln y_t = \tau_t + \beta \ln poil_t + v_t, \tag{1}$$

where τ_t is the trend component representing growth factors orthogonal to oil prices, $poil_t$ is real oil prices, β is the long-run elasticity of Russian GDP with respect to oil prices, and v_t is a zero mean reverting stochastic process that can correlate with oil prices.

We assume that the logarithm of oil prices follow a random walk, which is consistent with poor predictability of oil prices (Alquist et al., 2013). In this context, the current value of $\ln poil_t$ can be defined as a permanent level of this variable, while the value $\ln y_t^p = \tau_t + \beta \ln poil_t$ can be defined as a permanent level of GDP. We also assume that the MP regime change has no effect whatsoever on the component $\ln y_t^p$ but, rather, alters only the cross-correlation properties of the process v_t.

We also allow for breaks in the long-term growth of the component τ_t. Given the small number of observations at hand, we assume that there was a single structural change in the long-term growth rates of the variable τ_t at the point of time T_1, which we suppose to have occurred around the time of the 2008–2009 crisis. This paper considers two specifications. The first assumes that the variable τ_t is described by a random walk with drift and with structural changes in the drift parameter. Then, output and oil prices are not cointegrated time series, in which case we build a ARX model. In the second specification, we assume that τ_t is the segmented linear deterministic trend. Then, Russian GDP is cointegrated with real oil prices in a model with this deterministic trend, and an error correction model is a proper model for real GDP.

For the first case, the model is given as

$$\begin{cases} (\Delta \ln y_t - \mu_t) = \sum_{i=1}^{p_1} \alpha_i^1 (\Delta \ln y_{t-i} - \mu_{t-i}) + \sum_{j=0}^{q_1} b_j^1 \Delta \ln(poil_{t-j}) + \varepsilon_t^1, t < T_2 \\ (\Delta \ln y_t - \mu_t) = \sum_{i=1}^{p_2} \alpha_i^2 (\Delta \ln y_{t-i} - \mu_{t-i}) + \sum_{j=0}^{q_2} b_j^2 \Delta \ln(poil_{t-j}) + \varepsilon_t^2, t \geq T_2 \end{cases}, \qquad (2)$$

where T_2 is the date of the MP regime change, namely, in the fourth quarter of 2014, $\varepsilon_t^1 \sim N(0, \sigma_1^2)$, $\varepsilon_t^2 \sim N(0, \sigma_2^2)$, and the long-term growth rate μ_t is given as

$$\mu_t = \begin{cases} \mu_0, & t < T_1 \\ \mu_1, & t \geq T_1 \end{cases}, \tag{3}$$

The assumption that the long-run elasticity of output with respect to oil prices is invariant to the MP regime places the following restriction on the parameters under various regimes:

$$\frac{\sum_{j=0}^{q_1} b_j^1}{1 - \sum_{i=1}^{p_1} \alpha_i^1} = \frac{\sum_{j=0}^{q_2} b_j^2}{1 - \sum_{i=1}^{p_2} \alpha_i^2} \equiv \beta, \tag{4}$$

Juselius (2006) classifies this structural change as mean shift, which implies by itself that the first difference of time series over the period under review fluctuates around several mean levels (see Fig. 6.2, left-side panels), and the time series in the levels follows several trends with different slopes.

In the second case, the relation (1) takes the form

$$\ln y_t = c + \mu_0 t * (1 - dt_t) + \mu_1 t * dt_t + \gamma dt_t + \beta \ln poil_t + v_t, \tag{5}$$

where c is the constant, t is the linear trend, and the variable dt_t is a dummy variable of the form:

$$dt_t = \begin{cases} 0, & t < T_1 \\ 1, & t \geq T_1 \end{cases}. \tag{6}$$

In this model setup, the parameter μ_0 is the long-term growth rate of GDP under the regime preceding the structural change, and the parameter μ_0 denotes the long-term growth rate of output under the regime following the structural change at the point of time T_1. The parameter γ corresponds to the magnitude of the output jump at the point of structural change.

Before the structural change in 2007q3 deterministic trend change with rate equal to μ_0, after structural change with rate equal to μ_1. However, the rate of change of the deterministic component at the time of the break is not equal to $(\mu_1 + \gamma * \Delta dt_t)$. At time $t = T_1 - 1$, the value of the determined trend is $c + \mu_0(T_1 - 1)$, and at time $t = T_1$, the value of the

determined trend is $c + \mu_0 T_1 + (\mu_1 - \mu_0)T_1 + \gamma$. Then the first trend difference at the moment T_1 is equal to $\mu_1 T_1 - \mu_0(T_1 - 1) + \gamma$.

Then, an error correction model takes the form:

$$\begin{cases} (\Delta \ln y_t - \tilde{\mu}_t) = \theta^1 v_{t-1} + \sum_{i=1}^{p_1} \alpha_i^1 (\Delta \ln y_{t-i} - \tilde{\mu}_{t-i}) + \sum_{j=0}^{q_1} b_j^1 \Delta \ln(poil_{t-j}) + \varepsilon_t^1, t < T_2 \\ (\Delta \ln y_t - \tilde{\mu}_t) = \theta^2 v_{t-1} + \sum_{i=1}^{p_2} \alpha_i^2 (\Delta \ln y_{t-i} - \tilde{\mu}_{t-i}) + \sum_{j=0}^{q_2} b_j^2 \Delta \ln(poil_{t-j}) + \varepsilon_t^2, t \geq T_2 \end{cases} \quad (7)$$

Where:

$$\tilde{\mu}_t = \begin{cases} \mu_0, & t < T_1 \\ \mu_1 T_1 - \mu_0(T_1 - 1) + \gamma, & t = T_1, \\ \mu_1, & t > T_1 \end{cases} \quad (8)$$

a v_{t-1} is the corrective component lag.

Thus, the ECM model has an extra parameter of the jump in the output trend at the time of structural change T_1. In light of the above, the reader may ask why the ARX model does not include this parameter at the time of structural change. The answer is: We do not do this because we rely on the ARX model's assumption that the structural component is a stochastic trend. In this specification, all changes in the trend level are realized through stochastic trend shocks, and the analyzed changes are indistinguishable from deterministic jumps in the level.

Estimation of the model

The model was econometrically estimated using data for the period between 1999Q1 and 2018Q4. The multiplicative seasonal component was removed from the time series of real GDP using ARIMA-X-12 in Eviews. Given a number of lags and dates of structural changes, the model was estimated by a maximum likelihood method. In the ARX model, the likelihood function was maximized using the fmincon function in Matlab. The problem was thus reduced to maximizing a nonlinear function with no restrictions. OLS estimates of unrestricted models in sub-periods were used as starting values for searching the maximum.

For ECM estimation, we use a concentrated maximum likelihood approach where short-run parameters are estimated by the OLS method within fixed parameters of the long-run cointegrated relationship. The likelihood function with respect to the parameters of the cointegration relationship was also optimized using the fmincon function in Matlab, in which DOLS (Saikkonen, 1991; Stock and Watson, 1993) estimates of the cointegration relationship (5) were used as the starting value.

As noted above, the monetary policy regime change date T_2 is set in 2014Q4, when the Bank of Russia moved to the floating exchange rate and inflation-targeting regimes. For the purpose of simplicity, a consistent estimator from Polbin and Skrobotov (2016), which corresponds to 2007Q3 and was obtained by minimizing squared residuals in the cointegrating regression between GDP and real oil prices, was used as the date T_1 of the structural change in long-term growth rates. The results obtained in this paper appear stable, with a minor variance of the date of structural change in the long-term growth rates.

The number of lags was selected according to the Akaike information criterion (Akaike 1974):

$$AIC(p) = 2p - 2\ln(L), \tag{9}$$

where p is the total number of parameters under both regimes, which, in the ECM model, also includes 5 parameters of the cointegration relationship.

When estimating information criterion values in the ECM model, the number of GDP and oil price lags is selected up to 6 under the first regime and up to 2 under the second regime, due to a short sample length under the inflation targeting regime. Under the second regime, the sample comprises only 17 points for estimation. As we conduct pseudo out of sample forecasts under the second regime we need a wide and representative horizon to demonstrate forecasting performance. We also need a sufficient number of observation to estimate the parameters of the second regime. To achieve this goals we estimate long run elasticities in both models under the first regime sample (1999Q1-2014Q3) and use these

estimates as restrictions for long run elasticities when estimate the ARX and ECM model in the full sample.

Long-run parameters in the ECM model are derived from the cointegration relationship, while long-run elasticities in the ARX model are a function of all the lag polynomial parameters. Therefore, long-run multipliers may be highly underestimated if there is a small number of lags in the ARX model. For example, when estimating a VAR on monthly data, Bernanke et al.(1997) selected 7 lags, corresponding to a lag length of approximately half a year, according to the AIC information criterion. Hamilton and Herrera (2004) believe that Bernanke et al. (1997) obtained highly underestimated values of the impact of oil price shocks on the U.S. output because of the small number of lags in the econometric model compared with the standard specification (with a lag length of one year) in the literature and that the model poorly approximates the data generation process. In this paper, to ensure a better estimation of long-run multipliers, the number of lags is set to four with respect to GDP under the first regime, whilst the other lags are chosen according to the Akaike information criterion. Setting a fixed lag length is quite a standard procedure in the literature (Stock and Watson 1998; Stock and Watson 2002). The results of choosing models according to the Akaike information criterion are presented in Table 1.

[Table 1 near here]

After choosing the number of lags, we implemented the residual bootstrap to obtain confidence intervals of estimates of model parameters. Table 2 presents the estimates of long-run parameters, namely, the estimates of output elasticity with respect to oil prices and the estimates of long-term growth rates of the structural component of output in both models. Table 2 shows that the obtained growth rates of the structural component of real GDP are very close to each other. The structural component of long-term growth before and after T_1 is estimated at 5.3-5.5% and 1.2-1.5% per year, respectively. The point estimates of the models'

parameters show that, if oil prices rise by 10%, then Russia's GDP would increase in the long term by 0.95% in the ARX model and by 1.06% in the ECM model.

[Table 2 near here]

In this paper, we do not show the coefficients corresponding to short-run dynamics in autoregressive models because they are difficult to interpret, but, for ease of visualization, we build impulse response functions of Russia's real GDP adjustment to oil shock according to a particular regime. Figures 2 and 3 present the point estimates of impulse responses of real GDP to a 10% permanent real oil price shock in the ARX and ECM models, along with 16% and 84% quantiles.

[Figure 2 near here]

[Figure 3 near here]

Both models identify different short-run dynamics of GDP adjustment to the long-run equilibrium, as shown in the diagrams. GDP exhibits a hump-shaped response under the managed exchange rate regime. Against the backdrop of a permanent increase in global oil prices, the real GDP exhibits accelerated growth rates for 3–4 quarters, after which the oil shock effect on GDP begins to wear off gradually. In response to a 10% increase in oil prices, GDP at its highest turns out to be 0.06% higher than its long-run level in ARX and ECM models. Thus, the econometric estimation reveals that the permanent rise of global oil prices positively contributes to output growth rates over 3–4 quarters, after which the contribution of growth rates turns negative in the medium term and zero in the long term. The obtained estimates show, however, that the inflation targeting regime is best for stabilizing the business cycle, and, if there is a change in terms of trade, GDP adjusts gradually to its new long-run equilibrium under this regime.

The obtained results can be interpreted as follows. Under the first MP regime, the Central Bank of Russia dampened appreciation of the real exchange rate by keeping a lid on the nominal exchange rate against the backdrop of rising global oil prices. And, the increase

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in aggregate demand on the back of improved terms of trade translated into expanded demand for both imported and domestic goods. However, as the real exchange rate firmed up on the back of inflation, the domestic production lost its competitive position, and aggregate demand moved towards consumption of imported goods. Under the inflation targeting regime, however, under a positive terms-of-trade shock, the Russian ruble rapidly appreciated in response to a strengthening nominal exchange rate, and higher aggregate demand instantly moved toward imported goods. Russian GDP gradually rose on account of gradual expansion of production possibilities and capital formation.

Forecasting

We now turn to real GDP forecasting. We test the forecasting performance of the ARX and the ECM models in two pseudo out of sample experiments on the last two years of available sample. To predict GDP we also need oil price forecasts. Log oil prices are assumed follow a random walk, and we take 0 as the forecast for growth in the log of oil prices. This assumption about the expected oil price in the ARX and the ECM models allows us to construct us 4-step ahead forecasts for GDP growth rate in the first experiment. In the second experiment, we follow Porshakov et al. (2016), who show the applicability of main export prices (include oil prices) to nowcasting and forecasting in the context of the dynamic factor model for the Russian GDP. We follow their outcomes in experiment 2 to test nowcasting performance of the models. Thus in the first forecast period of the second experiment we use actual oil prices, and zero oil prices growth for remaining thee period of the forecast. We follow the standard practice in the literature of using a classical ARIMA model as the benchmark for comparing forecasts (Stock and Watson, 1998; Angelini et al., 2011). We apply the Akaike information criterion to select the optimal order of the ARIMA model; ARIMA(1,0,1) for the first differences of log of GDP is selected.

Figures 4-6 present a comparison between the forecasts and the actual dynamics of the time series obtained by the ARX, ECM, and ARIMA models in first experiment, respectively.

[Figure 4 near here]

[Figure 5 near here]

[Figure 6 near here]

In Tables 3 and 4 we present the results of first and second experiments, respectively. Table 5 presents systematization of the two experiments and estimates the relative RMSE of the forecasts by the ECM model to the forecasts by the ARX and ARIMA models.

[Table 3 near here]

[Table 4 near here]

[Table 5 near here]

It follows from the Tables that the ARX and ECM models greatly outperform the ARIMA model in terms of forecasting performance. However, the ARIMA shows the best forecasting performance in forecasting for the fourth period and worst on the rest.

In the first experiment the ECM model outperforms the ARX model by 6% and 13% respectively, and outperforms the ARIMA model by 9% and 16% respectively in terms of forecasting for the whole period on average. According to Tables 3 and 4, the usage of realized oil prices in the ARX and the ECM model is not helpful in nowcasting, but really helpful in improving forecasting accuracy on average for the whole forecast period. For instance, the ECM model first step forecast in the first experiment (RMSE=0.0078) is more accurate than first step forecast in the second experiment (RMSE=0.0076). However, this outcome is only characteristic of the first step of forecast. If we concern average RMSE values during the whole forecast period, they decrease from 0.0088 to 0.0085. This situation is similar to ARX model.

Next, we present scenario-based forecasts for the (quarter on previous year's quarter and year-on-year) output growth rate in 2019 in Table 6 based on the best model - ECM. Three

alternative nominal oil price scenarios for 2019 are considered: basic scenario of the Ministry of the Economic Development of the Russian Federation - $63.4/bbl (Ministry of Economic Development of the Russian Federation. October, 2018), Wolrd Bank scenario -$68.6/bbl (International Monetary Fund World Economic Outlook. October, 2018), and International Monetary Fund scenario -$69.4/bbl (International Monetary Fund World Economic Outlook. October, 2018). Real oil prices are calculated on the assumption that dollar inflation changes by 0.5% per quarter. Table 6 presents our forecasts.

[Table 6 near here]

We believe that the ECM-based forecasts are the most relevant because in all the experiments the ECM shows a higher out of sample forecasting performance. Note that all of our 2019 YoY forecasts are slightly lower than World Bank, which is 1.5%, International Monetary Fund forecast, which is 1.6% and the Ministry of Economic Development of the Russian Federation – 1.3%.

There are two reasons why the forecasts obtained in Table 6 are lower than the forecasts of the IMF, WB and MED. The first reason for such low forecasts is that in 2018 the Russian economy experienced an increase of 2.3% year-on-year, which was much higher than mentioned institutions forecasts. Because of this, both models give a forecast for the 2019 year in relation to the larger growth in 2018, due to which the forecast for 2019 is low. The second reason is that in 2018 average oil prices amounted to $71 per barrel. Thus, in all the scenarios, oil prices in 2019 are expected to fall, which also reduces the forecast for the 2019 year.

We also admit that IMF world GDP growth forecast for 2018 is equal to 3.3%. This fact means that even our most optimistic forecast for growth of the Russian economy much lower than the forecasted global growth rate by IMF. Thus, in the coming years, the Russian government will have to solve a rather difficult task, given the slowdown in the long-term

growth demonstrated in this paper, in that, to keep up with the rest of the world, Russia — a developing country — needs to grow at least twice as fast as it is doing.

Conclusion

This paper provides empirical evidence — based on the bivariate ARX and ECM econometric models — of the hump-shaped response of the Russian real GDP to the permanent oil price shock under the managed float exchange rate regime. That is, the managed float exchange rate regime induced more volatile fluctuations in the Russian economy's output in response to oil shocks. The inflation targeting regime was conducive to smooth adjustment of output to a new long-run equilibrium. The proposed ARX and ECM models attempt to factor in the structural changes in both the monetary policy and long-run economic growth rates. The out of sample forecasting experiments have shown a major improvement in the quality of forecasting by the ARX and ECM models over the baseline ARIMA model. The proposed modeling approach may be of practical value in describing economies that are highly dependent on terms of trade and countries in which monetary policy regime changes have occurred.

Declaration of Interest

The authors have no interest that can be interpreted as influencing the research. Conflicts of interest: None.

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Tables

Model	Lags in ln real GDP differences under the first regime p_1	Lags in ln real GDP differences under the first regime q_1	Lags in real GDP ln differences under the second regime p_2	Lags in ln real GDP differences under the second regime q_2	Real GDP long-run elasticity value with respect to real oil price
ARX	4	1	2	1	0.0951
ECM	1	1	1	1	0.1059

Table 1. Results of choosing lags according to the AIC criterion in ARX and ECM models

Parameter interpretation	ARX model		ECM model	
	Parameter	Estimate	Parameter	Estimate
Long-term growth rates of output under the regime before 2007q3	μ_0	0.0138 [0.0089;0.0152]	μ_0	0.0132 [0.0112;0.0219]
Long-term growth rates of output under the regime after 2007q3	μ_1	0.0030 [0.0001;0.0065]	μ_1	0.0037 [0.0015;0.0055]
Long-run elasticity value with respect to oil prices	$\dfrac{\sum_{j=0}^{q_1} b_j^1}{1-\sum_{i=1}^{p_1}\alpha_i^1} = \dfrac{\sum_{j=0}^{q_2} b_j^2}{1-\sum_{i=1}^{p_2}\alpha_i^2}$	0.0951 [0.0585;0.138]	β	0.1059 [0.0515;0.1538]

Note: 95% bootstrap confidence intervals in brackets

Table 2. Resulting estimates of long-run parameters in ARX and ECM models

	ARX	ECM	ARIMA
RMSE one step ahead forecast	0.0093	**0.0076**	0.0105
RMSE two steps ahead forecast	0.0099	**0.0086**	0.0114
RMSE three steps ahead forecast	0.0098	**0.0096**	0.0109
RMSE four steps ahead forecast	0.0081	0.0092	**0.0075**
Average RSME for 1-4 periods	0.0093	**0.0088**	0.0101

Note: the best model at each forecasting step is shown in bold

Table 3. Each step's out of sample RMSE values for the models, first experiment

Step	ARX	ECM	ARIMA
RMSE one step ahead forecast (nowcasting)	0.0095	**0.0078**	0.0105
RMSE one step ahead forecast	0.0092	**0.0074**	0.0114
RMSE two steps ahead forecast	0.0094	**0.0094**	0.0109
RMSE three steps ahead forecast	0.0086	0.0094	**0.0075**
Average RSME for 1-4 periods	0.0092	0.0085	0.0101

Note: the best model at each forecasting step is shown in bold

Table 4. Each step's out of sample RMSE values for the models, second experiment

	ECM to ARX Experiment 1	ECM to ARIMA Experiment 1	ECM to ARX Experiment 2	ECM to ARIMA Experiment 2
RMSE one step ahead forecast	0.82	0.72	0.81	0.74
RMSE two steps ahead forecast	0.86	0.75	0.79	0.65
RMSE three steps ahead forecast	0.97	0.88	0.99	0.86
RMSE four steps ahead forecast	1.11	1.23	1.06	1.25
Average RSME for 1-4 periods	0.94	0.87	0.91	0.84

Table 5. Relative RMSE ECM to ARX/ARIMA for all experiments

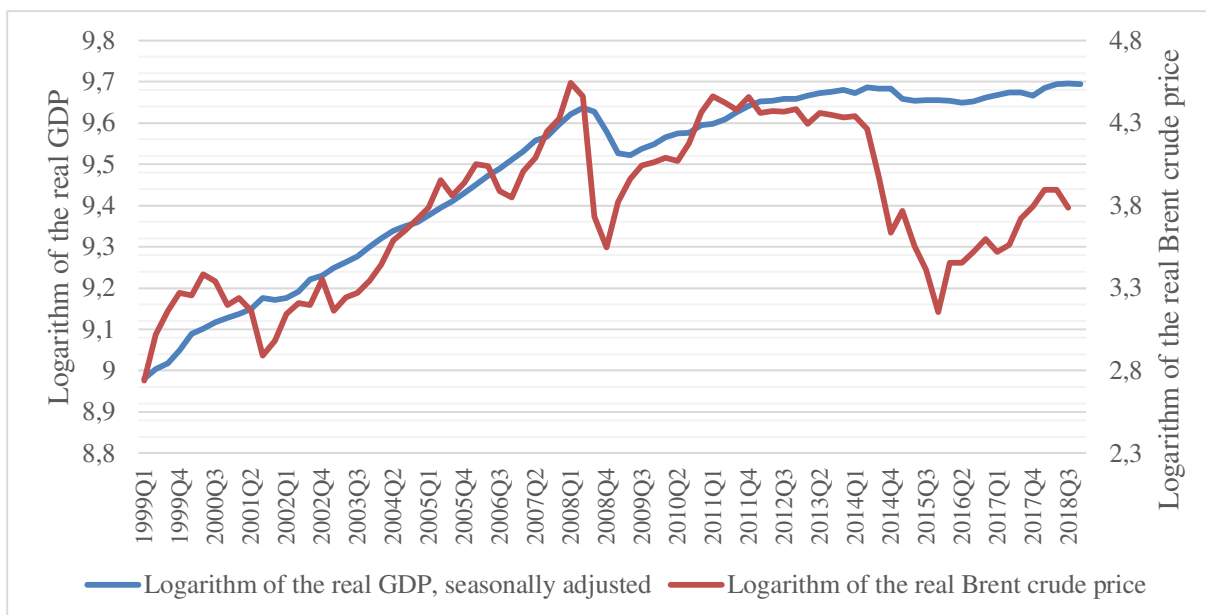|	ARX $63.4/bbl	ECM $63.4/bbl	ARX $68.6/bbl	ECM $68.6/bbl	ARX $69.4/bbl	ECM $69.4/bbl
2019Q1, QoQ	0.56%	0.82%	0.73%	0.95%	0.75%	0.97%
2019Q2, QoQ	-0.54%	0.01%	-0.06%	0.39%	0.01%	0.45%
2019Q3, QoQ	-0.68%	0.11%	-0.09%	0.52%	-0.01%	0.58%
2019Q4, QoQ	-0.37%	0.57%	0.30%	1.01%	0.39%	1.07%
2019, YoY	-0.26%	0.38%	0.22%	0.72%	0.29%	0.77%

Table 6. Models-based forecasts for 2019

Figure 1. Logarithm of the real GDP and Logarithm of the real Brent crude price
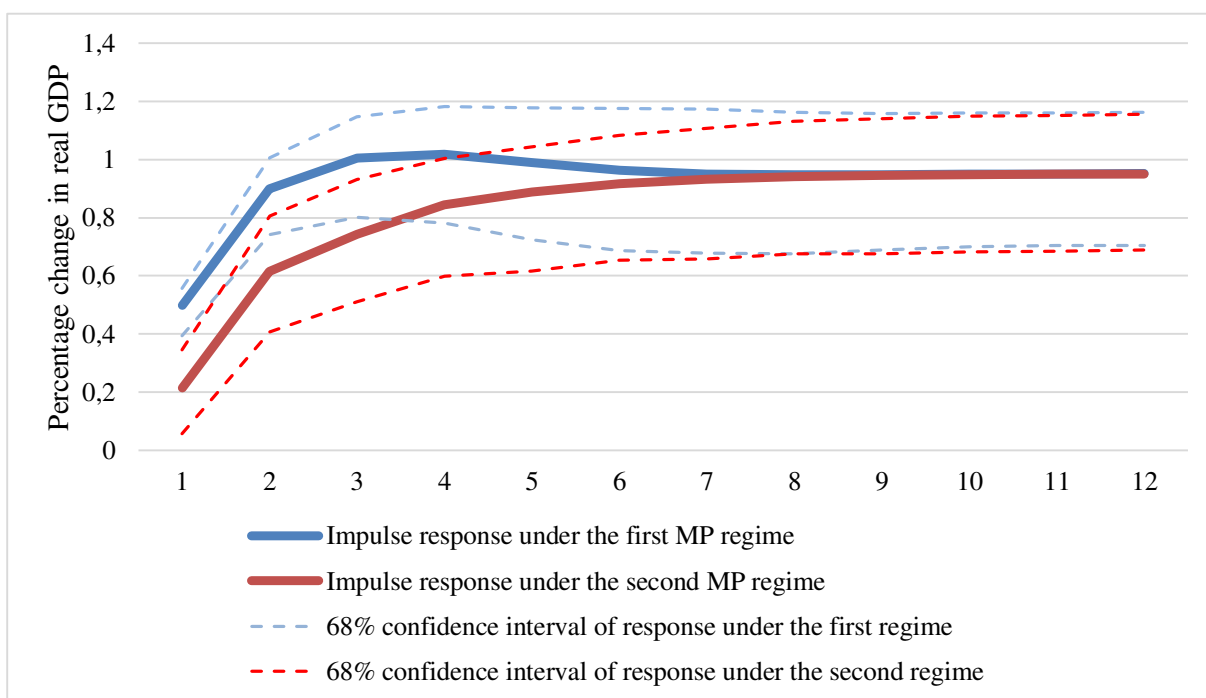
Figure 2. Impulse responses of real GDP to a 10% permanent real oil price shock under MP regimes, ARX model
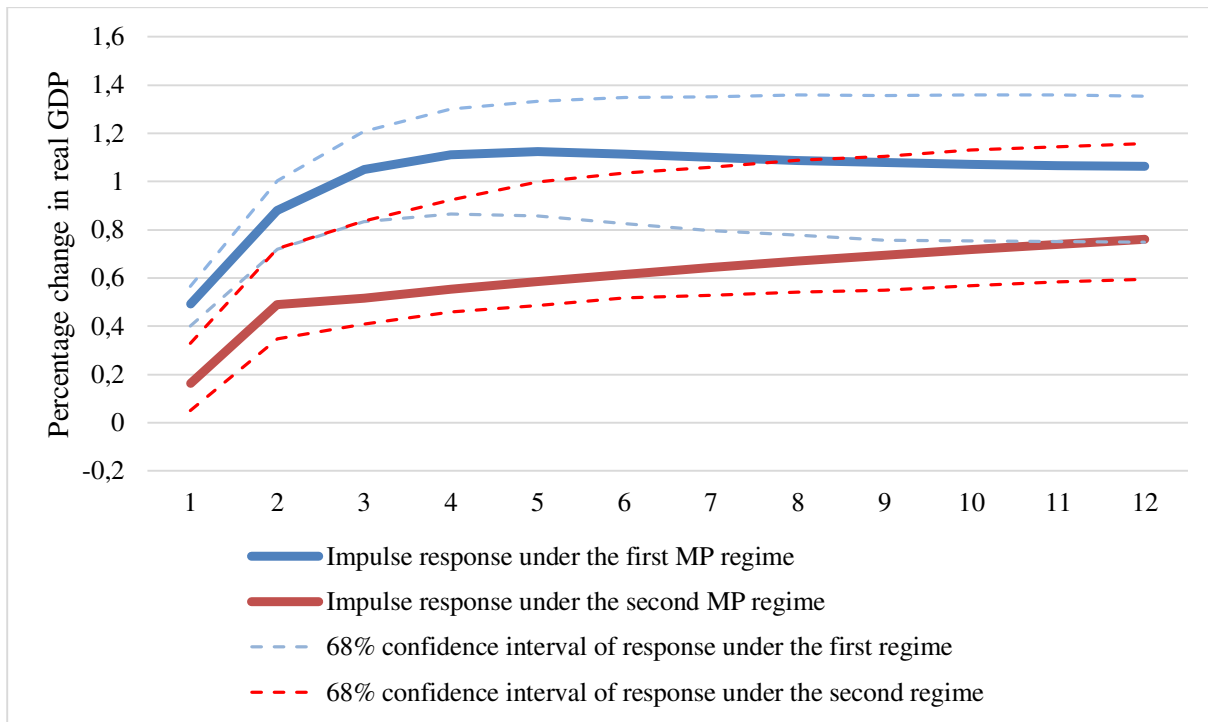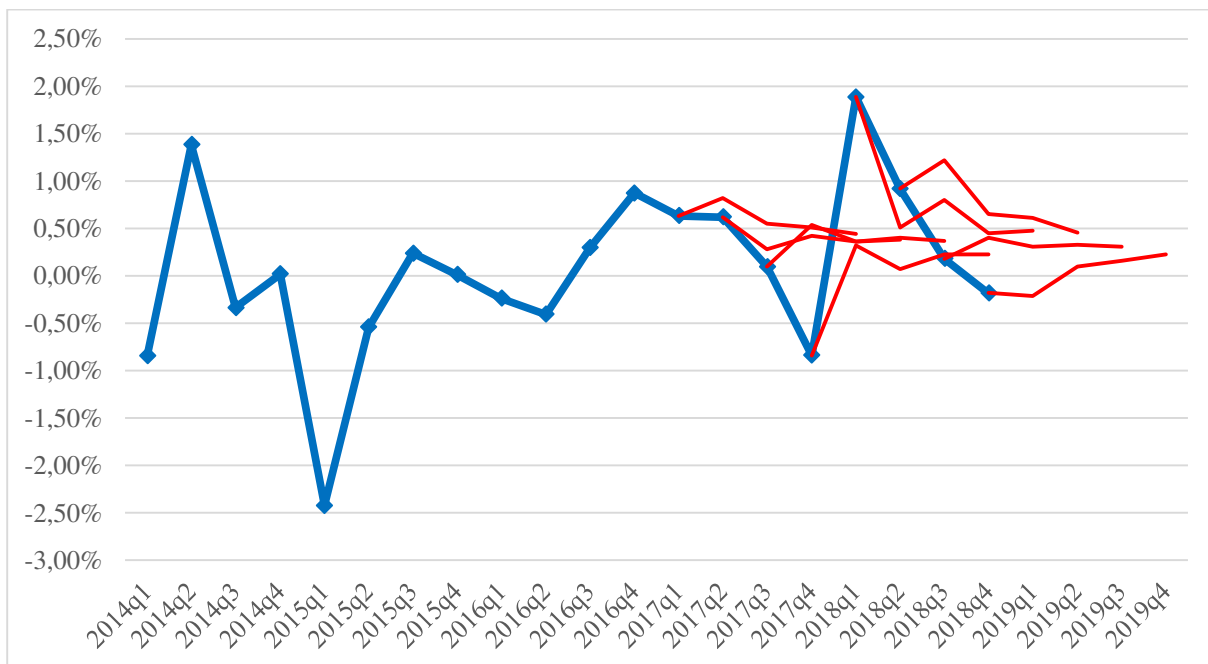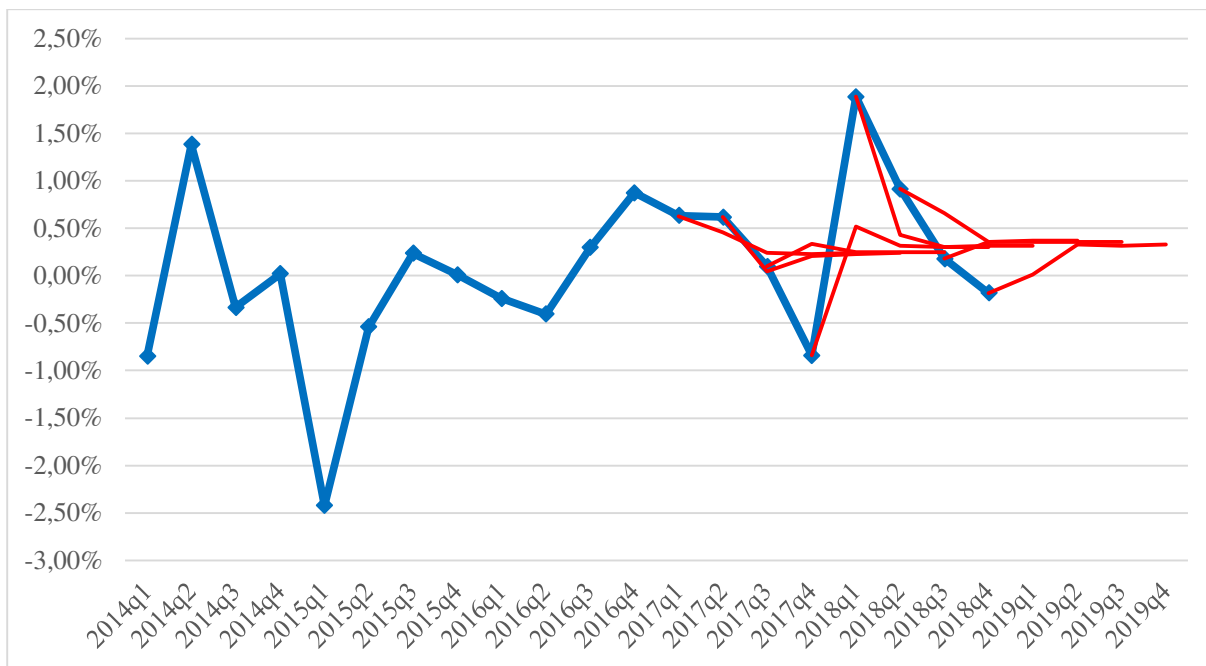
28

Figure 3. Impulse responses of real GDP to a 10% permanent real oil price shock under MP regimes, ECM model
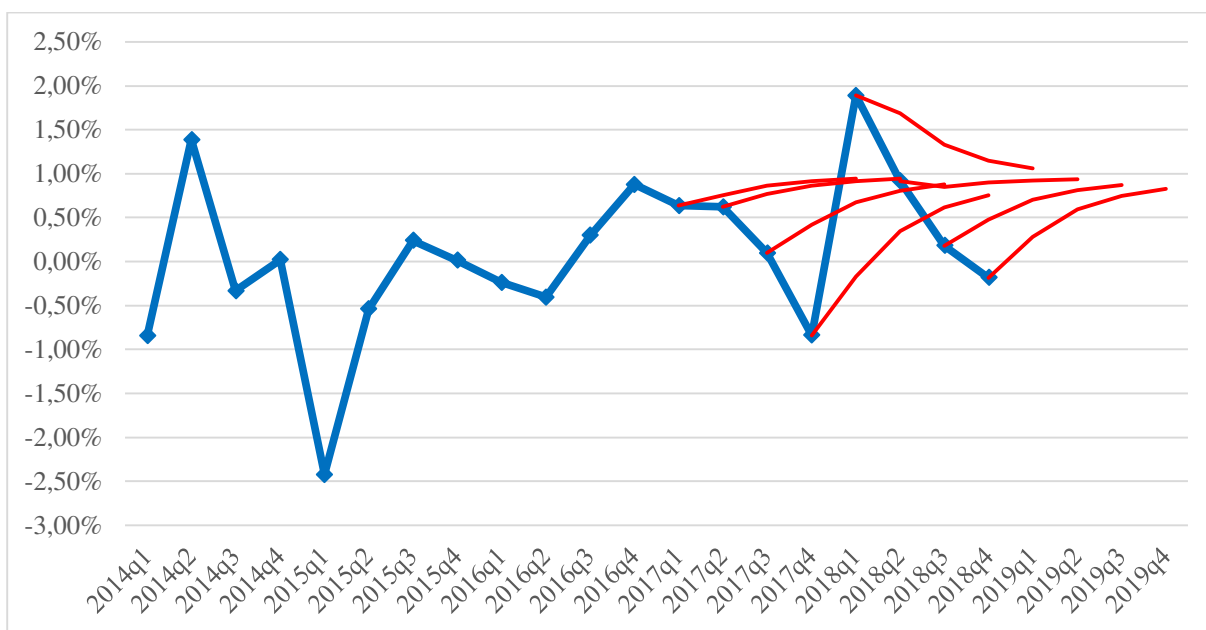

Note: blue line — real GDP growth rate, red lines—4-step ahead forecasts

Figure 4. Out-of-sample 4-step ARX-based forecasts, first experiment.

Note: blue line — real GDP growth rate, red lines — 4-step ahead forecasts

Figure 5. Out-of-sample 4-step ECM-based forecasts, first experiment.

Note: blue line — real GDP growth rate, red lines — 4-step ahead forecasts

Figure 6. Out-of-sample 4-step ARIMA-based forecasts, first experiment.