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5 April 2019

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Abstract : In this paper we use the Bayesian Structural VAR framework to identify the major shock monetary policy shocks in Tunisia over the 1997-2015 and to provide information concerning the evolution of the economy response to these shocks. Compared with previous studies of this country, the main finding is the statistically significant effect of interest rate on the variables of the real economy. The article shows also that Bayesian Structural VAR model can explains the 2011 recession.

Key words: Bayesian analysis; Structural Vector Autoregression; Monetary Policy; Tunisia.

1 Introduction

For centuries, economic studies have been interested in the mechanisms of economy, especially through the study the monetary exchanges. These exchanges were started in history, by bartering, to give birth to monetary circuits defined by the supply and demand of money. As we move into economic history, we find that these processes have extended to finance and the appearance of the banking markets and other markets that we see today, especially after the 2000s (stock markets, foreign exchange, credit markets, derivatives markets ...).

Initially, the strategies of monetary policies were based on concepts of philosophy and sociology (Keynes theory, neoclassical theory ...). With the integration of the mathematical concept into the economy, monetary policy

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studies have taken a more scientific that attempts to accurately analyse the impact of each decision that might be made by the decision maker.

This complexity is mastered thanks to monetary policies established by central banks. However, the role of money is not confined to ensuring trade. Indeed, studies by Gerlach and Smets (1995) have shown that currency fluctuations impact the real economy through different mechanisms, such as inflation. For this reason, the central banks take on the task of setting up an effective monetary policy, which supports the economy and controls inflation.

Thus, several scientific studies have been conducted to explain the mechanisms of economic policies in order to deduce the impact of any strategy on the real economy. Therefore, using the vector models it can simultaneously study several interacting variables (monetary variables, economic variables, financial variables ...). Thus, such modelling allows to analyse the impact of any variable on the rest of the components of the economy.These studies have generally been based on econometric modeling approaches, such as: simultaneous equation modeling, VAR modeling (Sims (1980)) and SVAR modeling (Blanchard and Quah (1989) and Gali (1999).

Despite the theoretical and empirical success of this approach, several authors have criticized it and consider that this approach based only on the information obtained from historical data. To remedy its limitations, recent studies propose to introduce additional information on modelling by introducing a prior distribution on the matrix of the instantaneous effects before proceeding to the estimation of the model.

Thus several works have tried to introduce other information on the SVAR model, through the adoption of the Bayesian approach. It is within this framework that authors such as Sims and Zha (1998) have introduce a complete framework for B-SVAR modelling. This modelling will give, according to the theoretical and analytical results, a better precision to the model as well as richer interpretations.

Technically, the use of the Bayesian approach in simultaneous models of macro-econometrics further enriches estimates and econometric analyses. Indeed, the technical contribution of such a methodology is proved by several authors such as Sims and Zha (1998) and Kadiyala and Karlsson (1997) and Brandt and Freedman (2006).

Wagoner and Zha (2003) proved that the combination between the prior distribution and the likelihood function solves the problem of identification, by assuming a prior distribution on the parameters. The Bayesian approach, which offers the ability to combine multiple sources of information through prior distribution.

This study has two major contributions. Firstly, the Bayesian SVAR modelling has not been frequently used for the purpose of a macro monetary analysis of the Tunisian economy. Secondly, The classical SVAR approach suffers from the loss of degrees of freedom which exponentially decrease with respect to the number of lags included. The Bayesian approach proposes a solution to the over-fitting phenomenon, due to the fact that it does not ponder too much any of the parameters of the model. However the emphasis falls on the use of prior distributions for the parameters, the prior distributions being a key factor in the BSVAR approach.

This work is structured as follows: The SVAR Bayesian model is presented in the second section. Then, the third section described methodology and the data used for this study. In the third section, the main results obtained are presented and the last section is dedicated to the presentation of the conclusions.

2 The SVAR Bayesian model

Lutkepohl (2005) defined the SVAR model with k variables and p delays in the following matrix form:

$$A_0 y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \epsilon_t$$

A_p: is a matrix $(m \times m)$ composed with the coefficients to be estimated
ϵ_t: check the conditions of a white noise.
Sims and Zha (1998) made modifications to the prior distribution proposed by Litterman (1986) which known as "prior Minnesota" to adapt it to the case of the structural model. To do this, the authors assume a conditional prior distribution on the variance-covariance matrix of the coefficients of A, following the Litterman approach in the case of a reduced model. Therefore, the coefficient corresponding to the lag ℓ of the variable j in the equation i is:

$$\Phi_{l,i,j} = \frac{\lambda_0 \lambda_1}{\sigma_j \ell^{\lambda_3}}$$

λ_0: Controls the degree of confidence in the coefficients of the instantaneous effects matrix A_0 and it is a real belonging to the interval $[0, 1]$.
λ_1: indicates the level of confidence with respect to Litterman's hypothesis that each variable follows a random walk, it is a real that belongs to $[0, 1]$.
λ_3: checks the decay rate of the variance a priori considering the increase of the delay.
For the rest of the σ_j, Litterman determined it as the standard deviation of the $AR(1)$ process estimate each variable of the SVAR model studied. For the other hyperparameters, Sims and Zha, add the two parameters λ_4 and λ_5 which represent respectively:
λ_4: the standard deviation around the deterministic trend.
λ_5: the standard deviation around the coefficients of the exogenous variables.
To obtain the best distribution a priori, we will simulate several cases of figures, according to the variation of the different hyperparameters, and we will choose all of them which will offer us the best estimate, the best forecast and the best representative information of the model. To do this, our choice will be based on the following three statistical indicators:
- Root Mean Square Error (RMSE): This is the square root of the mean squared error.
- MAE (Mean Absolute Error): This is the average absolute error.
- Log MDD (Log Marginal Data Density): This is the logarithm of the marginal density.

3 Methodology and variables

After the presentation the Bayesian SVAR models, we apply this methodology for determination of the effects of monetary policy in Tunisia. To do this, we begin by briefly presenting the main variables to use. For the calculation tools, we used the packages of software R, "vars" and "MSBVAR" proposed respectively by Bernhard Pfaff (2008) and Patrick Brandt (2016).

3.1 Statistical properties of variables

Our database contains four variables: Consumer Price Index **(CPI)**, Industrial Production Index **(IPI)**, Money Market Rate **(MMR)** and Money Supply **(MS)**. Since they are macroeconomic variables , all the variable are calculated in logarithm, except MMR because it is expressed in percentage terms. Data are quarterly from the first quarter of 1997 to the last quarter of 2015, so giving us 76 observations for each of the four variables. These data were collected from the International Monetary Fund database.

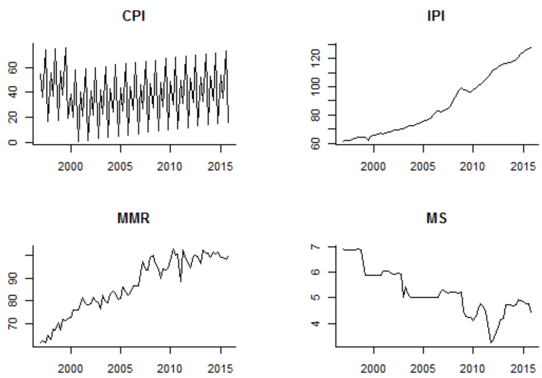

Figure 1: The temporal evolution of the variables

From the Figure (1), we notice that the variable MMR decreases progressively from one period to another, where it start from 7 % in 1997 to less than 4 % at the end of the year 2011, then it takes a growing path to 5 %

until the end of 2015. On the other side, the IPC and MS variables increase from one period to the next, without no decline. Finally, we note that the IPI variable fluctuates over time, always keeping a growing trend.

The usual unit root tests (Dickey-Fuller (1981), Phillips-Schmidt (1992)), indicated that all the variables of the model are non-stationary in level, and stationary in difference. The multivariate analysis of the rank of cointegration, according to the Johansen (1988) methodology, leads to the conclusion that there is no cointegration relationship. Therefore, we postulate a representation VAR of the dynamics of stationary series, without cointegration. The order of the VAR model based on a statistical criterion (Akaike (1971)) is 8 delays.

3.2 Specification of identification constraints

In order to fix our identification constraints, we have covered several articles and works on monetary policy in different countries. Following these readings, it was deduced that at each work, there is a specificity in the introduction of constraints, which sometimes depends on the country and sometimes the period of the study.

To meet our objectives, we used the causality test developed by Granger (1983). The idea is to be able to test the nullity of the coefficients in the case of an equation which links the process x_t to the process y_t, and under this hypothesis of nullity (non causality), one carries out a Fischer test. Thus, the absence of causality will be considered as an identification constraint that will allow the estimation of model parameters.

According to the Table (1), only the IPI variable has a short impact on Tunisia's price levels. There are therefore two short-term constraints on the MMR and MS variables. All variables have instant relationships with the IPI variable except the TMM variable. Therefore, an additional constraint is retained. The MMR variable is not influenced in the short term by the IPC and MS variables. Thus the variable IPI undergoes an instantaneous shock.

Table 1: The results of the Granger causality test

H_0	Statistic of Fischer	P-value	Assumed Hypothesis
IPI do not cause PCI	4.7737	0.03215	presence of causality
MMR do not cause PCI	1.4474	0.2329	absence of causality
MS do not cause PCI	0.3065	0.5816	absence of causality
PCI do not cause IPI	6.4846	0.01302	presence of causality
MMR do not cause IPI	2.744	0.102	absence of causality
MS do not cause IPI	5.3724	0.0233	presence of causality
PCI do not cause MMR	0.3358	0.5641	absence of causality
IPI do not cause MMR	8.3237	0.005159	presence of causality
MS do not cause MMR	0.7371	0.3934	absence of causality
PCI do not cause MS	4.9584	0.02909	presence of causality
IPI do not cause MS	14.281	0.0003217	presence of causality
MMR do not cause MS	2.3477	0.1299	absence of causality

Through these two additional constraints, we arrive at five short-term identification constraints. The money supply MS is influenced by the variables PCI and IPI. From where we release another constraint of identification, according to the test of causality carried out.

As a result, six short-term identification constraints are retained based on the tests performed. So, the matrix of instantaneous effects will have the following form:

$$A_0 = \begin{pmatrix} a_{11} & a_{12} & 0 & 0 \\ a_{21} & a_{21} & 0 & a_{24} \\ 0 & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & 0 & a_{44} \end{pmatrix}$$

4 BSVAR model estimation results

In a first step, we will focus on determining the best choice of hyperparameters of the priori distribution. Then we will analyse the dynamics of the variables and the economic interpretation.

4.1 The choice of hyperparameters of the prior distribution

Considering the range of definition, the values of the hyperparameters will be varied until the best combination is obtained. Thus, to reduce the number of iterations, we fix $\mu_5 = \mu_6 = 1$, like the one identified by Sims and Zha (1998). According to the Table (2), we concluded that the combination

Table 2: The results of the simulations for the choices of the distribution a priori

λ_0	λ_1	λ_3	λ_4	λ_5	μ_5	μ_6	EQM	MAE	logMMD	Simulation
0,3	0.3	0.5	1,5	0	1	1	-	0.2722110	171.8679	priori 1
0,5	0,5	0,5	3	0	1	1	-	0.2676047	160.2402	priori 2
0.5	0.5	1.5	5	0	1	1	0.3444095	-	157.3084	priori 3
0.7	0.7	1.5	7	0	1	1	-	0.2691362	153.6481	priori 4
0.7	0.7	2	7	0	1	1	0.3437670	-	152.0187	priori 5
1	0,2	1	1	0	1	1	0.3491529	0.2714602	156.1206	prior SZ

that gives us the lowest torque (RMSE, MAE) is the prior 5. Therefore, a prior distribution is retained with the following hyperparameters:

$$\lambda_0 = 0.7,\ \lambda_1 = 0.7,\ \lambda_3 = 2,\ \lambda_4 = 7,\ \mu_5 = 1,\ \mu_6 = 1$$

4.2 Analysis of structural shocks

After the Bayesian estimation of the parameters of SVAR model through Gibbs sampler, we adopted an impulse response study to analyse the reaction of each variable to the different structural shocks resulting from inflation, growth or monetary variables.

4.2.1 Shock of inflation

The first column of the graphs in Figure (2) represents the impact of shock price on the other variables. The price shock has a negative impact on growth, due to the deterioration of the individuals purchasing power and a failure of

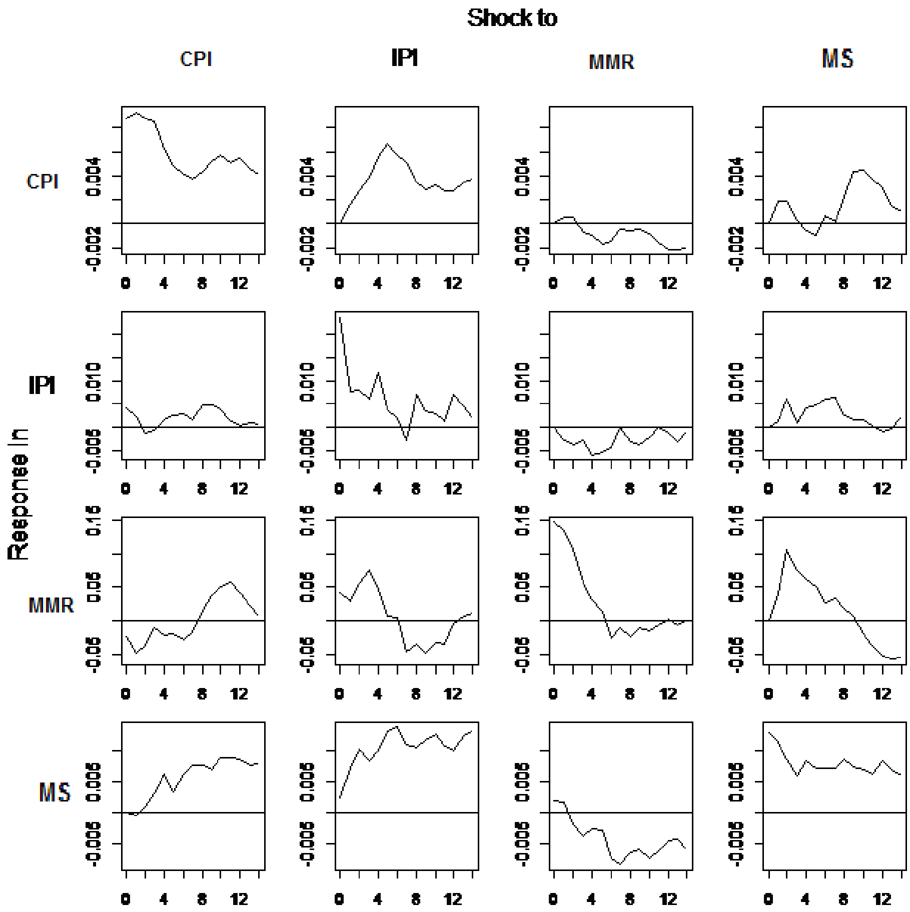

Figure 2: Responses to structural shocks for the B-SVAR model

the Government's anti-inflation policy system through price controls. But the price shock has a positive impact on the MMR and MS.

4.2.2 Shock of growth

The second column of Figure (2) represents the impact of the growth on the other variables. The impact of the growth shock on inflation is positive throughout the period and remains stable from the 10th quarter. This proves that if growth persists, inflation remains at a balanced level, so the Tunisian central bank has an interest in maintaining a more flexible level of growth in order to fight against inflation. Growth keeps MMR at a low and stable level, which proves that growth is a good economic indicator to improve the economic situation of Tunisia.

4.2.3 Shock of the money market rate

The third column of the Figure (2), shows us the shock of the MMR on other endogenous variables. The shock of the MMR on growth is a positive, which means that the decline of MMR will in no way promote growth. For this purpose the central bank must be very cautious following the fall of a MMR in Tunisia, because the decline of a MMR means flexibility in terms of credit agreement. On the basis of these forecasts the credits will not be productive. So the decision in terms of credit agreement will play a leading role in terms of growth.

4.2.4 Shock of the money supply

The fourth column of the Figure (2), which explains the shock of the money supply on other endogenous variables. The shock of the money supply on inflation is positive. This means that an increase in money supply causes inflation, for this reason the central bank must pay particular attention to this type of injection of money. In terms of the shock of the money supply on growth, we notice that the latter makes improve growth but in a way that is not significant, for this purpose the Tunisian central bank should not put too much on the money supply to improve growth in Tunisia.

5 Conclusion

Based on Bayesian SVAR modeling, we are interesting to discover the interactions between macroeconomic and monetary variables. Admittedly, this modeling approach has allowed us to understand the dynamics and predict the impact of the variables following the various shocks that may arise in the Tunisian economy. Indeed, the results have shown that the central bank, can impact the real economy in the positive direction as in the negative sense, according to its strategies and its policies followed. This economic component has been demonstrated by the application of a B-SVAR approach.

In this modelling approach, which tries to improve the performance of econometric models, central banks all over the world are developing new approaches in order to have a better visibility on their strategies and on the impact of their monetary policies on the real economy. In fact, we found from our analysis that there is in most cases a negative relationship between inflation and MMR and a positive relationship between growth and MS.

Finally, following the analysis of the shocks, it can be concluded that the central bank must strike a balance between the money supply and the MMR in order to control growth and maintain inflation at a suitable rate. Indeed, this structure must control inflation and it plays the role of strengthening the banking sector so to impact negatively the consumption and quality of life in Tunisia.

Further studies on this subject should include additional factors with regard to the policy variables, such as the period of government subsidy or fiscal policy. Moreover, nonlinear VAR models should be compared to BSVAR because the time series variables behave in a fluctuating manner.

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