MONETARY POLICY TRANSMISSION MECHANISM AND DYNAMIC FACTOR MODELS

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Abstract: The main objective of a Central Bank is price stability, without neglecting, however, a sustainable economic growth in the long run. Therefore, an important challenge is to identify whether the effect of monetary policy has changed over time and for this purpose, a Dynamic Factor Model with time-varying parameters is estimated. The model is applied to Romanian economy, on a sample database consisting of 90 time series representing various macroeconomic variables. Monthly data, starting with 2000 and ending with 2013 are being used for the analysis. The reason for using a large dataset is to avoid issues such as omitting important information when considering a small set of variables. A much smaller number of Factors is extracted by using Principal Component Analysis and with these factors the TVP-FAVAR model is estimated. Time variation of the parameters allows for a comparative analysis of the monetary policy transmission mechanism in time. Once the impulse-response functions are estimated, several conclusions are to be drawn, such as: whether monetary policy actions have or do not have an impact over the evolution of the rest of the economy and whether the effect of these measures have changed over the years.

Keywords: Factor Augmented Vector Autoregression, Monetary Policy Transmission Mechanism, Romanian Economy, Time Varying Parameters

JEL Classification: E31, E52, C15, C58, C82

1 INTRODUCTION

The effect of the monetary policy on the economy and its evolution over time poses the analysis in front of a very challenging task due to the importance of understanding the degree of effectiveness of the monetary policy nowadays. The

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main objective of the Central Bank became price stability once the inflation targeting regime was adopted. In ensuring price stability, the bank should not neglect the sustainability of the economic growth.

Structural vector autoregression models are widely used in order to trace out the effect of monetary policy innovations on the economy. However, there are some drawbacks of these models, one of them being the potential lack of information that could arise due to the fact that a small subset of variables is included in these models. Policymakers are considering a wide number of variables when adopting a certain decision and for this reason, estimated models should be adjusted such that to consider this aspect.

By combining the theoretical insights provided by the VARs with the factor methods’ ability to extract information in large datasets, motivates the development of factor augmented VARs or FAVARs.

This paper is organized as follows: a description of the model is done in the second section, Model Framework, the third section presents the Results of the Estimation and the final section concludes and also provides some ideas for further research.

2 Model Framework

2.1 TVP-FAVAR Methodology

The model used in this paper is a Time Varying Parameter FAVAR (TVP-FAVAR), having both drifting coefficients and drifting variance-covariance matrix. Similar to Primiceri (2009), these drifting coefficients are used to capture time variation in the lag structure of the model. And the stochastic volatility is used to capture possible nonlinearities in the simultaneous relations between the variables of the model.

A structural VAR has the following representation:

\[ y_t = b_1 y_{t-1} + \ldots + b_p y_{t-p} + v_t \]

where \( y_t^* = [x_t^*, r_t] \), \( x_t \) is a \((n \times 1)\) vector of variables such as industrial production indexes, industrial production prices, monetary aggregates, exchange rates, interest rates, indexes of consumer prices, employment rates. \( r_t \) could include only the monetary policy instrument, or some other variables too, such as
inflation rate and unemployment rate in the following order: inflation first, unemployment rate second and monetary policy interest rate last. The coefficients \( b_{i,t}, i = 1, \ldots, p \) are of dimension \((n \times n)\) and \( v_t \sim N(0, \Omega)\) with \( \Omega \) a \((n \times n)\) covariance matrix.

By decomposing an \( n \)-dimensional vector of observables \( x_t \) into a lower dimensional vector of \( k \) (much smaller than \( n \)) unobserved factors, \( f_t \), there could be considered hundreds of variables. What needs to be mentioned is that all the parameters of the FAVAR are stochastic.

The time-varying parameters factor-augmented VAR has the following representation:

\[
y_t = b_{1,t}y_{t-1} + \ldots + b_{p,t}y_{t-p} + v_t
\]  

(2)

where \( y'_t = [f'_t, r'_t] \), \( f'_t \) is a \((k \times 1)\) vector of latent factors and \( r'_t \) having the form described before. The coefficients \( b_{i,t}, i = 1, \ldots, p \) are of dimension \((k \times k)\) and \( v_t \sim N(0, \Omega_t)\) with \( \Omega_t \) a \((k \times k)\) covariance matrix for each \( t = 1, \ldots, T \). This is the measurement equation.

The link between \( x_t \) and \( f_t \) is given by the transition equation, which takes the following form:

\[
x_t = \lambda^f_t f_t + \lambda^r_t r_t + u_t
\]  

(3)

where \( \lambda^f_t \) is a \((n \times k)\) matrix, \( \lambda^r_t \) is \((n \times 1)\) and \( u_t \sim N(0, H_t)\) with \( H_t = diag(\exp(h_{1,t}), \ldots, \exp(h_{n,t}))\) of dimensions \((n \times n)\), for each \( t = 1, \ldots, T \).

Also, \( E(u_{i,t} f_t) \) and \( E(u_{i,t} u_{j,s}) \) are assumed to be zero, for \( i, j = 1, \ldots, n \) and \( t, s = 1, \ldots, T \) for \( i \neq j \) and \( t \neq s \).

Due to the fact that the covariance matrix from the measurement equation is assumed to be a diagonal matrix, the parameters from this equation can be estimated equation by equation.

The following triangular reduction of \( \Omega_t \) is considered:

\[
A_t \Omega_t A_t' = \Sigma_t \Sigma_t'
\]  

(4)

\( A_t \) is a unit lower triangular matrix:
is a unit lower triangular matrix:

\[
A_t = \begin{bmatrix}
1 & 0 & \cdots & 0 \\
\alpha_{21,t} & 1 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
\alpha_{(k+1)1,t} & \cdots & \alpha_{(k+1)k,t} & 1
\end{bmatrix}
\]

\(\Sigma_t\) is a unit lower triangular matrix:

\[
diag(\sigma_{1,t}, \ldots, \sigma_{k+1,t})
\]

The list of parameters that are to be estimated are: \(B_t, \alpha_t, \log(\sigma_t), \lambda_{i,t}\) and \(h_{i,t}\), where \(B_t = (b_{1,t}^{i}, \ldots, b_{p,t}^{i})\). All these parameters are modeled as random walks, except \(\sigma_t\), who is assumed to evolve as geometric random walks. The random walk assumption presents the advantage of focusing on permanent shifts and reducing the number of parameters in the estimation procedure.

Principal component analysis is a multidimensional analysis technique which has as a main purpose the decomposition of the total variability of the initial space with a minimum loss of information. Moreover, this decomposition is done by keeping only a small number of components and making sure that it does not include informational redundancy. The new characteristics that were obtained after applying a certain transformation to the initial characteristics are called principal components. The transformation mentioned before has to be optimal and this optimality consists in ensuring a representation of the objects with a minimum loss of information when passing from the old characteristics to the new ones. Therefore, a condition is imposed: minimizing the loss of information. One measure of the importance of a principal component is to assess the proportion of the total variance attributed to that principal component.

### 2.2 Bayesian inference

The posterior distributions of the parameters of interest which are the unobservable states and the hyper-parameters are evaluated by using Bayesian methods. Classical maximum likelihood estimator is not used because of the following drawbacks: difficulties in dealing with high dimensionality and nonlinearity. Moreover, even though it might be possible to write down the likelihood, it is very difficult to maximize it over such a high dimensional space.

Bayesian methods are those that deal efficiently with the issues related to high dimension of the parameters space and the non-linearity of the model. Also, one reason for using these methods is given by the existence of unobservable components. A particular variant of Markov Chain Monte Carlo methods is Gibbs
sampling, which is used for posterior numerical evaluation of the parameters and consists of drawing from conditional posteriors with lower dimension than joint posterior of the whole parameter set.

3 RESULTS OF THE ESTIMATION

3.1 Data Transformation

The matrix $\mathbf{x}_t$ is made out of 92 variables, with data starting from 2001:M1 up until 2013:M6 and covering Romanian economy. Just as mentioned before, there are variables are: industrial production indexes, industrial production prices, monetary aggregates, exchange rates, interest rates, indexes of consumer prices, employment rates. $\mathbf{r}_t$, on the other hand, is made out of inflation rate, unemployment rate and money market interest rate. All series were already downloaded as seasonally adjusted from Eurostat for consistency regarding the methodology.

Several transformations were applied afterwards, such as: level (no transformation), first difference, log-level, log-first difference. The following step into transforming the data so that to be able to run the, was to check for the existence of unit roots. For this purpose, Augmented Dickey Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test were applied. They both deliver the same results and the reason they are used together is to ensure better evidence regarding the stationarity of the data. In the end, the time series were standardized in order to allow for principal components extraction.

3.2 Factors and Variability

Empirical studies, such as Stock and Watson (1999) showed that the first three to seven principal components capture most of the variance in the series. Therefore it can be noted that, for example, the first three components retrieve approximately 35.07% from the total amount of information and the first five components retrieve approximately 46.38% from the total amount of information (fig. 1). Bernanke, et al. (2005) stated that the number of factors that is suggested by a statistical criterion may not coincide with the real number of factors. Two situations are investigated in this paper: with three factors (meaning a VAR with six variables – three unobservable and three observable components) and with five factors (meaning a VAR with eight variables – five unobservable and three
observable components) and the delivered results do not vary too much. Just as Korobilis (2009) mentioned, choosing this number of factors doesn’t necessarily mean that there is possible misspecification, since three and four factors perform really well in many empirical applications.

![Cumulative Percentage Variance explained by Factors](image.png)

**Figure 1** Cumulative Percentage Variance explained by each one of the 92 factors, sorted in descending order

### 3.3 Impulse response analysis

The measure of non-systematic policy actions is given by the identified monetary policy shocks (fig. 2). The responses of inflation and unemployment rate after a shock in interest rate are plotted. Three points in time are investigated: 2006: M1 (after the adoption of inflation targeting monetary policy strategy), 2009:M6 (during the latest economic crisis) and 2012:M10 (in order to form an image on the current economic situation).
Figure 2 Impulse responses over a horizon of 21 months, after a shock to Interest Rate, in the three moments in time

It can be see that after an increase in the level of interest rate, inflation decreases in each one of the three moments of time, which is according to the theoretical view. The response is more pronounced in 2006, which means that after adopting the inflation targeting strategy, monetary policy interest rate was a more efficient instrument. In 2012, after the period of crisis, the impact the monetary interest rate had on the evolution of other economic variables decreased. After several periods of time, the response of inflation dissipates, which confirms the theory regarding the long term neutrality of money.

After an increase in the level of interest rate, unemployment increases. This is according to the theoretical view because investments become less attractive and the costs for the companies to continue with their activity are higher. The response of unemployment dissipates too in time and the differences between responses prove also that the estimated coefficients show time variation.

The response of the interest rate after a shock in interest rate itself has a lower informational content than the rest of the graphs, but what should be mentioned is that the response is seen immediately and not with lags and it is adjusting back to the initial value over time.
4 CONCLUSIONS

In this paper the evolution of inflation rate and unemployment after a shock in monetary policy interest rate is estimated, by using a TVP-FAVAR mode. The conclusion is that responses were more inline with the theoretical view after the adoption of inflation targeting strategy and gradually diminished with the appearance of the crisis. Measures are searched at this moment, at the level of European Union, in order to stimulate the economy, more precisely, the economic growth. As further research, a switching regime model could be estimated.

REFERENCES