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Assessing the impact of energy and macroeconomic shocks on the Romanian economy: a Bayesian VAR approach

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Abstract. *This paper investigates the impact of both energy prices and macroeconomic variables on the Romanian economy using a Vector Autoregressive model (VAR), estimated using Bayesian inferences. Romania, a small emerging economy, has suffered considerable shocks in recent years, including the outbreak of the pandemic crisis, energy prices liberalization and the ongoing war in Ukraine. These shocks have increased the risk premium (through the exchange rate transmission channel), causing macroeconomic instability. The analysis investigates the transmission mechanism of both demand and supply shocks, with a focus on energy prices (oil and gas), inflation, economic growth, interest rate, real exchange rate and a sentiment indicator. Two separate models (including the oil price and, respectively, the gas price) show different dynamics in the responses of the Romanian macroeconomic variables.*

Keywords: macroeconomic shocks, econometric testing, finance, energy markets.

JEL Classification: C11, C30, C51.

1. Introduction

In the last two decades, the global economy has been characterized equally by regular times when the economy might evolve with a relatively steady and predictable path and by turbulent and crisis times for which the effects of unanticipated permanent or transitory adverse shocks are extremely difficult to predict. Among others, some of the most essential shocks that hit the global economy are the global financial crisis from 2008, the pandemic crisis, the energy crisis, the global supply-chain bottlenecks, the unprecedented inflationary surges that started in 2022, and the war in Ukraine. Thus, the analysis of the mechanism of the transmission of shocks has reached increased interest among researchers. One of the most popular tools to assess the impact of structural economic shocks is the class of Vector Autoregressive (VAR) models. This multivariate regression allows all the variables to be endogenous in the system and driven by different economic shocks.

In this paper, we propose an empirical analysis regarding the identification of economic shocks in a VAR model estimated using Bayesian techniques for the Romanian economy. Our motivation for this choice is driven by the fact that Romania is an emerging and small open economy that suffers from a limited dataset that was frequently subject to revisions in the last few years. Moreover, even if the economy registered after the recovery from the pandemic as one of the region's highest real GDP growth rates, the adverse effects of shocks were significant, especially in the context of Romania's geographical proximity to the war zone. Moreover, the risks and the uncertainties surrounding the macroeconomic developments continue to remain elevated.

2. Literature review

Since the introduction of the VAR models by the seminal work of Sims (1980), the methodology has received a remarkable interest within academia and central banks in macroeconomic modeling to analyze and forecast economic developments. However, traditional VARs suffer from at least two drawbacks. First, when we include many lags to capture the joint behavior of multiple variables based on their previous values and improve in-sample fit, the model can be over-parameterized, resulting in a loss of degrees of freedom and, consequently, low accuracy in terms of out-of-sample predictions. Second, an important issue (that is related to the first observation) is that for emerging economies, the availability of datasets is limited and usually time series are subject to frequent revisions which question the data quality. Therefore, the Bayesian estimation techniques into the VAR framework introduced by Doan et al. (1984) could alleviate these issues. The shrinkage priors for Bayesian prediction provide precise results without over-fitting the model, while the prior beliefs with which we enrich the model compensate for the lack of reliability of the data. Moreover, VAR models are preferred in research studies because they allow for the introduction of the impulse response function (IRF) analysis to assess the effects of shocks.

Therefore, evidence regarding the mechanism of the transmission of shocks is widely discussed in the "small-scale" VARs literature. Most empirical evidence focuses on the channels of monetary policy transmission mechanism in emerging markets, which is a fundamental issue in the decision process. The results of VAR analysis show that after a monetary policy shock, the economy expects a transitory decrease in output along with a persistent decline in prices (Aucremanne and Wouters, 1999; Ouchchikh, 2017; Disyatat and Vongsinsirikul, 2003). Regarding the Romanian economy, the monetary policy transmission mechanism in assessed by Andries (2008), Spulbăr et al. (2010), Birman (2012).

In the context of recent periods marked by a multitude of adverse shocks and a high level of uncertainty regarding the timing and the effect of these shocks, the literature started to focus on the energy shocks, oil price shocks, or the impact of supply chain disruptions. For example, Neri et al. (2023) investigate the role of energy prices on inflation, finding both direct and indirect effects on inflation and evidence of an increased pass-through of energy prices to core inflation after the pandemic crisis. Tillman (2023) estimates the effect of recent global supply chain disruptions on inflation for a panel of European economies and found evidence of asymmetry, i.e., adverse shocks are stronger and have more persistent effects than positive shocks.

Primiceri (2005) proposes a time-varying VAR model where both the coefficients and the covariance matrix of residuals are allowed to vary at each moment to analyze the dynamics of the contemporaneous relations between variables. They found evidence of time variation in the US monetary policy with implications on developments in inflation and employment. Moreover, it is essential to distinguish between the size of the exogenous innovations and changes in the transmission mechanism.

Mumtaz and Surico (2009) developed a factor-augmented VAR model (FAVAR) applied to the UK economy that is similar to Bernanke et al. (2005) to solve the limited information problem given by small-scale empirical models. The authors introduce the interaction between domestic and foreign developments and find some evidence that an expansionary foreign demand shock has a favorable impact on UK inflation and economic growth. Moreover, using a high-dimensional model, the effects of monetary policy shocks provide little evidence regarding price, exchange rate, or liquidity "puzzles" (i.e., the responses of macroeconomic variables to a shock that contradicts economic fundamentals).

In the VAR framework, one of the frequently used methods for identifying the shocks is the Cholesky decomposition of the matrix of residuals. This recursive identification scheme, which is based on short-run exclusion restrictions, implies that only the first shock contemporaneously affects all the variables, while the last shock affects the last variable ordered in the system (see, for example, Caldara and Kamps, 2008; Inoue and Killian, 2013; Castelnouvo, 2016). The argument behind this approach is based on economic reasoning, given that certain variables are sticky and might respond immediately to different types of shocks (e.g., real economic variables). However, a new agnostic procedure developed by Uhlig (2005) to identify the monetary policy shock is to impose sign restrictions on the effects of shocks, according to economic theory. In particular, monetary contractions that increase the policy rate are expected to lower prices and reduce output. This identification scheme might eliminate several "puzzles" found in the literature (Kim and Roubini, 2000). A relatively new method Antolin-Diaz and Rubio-Ramirez (2018) proposed is the narrative sign restrictions constraining structural shocks and historical decomposition by narrative accounts, ensuring they align with historical events. For ease of doing and due to data limitations, we use the Cholesky decomposition in this paper, and we order the dataset to start with slow-moving variables and place the fast-moving ones at the end (for details, see Data section).

Regarding the hyperparameters used in the Bayesian estimation, we employ the analysis using the Minnesota prior, which is one of the most flexible and common approaches put forward by Litterman (1986). It was further developed by Giannone et al. (2015), Korobilis and Pettenuzzo (2016), and Chan (2021).

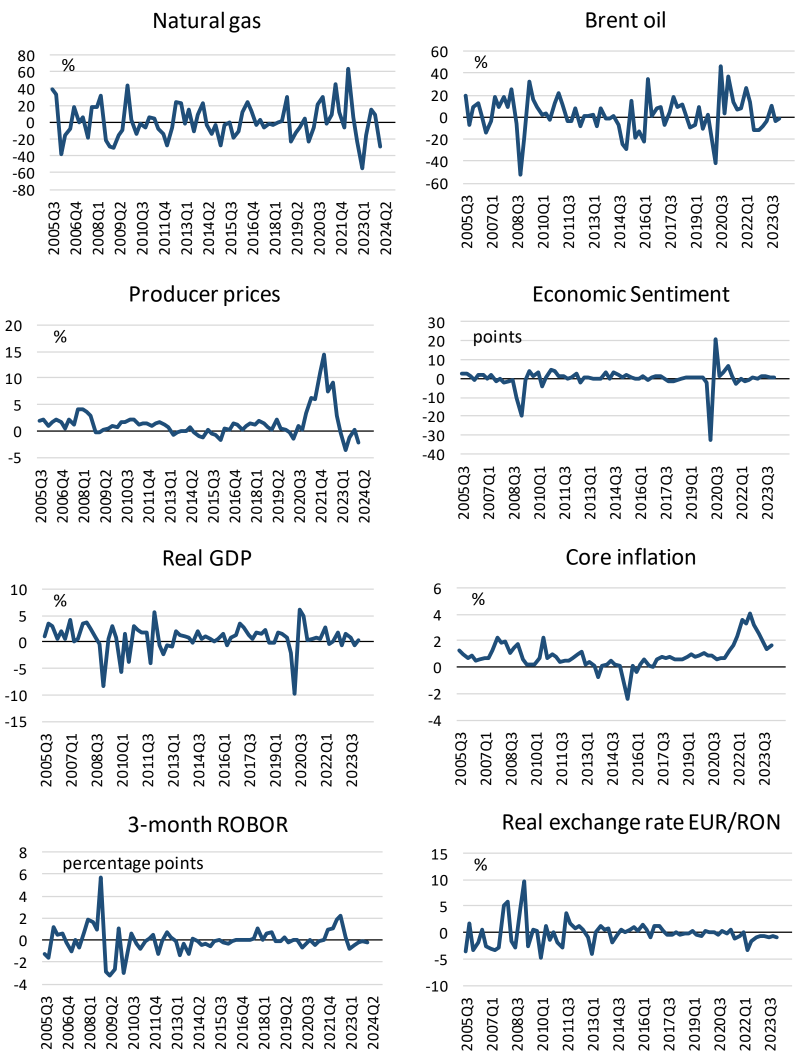
The rest of the paper is structured as follows. The next section will briefly describe the Bayesian VAR model. Then, we will present the dataset and the main results obtained from the estimation, which are of significant importance. The final section will conclude our findings.

3. Data and methodology

The dataset gathers eight quarterly variables representative of real economic activity, prices, interest rates, the energy and gas markets, confidence, and the financial market. We specify two different VAR models with seven variables. These two specifications have the same dataset, except for one energy indicator, which could be the Brent oil spot price or natural gas price. The analysis is carried out during the period 2005Q3 – 2024Q2. The ordering in the VAR model is, as previously mentioned, according to Cholesky decomposition.

Thus, we first include slow-moving variables, and then we introduce fast-moving ones with interest rates within these two blocks in decreasing order of exogeneity. Therefore, we introduce the quarterly growth of Brent oil provided by the Energy Information Association or the quarterly growth of natural gas prices to estimate the effects of energy shock in two different VAR models. The growth of producer prices and economic growth (calculated by using real GDP growth), both available on the National Institute of Statistics database and the difference in the Economic Sentiment index calculated by the European Commission. As for monetary policy shock, we include the short-term interbank interest rate, i.e., 3-month ROBOR, to underline the central bank's interventions on the money market available on the National Bank of Romania database. The last indicator is the quarterly change of the real euro exchange rate relative to domestic currency leu (EUR/RON). The evolutions of the data series throughout the sample period are represented in Figure 1.

Figure 1. *The evolution of the dataset between 2005Q3 and 2024Q*



Source: National Institute of Statistics, National Bank of Romania, European Commission, Energy Information Administration.

A general VAR model with n endogenous variables and p lags can defined in a compact form as

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + \varepsilon_t$$

Where Y_t denotes a $N\ x\ 1$ vector of endogenous variables, B_0 represents a $N\ x\ 1$ vector of constants, $B_i,\ i = 1 \ldots p$ are $N\ x\ N$ p matrices of parameters and ε_t is a $N\ x\ 1$ vector for the independent and identically distributed non-autocorrelated residuals following a multivariate Normal distribution with zero mean and covariance Σ.

Given that each equation in the VAR has identical regressors, the eq. (1) can be rewritten as

$$Y_t = X_t b + \varepsilon_t$$

Where $X_t = I_N \otimes [1,\ Y'_{t-1}, \dots Y'_{t-p}]$ is a $N\ x\ N\ (Np+1)$ and $b = vec(B)$ is a $N\ (Np+1)\ x\ 1$ vector with $B = [B_0,\ B'_1, \dots B'_p]$. In this context, we need to estimate b and Σ parameters.

In Bayesian econometrics, every parameter is treated as a random variable defined by underlying probability distribution. The general Bayes' principle is that the posterior distribution $p\ (b, \Sigma \mid Y)$ is proportional to data likelihood $p\ (Y \mid b, \Sigma)$ and the prior distribution $p\ (b, \Sigma)$

$$p\ (b, \Sigma \mid Y) = \frac{p\ (Y \mid b, \Sigma)\ p\ (b, \Sigma)}{p(Y)} \propto p\ (Y \mid b, \Sigma)\ p\ (b, \Sigma)$$

The simplest and widely used form of prior distribution for VAR models have a Minnesota form (as in Litterman (1986) and Doan et al. (1984)). This imply that the VAR residual variance-covariance matrix Σ is known, equal to the residual variance of individual AR models on each variable. Thus, we assume that *a priori* $p(b) \sim N(b_0, V_0)$. Following Litterman (1986), as the most observed macroeconomic variables have unit root, our prior belief must be that for each endogenous variable we imply a unit root for its first own lag and zero for the further and cross - variable lags. For the variance-covariance V_0 we assume that we have different cases for each element as:

$$ar(b_{ij}^l) = \begin{cases} \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, i = j \\ \left(\frac{\lambda_1 \lambda_2}{l^{\lambda_3}} \frac{\sigma_i}{\sigma_j}\right)^2, i \neq j \\ (\sigma_i\ \lambda_4)^2, \quad constants \\ 0, \quad otherwise \end{cases}$$

Where l is the lag considered by the coefficient, λ_1 the is an overall tightness parameter, σ_i^2, σ_j^2 are OLS residual variance of the autoregressive models estimated for variables I and j, λ_2 controls the lags for cross-variables, λ_3 controls the degree to which coefficients on lags higher than 1 are likely to be zero and λ_4 is the prior variance of the constant terms.

Finally, we can define the posterior distribution

$$p\ (b \mid Y) \sim N(\widetilde{b}, \widetilde{V})$$

where $\widetilde{V} = \left[V_0^{-1} + \widehat{\Omega}_{OLS}^{-1} \otimes (X'X)\right]^{-1}$

and $\widetilde{b} = \widetilde{V}\left[V_0^{-1}\ b_0 + (\widehat{\Omega}_{OLS}^{-1} \otimes (X'X))\hat{b}_{OLS}\right]$, having $\hat{b}_{OLS}$ and $\widehat{\Omega}_{OLS}^{-1}$ the OLS estimates for a classical model.

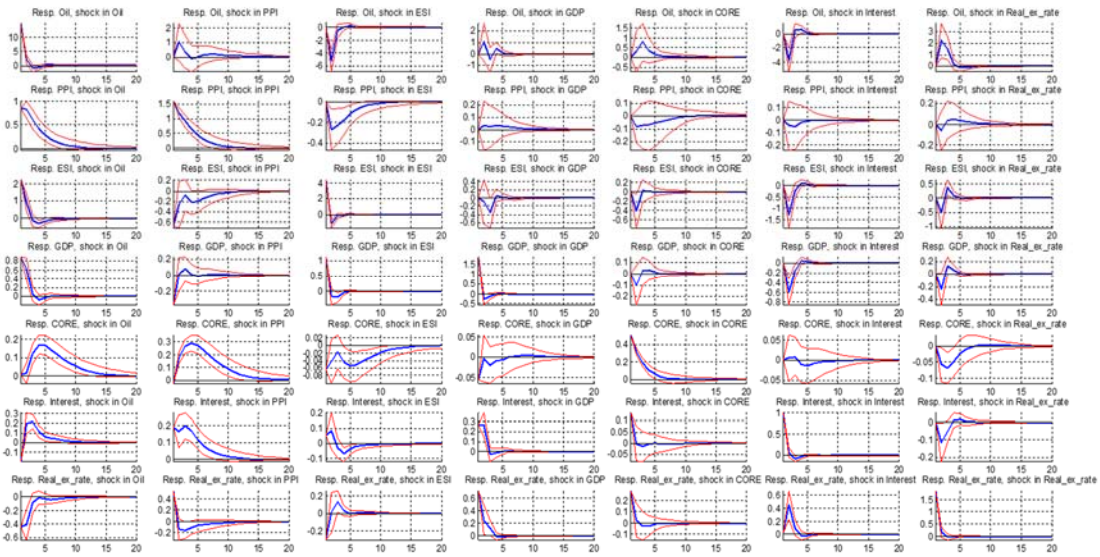
4. The evolution of the banking sector between two crises

The first scenario analyzed (Figure 2) is the case of a demand shock in the oil price. We can see that when there is a rise of 10 percentage points in the oil price, the response of producer prices shows an upward pressure of about one percentage point, whilst core inflation increases by only 0.2 percentage points with a lag through the transmission channel of production costs. At the same time, when fuel demand grows, confidence in the economy strengthens and leads to a 0.8 percentage points increase in economic activity. There is also captured the central bank's response in order to stabilize the demand shock. Thus, the short-term interbank interest rate shows a surge of 0.2 percentage points and it lasts 2 quarters ahead in order to bring inflation back to the target value.

On the other hand, for a supply shock (characterized by the recent adverse event of the Ukrainian invasion), we have analyzed two different shocks, namely a producer price shock (the second column) and a core inflation shock (the fifth column). The former emphasizes a surge of 1.5 percentage points in PPI, which leads to a decrease in economic confidence and activity. In comparison, the core inflation absorbs roughly 0.3 percentage points of the inflationary pressure. The national currency is depreciating in real terms against the euro. Next, we study a tight monetary policy of the central bank, captured by an increase in short-term interest rate. At an increase of one percentage point, the GDP growth declines by 0.6 percentage points, as does the sentiment indicator.

What is noteworthy is that the model did not significantly capture the responses of both producer and core inflation. Therefore, a different specification was adopted, including the gas price instead of the oil price in the model.

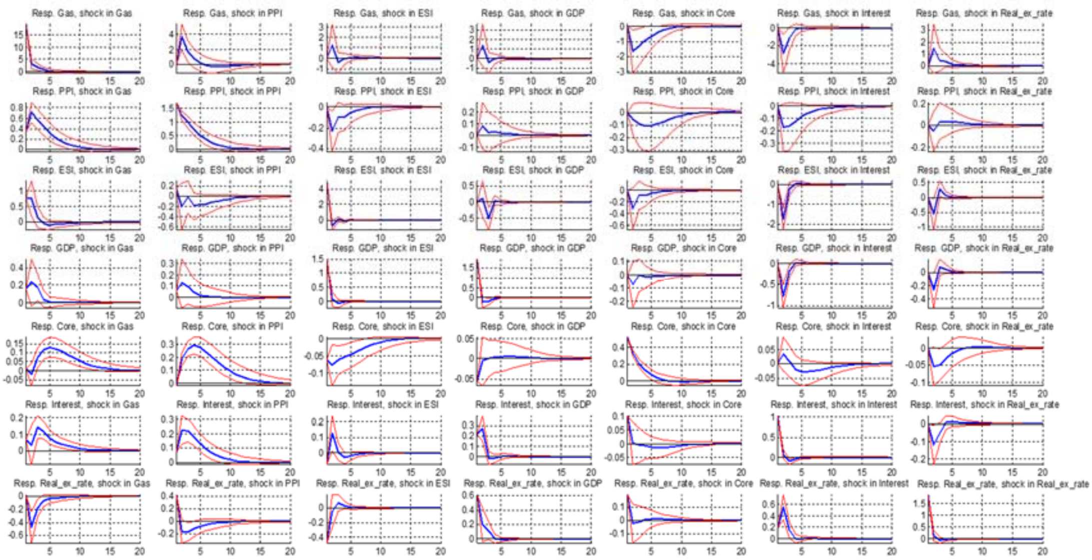
Figure 2. *The Impulse Response Functions of macroeconomic variables to each specific shock (oil specification). The blue lines represent posterior medians, while the red lines indicate posterior confidence intervals with a probability of 68%*



Source: Own research.

The second estimated model includes gas price growth instead of oil price dynamics as the energy variable, owing to the recent huge increase in natural gas prices since the outbreak of the war. The gas shock was also captured as a demand shock, since after a 15 percentage points increase in natural gas price, GDP increases by 0.2. It is worth mentioning that Romania is a natural gas producer country, and thus, the economic growth is strongly correlated with gas price (of course, when analyzing a demand price shock). Additionally, the producer inflation went up by 0.7 percentage points while core inflation picked up just a 0.1 response to the shock. Central bank hikes its benchmark rate, putting pressure on the volume of lending in order to stem the upward momentum in prices. In this context, using gas price instead of oil price, one may see that when a monetary shock occurs, the producer price inflation responds negatively, decreasing by about 0.2 percentage points. However, the response of core inflation is still insignificant.

Figure 3. *The Impulse Response Functions of macroeconomic variables to each specific shock (gas specification). The blue lines represent posterior medians, while the red lines indicate posterior confidence intervals with a probability of 68%*



Source: Own research.

5. Conclusions

Within a Bayesian VAR, this study emphasized that economic shocks, whether related to energy prices or specific demand/supply/monetary shocks, have significant effects on the Romanian economy. Notably, demand oil price shock leads to a surge in inflation and a moderate increase in economic activity, while gas price shocks, due to Romania's domestic production capability, have a positive impact on GDP growth as well. The central bank's response to inflationary pressures through monetary policy interest rate adjustments illustrates the economy's sensitivity to external shocks. Nevertheless, the study highlights the limitations in capturing core inflation responses using the Choleskey decomposition of shocks identification scheme, suggesting that alternative identification might be needed to fully understand the monetary policy transmission channel.

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