SHORT-TERM BAYESIAN INFLATION FORECASTING FOR TUNISIA: SOME EMPIRICAL EVIDENCE

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Abstract
In order to explain clearly inflation forecasting and the dynamic of Tunisian prices, this paper uses two econometric approaches, the Standard VAR and Bayesian VAR, to assess three models for predicting inflation, the mark-up model, the monetary model and Phillips curve over the period 1990 Q1 – 2013 Q4.In order to compare predictions, an out-of-sample estimation was conducted. We used the structural break test of Bai &Perron (1998, 2003) and the RMSE criterion for both inflation indices: CPI and PPI. We found that the BVECM mark-up model is best suited to forecast inflation for Tunisia. Our conclusions corroborate the literature of Bayesian VAR forecasting. Our findings indicate that the models which incorporate more economic information outperform the benchmark autoregressive models (AR (1) and AR (2)). The results reveal that forecasting with the BVECM markup model leads to a reduction in forecasting error compared to the other models. The results of the study are relevant to decision-makers to predict inflation in the short- and long-terms in Tunisia and may help them adopt the appropriate strategies to contain inflation.

Keywords: *bayesian VAR; bayesian VECM;inflation forecasting; mark-up model, monetary model and Phillips curve*

JEL Classification: *C11, C51, C53, E31, E37*

I. INTRODUCTION

Everywhere in developed countries or emerging economies, keeping a strong control on inflation turned out to be one of the main objectives of regulators.This is true if we know that inflation increases uncertainty in the minds of economic agents, either consumers or producers. As the economic effect of monetary policy takes time to be in action (called the lag effect between decision and action) and since decision-makers need frequent updates on inflation, monetary authorities may obtain prior indication of possible future inflation through inflation forecasts. Generally, we can group forecasting models, especially for inflation or for any macroeconomic variable, into two families: Under the first, forecasts depend only on past values of the forecast variable like univariate approaches such as ARIMA models, (studies ofAtkeson and Ohanian (2001) and Faisal (2012)). Under the second family, the models of inflation forecasts incorporate more than past inflation (multivariate approaches), and include other variables that may be important in predicting inflation like in the VARmodels and the vectors autoregressive models (Boschi and Girardi (2007),Alexová (2012), F. Liew (2012), F. Öğünç et al (2013).

In our study, we will try to compare the two families: the univariate approach and the multivariate approach. Indeed, VAR models have proven to be reliable tools tomodel and forecast various macroeconomic variables. In this study, we will try to predict inflation in the short term in Tunisia.In fact, the main objective of the Central Bank of Tunisia (CBT) has been to achieve price stability and maintain a stable inflation through an inflation targeting policy since 2006.However, this strategy remains currently suspended. Therefore, predicting the future course of inflation in a precise manner is a crucial step to reach that goal. To forecast inflation, the Central Bank uses different sets of information from experts, using a variety of models ranging from simple traditional time series models to dynamic stochastic general equilibrium models (DSGE), theoretically well-structured under a Keynesian framework. The model, which has a Keynesian theoretical basis, is based on the global projection model (GPM) developed by the IMF estimated with a Bayesian technique, that takes into account the specificities of the Tunisian economy (Lajmi and Khadraoui, CBT, 2014).

This paper aims atcontributing to this set of information by opting for the same empirical methods (Bayesian estimation), while providing a rich set of inflation forecasts based on three types of short-term inflation models (Dahem et al 2015) and combining two important econometric approaches: standard VAR and Bayesian VARmodels.

Academically, standard VAR and Bayesian VAR models are at the heart of the modern forecasting modeling approaches and of the analysis of monetary policy in general. In particular, Bayesian VAR models have proven to be reliable tools for modeling and predicting various macroeconomic variables (Litterman (1980, 1986), Sims (1998) ...). Indeed, estimations using traditional econometric methods (OLS, DOLS, GMM ...) seem inappropriate because of the relatively small samples size.

The Bayesian method could remedy this deficiency. Bayesian technology outperforms GMMand maximum likelihood estimations for small data samples. In addition, it overcomes poor specification and problems of over-parameterization that may arise. In recent years, the Bayesian approach has become the preferred technique for most macroeconomists and researchers, like Smets and Wouters (2003), Fernandez et al. (2006) and Wieland et al. (2012). The approach consists in combining information delivered by some prior parameters of a model, which are generally synthesized from earlier work or simply deduced from economic theory. Empirically, the Bayesian approach begins with the formulation of a prior distribution for the unknown parameters of the model, which represent our belief about the situation before the observation data. In other words,it is about information available on the parameters: choosing the values of the means, the standard deviation and the appropriate probability distribution for each parameter. Then, it is about choosing the conditional joint density of endogenous variables to the parameters, which is to calculate the probability from observed data. Finally, we apply Bayes' formula to obtain a posterior distribution of the parameters, which takes into account both prior information and the data (Neal (1998).Two main reasons may explain its success. The first is conceptual and relates to the inclusion of prior information in the structural parameters of the model. The second reason is rather digital and relates to technological revolution, which has allowed the development of numerical calculation software and algorithms facilitating the adoption of this approach (such as the R software, Matlabsoftware, WinBugssoftware ...).

Theoretically and empirically, most studies show that it is difficult to outperform, in terms of forecasting, the famous vector autoregressive VAR models, particularly its Bayesian variant BVAR (Banbura et al (2008), and F. Öğünçet al (2013) ....). The interest in this modeling approach shown by international economics has been debated by the recent literature on its ability togo beyond the aim of forecasting inflation and to provide a ground toanalyze monetary policy. Indeed, Jaromíret al (2014) have used a Bayesian model for the Phillips curve with time variation of the parameters to provide a new perspective for the dynamics of inflation under inflation targeting, focusing on three countries that have adopted an IT strategy at the same time and in similar environments in Central Europe. Likewise, Yong Ma and Li Shushu (2014) constructed a DSGE model with a Bayesian estimation to examine the transparency of monetary policy in China as well as its macroeconomic implications. The Bayesian estimation is used as the main tool to estimate the model. In addition, KostaJ. et al (2014) have contributed to the literature on the responses of monetary policy in emerging countries to international financial crises. They analyzed the responses of monetary policy to common financial shocks during the period 1995-2010 over a sample of ten emerging European countries, using a structural Bayesian vector autoregressivemodel (SBVAR). The studies ofGamberE.N. (2013)examined inflation persistence in the US over the period 1947- 2010. The econometric analysis uses both the frequentist approach and the Bayesian approach to identify breaks. Both frequentist and Bayesian results indicate that inflation persistence has undergone significant changes over the past 60 years.

However, theoretical and empirical research is still mixed on this issue of forecasting inflation and the work that has begun on this issue is very rare in emerging countries in general and in Tunisia in particular. In this regard, we estimate a series of models that are frequently used in predictive studies of most central banks and in previous research. Our benchmark models are those used in the study of Dahem et al (2015). Our empirical methodology is based on two approaches for both inflation indices (CPI and PPI): a univariate approach: AR (1) and AR (2), a multivariate approach: the vector autoregressive (standardVAR and Bayesian VAR). To finally compare the forecasting ability of these two approaches,we opted for an out-of-sample estimation.

In our study, the period ranges from 1990Q1 to 2013Q4 for theTunisian context. Our sample includes financial crisis periods, revolution and changes in the structural inflation regime in Tunisia. To do this, we used Bai and Perron'sstructural break test (1998, 2003) that determine endogenously the date of possible breaks, which should be taken into account in particular while forecasting. The findings of this paper indicate that, on the one hand: the multivariate approach outperforms univariate models (AR (1) and AR (2)) for inflation forecasting in Tunisia. The models that exploit larger data sets and contain more information on inflation can better catch the dynamics of inflation, which is relatively unstable in an emerging market unlike in an advanced one. On the other hand, the Bayesian approach, specifically the BVECM mark-up model, is best suited to forecast inflation. The results show that with the prediction of BVECM mark-up model (with Bayesian estimation) leads to a reduction in forecasting error compared to the other models. In fact, the validity of the models was tested using standard statistical techniques and the best model is chosen on the basis of a selection and evaluation criterion (RMSE). The results of the study mayprovide decision-makers with a short and long-term look at inflation in Tunisia and help them adopt appropriate strategies to contain inflation.

The rest of the paper is structured as follows. Section 2 briefly summarizes monetary policy and inflation dynamics in Tunisia. In Section 3, we present the empirical methodology, models and Bayesian inference. In Section 4, we explain impulse functions. Section 5 compares forecasts. Finally, Section 6 concludes the paper.

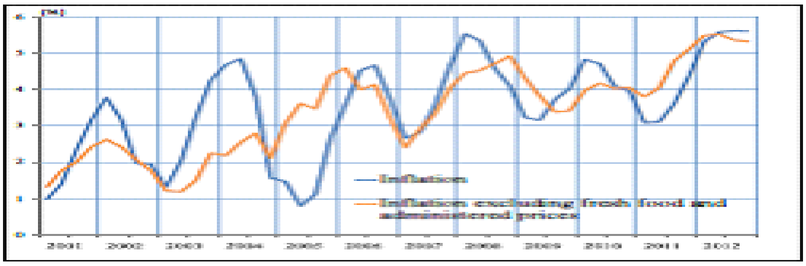
II. INFLATION AND MONETARY POLICY IN TUNISIA

In Tunisia, we distinguish three important periods for inflation dynamics and the monetary policy regime. From 1990 to 2000: there was a monetary policy that was more oriented towards supporting economic activity and preserving financial stability.

From 2000 to 2010: during this period, Tunisia has managed to keep inflation under control and from 2006 CBT announced as its first objective: price stability through aprices administration policy that has managed during this period to counter the impact of international prices of basic products (raw materials) and energy and contain inflation within acceptable levels.Three characteristics mark the evolution of prices during this period: i. a relatively high volatility and cyclical pattern, in particular changes in prices of fresh food. ii. presence of an upward trend because of the continued rise in import prices mainly due to the depreciation of the dinar's exchange rate. iii. the high share of administered prices in the consumer basket, despite the liberalization process initiated by the Government. Therefore, with an unexpected price adjustment, commodity administered is likely to cause a budgetary bias in inflation control and reduce the impact of interest rate in the transmission of monetary policy impulses. (Lajmi and Khadhraoui, CBT 2014)

From 2011 to 2013: this period was marked by revolution and upheaval at the political and economic levels. Inflation recorded its highest levels in 2012. The events that accompanied the revolution in 2011 resulted in a deterioration of security, proliferation of the informal sector and the establishment of a new balance of social power resulting in a disproportionate salary review. This particular context has contributed to the resurgence of inflationary pressures. (Lajmi and Khadhraoui, CBT 2014)

Figure 1: Graph of inflation and underlying core inflation(CPI)



Source: Lajmi and Khadhraoui, CBT (2014)

III. THE EMPIRICAL STUDY

3.1 Methodology: Models and Data

* The Univariate approach: AR regression (1) and AR (2)

* The Multivariate Approach: Our models are benchmarks of the work of Dahem et al (2015). Our research will focus on estimating three models of three aspects of inflation (inflation BY monetary factors - cost push inflation –demand-driven inflation). The choices were based on a reasoning that these models have been widely used in the literature and incorporate variables that can represent most causes of inflation, which enables us to conveniently respond to our research problem.

The Mark-up Model :

$$\Delta p_t = \alpha_0 + \alpha_{pi}\Delta p_{t-i}) + \alpha_{wi}\Delta w_{t-i}) + \alpha_{ei}\Delta E_{t-i}) + \alpha_{fpi}\Delta fp_{t-i}) + \delta\ EC_{t-1} + \varepsilon_t \qquad (1)$$

With: **Pt**: price level in our study is the consumer priceindex (CPI) and the producer priceindex (PPI). **wt**: the individual's Average Salary per quarter for the whole economy. **Et**: the nominal exchange rate: TND / EUR (quotation at certain). **fpt**: foreign price: it is the consumer price index (CPI) of the Euro zone. **ECt**: error correction: the long term equilibrium relationship, the residue of the equation at first level.

The Monetary Model :

$$\Delta p_t = \alpha_0 + \alpha_i\Delta p_{t-i}) + \beta_i moneygap_{t-i}) + \varepsilon_t \qquad (2)$$

With: p_t**:** the same like for the first Mark-up model: level of prices measured either by the consumer priceindex (CPI) and the producer priceindex (PPI).**moneygap**$_t$**:** it is the difference between money supply and the trend of long-term demand for money. For the monetary variable, we take the monetary aggregate M3 as a measure of stock currency. To determine the trend in the demand for money in the long-run we have had recourse to the Hodrick-Prescott filter (HP), which allows excluding the cyclical component of the evolution of the relevant variable.

Phillips Curve:

$$\Pi_t = \alpha + \beta_1(L)\ \Pi_t + \beta_2(L)\ \text{outputgap}_t + \beta_2(L)\ \Delta S_t + \varepsilon_t \qquad (3)$$

With **Πt:** inflation rate, since in the first two models it is measured by the consumer priceindex (CPI) and the producer priceindex (PPI). **St:** the bilateral nominal exchange rate, in this case: EUR / TND (quotation at uncertain). **Output gap$_t$**: is the gap between actual production and potential long-term production. As is already shown before for calculating money gap, we use the HP filter to calculate the potential output.

**** Data :***

The study period runs from 1990Q1 to 2013Q4. The sources of these data are the International Financial Statistics of the IMF and the Central Bank of Tunisia. Inflation is represented by two inflation indices: CPI, PPI. In our study, we will refer to the Bayesian estimation technique through a comparison of the predictions of standard VAR and Bayesian VARmodels.

3.2 Bayesian inference

In this paper, Bayesian estimation is used as the main tool to estimate the model. Bayesian analysis allows expressing subjective prior beliefs of the potential values of the parameters and latent variables that characterize the Tunisian economy by certain formulations of the prior distribution that subsequently modifies the data in the likelihood function.Bayesian estimation gives many advantages over standard techniques that address problems of identifying reduced form models. As pointed by Lubik and Schorfheide (2005), it overcomes poor specification,which is a potential problem in the comparison of DSGE models. Moreover, as pointed by Fernández-Villaverde (2010), it outperforms GMM and maximum likelihood estimates for small data samples. In case of missing data, it allows forovercoming this problem, which is the case in our study for wages (the mark-up model) and GDP (Phillips curve), through a priori formulation (there are several types of a-priori distribution).This technique has become the preferred tool of some macro-economists such as Smets and Wouters (2003), Fernandez et al. (2006) and Wieland et al. (2012). The Bayesian method combines the information provided by the data with prior information (a priori) on the parameters of the model, which is usually made on the basis of knowledge and / or simply deduced from experts and economic theory. In our study, this technique allows fortaking into account inflation dynamics and the possible specific nature of the studied country: Tunisia.

****Steps of Bayesian inference:***

Explicitly, the application of the Bayesian approach assumes that we know the following amounts: i.the prior density of the vector's parameters, which summarizes the information available on the parameters. It requires choosing the values of mean and standard deviation andthe appropriate distribution for each parameter. ii. Then, it measures the conditional joint density of endogenous variables to parameters, which is to calculate the probability from observed data. iii. Finally,it sets the Bayes formula that determines the posterior from the prior density and likelihood.

****Choice of Priors:***

Litterman (1981) used a multiple series of "a priori" data. In fact, without preliminary information, it is difficult to obtain accurate estimates of the several factors and, therefore, features like impulse responses.Then, forecasts tend to be imprecisely estimated (like the posterior predictive error which can be important). A variety of priors can be used with VAR modeling, Gary Koop & Dimitris Korobilis (2010) distinguish six priors for a VAR model. The most popular priors are called "Minnesota". The basic principle behind "Minnesota" is importantly all equations are centered on a random walk with drift. This proposal has been modified by Kadiyala and Karlsson (1997) and Sims and Zha (1998). In our study, we will look at only two: the Minnesota / Litterman Prior and the Normal-Wishart Prior.

**** Markov Chain Monte Carlo Simulation (MCMC):***

To carry out Bayesian inference in these models (listed above), specifically a posterior distribution will need algorithms of posterior simulations. In this case, there are 2 types: i. the simulation methods dated before 1990,likeDirect sampling, Acceptance sampling, Importance sampling (Hammersly and Handscomb (1964)) ii. Simulation methods after 1990,like the methods of Markov Chain Monte Carlo MCMC, including Gibbs sampling introduced by Gelfand Smith (1990) which we apply in this study.

****The Bayesian VAR (BVAR):***

VAR models are useful for economic modeling because they allow interaction of different related variables in forecasting macroeconomic variables. However, the problem of a standard VAR is the loss of degrees of freedom due to an excess of parameterization. Indeed, in VAR models, the number of parameters to be estimated increases geometrically with the number of variables and proportionally with the number of lags included. When the number of parameters is large compared to the number of observations available, the estimates are heavily influenced by noise, as opposed to the signal. On the other hand, when it comes to economic forecasts, it is possible that many variables may be relevant, which are many more than a standard VAR may incorporate. However, Bayesian vector autoregressive models have been proposed by Litterman (1980) as an alternative to standard VAR models to overcome the problem of dimensionality. The Bayesian approach (BVAR) addresses this problem by reducing the dimensionality of the parameters via the imposition of the "a priori" law. The Bayesian VAR model, as described in Litterman (1981), Doan et al. (1984), Todd (1984), Litterman (1986) and Spencer (1993) has become a very popular approach to overcome the parameterization. One of the main problems in the use of standard VAR models is that many parameters are estimated, although some of them may be insignificant. This problem of over parameterization, leading to multi-collinearity and loss of degrees of freedom, led to inefficient estimates. Instead of eliminating the longer shifts, the Bayesian VAR imposes restrictions on the coefficients, assuming that they are more likely to be close to zero for shorter delays. The literature shows that the gains are better for modeling based on VARmodels especially Bayesian VAR models that seem better to fit the data (F. Öğünç et al (2013)). The ability of forecasting improves with BVAR. Bayesian VAR models have proven to be reliable tools for modeling and forecasting.

IV. IMPULSE RESPONSE FUNCTIONS

The objective of impulse functions in the analysis is to reflect the impact of a specified variable's shock on the other variables since there is a dynamic structure in the composition of a VAR system as far it represents the effect of an impact of an innovation on the other variables. Impulse responses remain one of the most appropriate techniques to explain sources of shock propagation. They allow synthesizing most of the information contained in the internal dynamics of the model. In general, an impulse response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. In our case, we are interested in particular inthe impact of the effects of different variables on inflation. By analyzing the impulse response function, it will allow us to observe how the consumer priceindex and the producer priceindex react to shocks on other variables (exchange rates, wages, foreign price, monetary aggregate, output gap ....). The factors that could explain excessive inflation may include secondary supply factors, such as inflation pushed costs and the relationship with exchange rate effects.

1-Figure 3 in Appendix 2 describes all the impulse responses of the key variables (CPI and PPI) to a shock of another variable for VAR and VECM standard:

*When the pulse is wages, inflation response is positive at any time throughout the period and there will be an upward trend over time,

*When the pulse is exchange rate: i. TND/EUR, inflation response (CPI) is negative at any time throughout the period and there will be an upward trend over time, while it is the opposite for PPI (low). ii. EUR/TND, inflation response (CPI) is positive at any time throughout the period and there will be an upward trend over time (a phenomenonof exchange ratepass-through)

*When the pulse isforeign prices, inflation response (CPI) is almost zero at any time over the period while it is the opposite for PPI.It reacts to a rise in the first quarter.

*When the pulse is money supply: inflation (CPI) oscillates around its long-term trend. The value fluctuates around the zero line, while PPI reacts downward in the first quarter and after it fluctuates around zero.

*When the pulse is the output gap: the inflation is negative at any time throughout the period

2-Figure 4 in Appendix 3 describes the set of impulse responses of the key variables (CPI and PPI) to a shock of another variable for Bayesian VAR and VECM.

V. COMPARISON OF FORECASTS

To compare forecasts, we will make an out-of-sample estimation that consists in dividing the period into twoto estimate the models for the first period and consider the observations as forecast for the second period. The choice of forecasting period is determined by the structural break test of Bai and Perron (1998, 2003). (See Appendix 4).In fact, the test indicates several break dates. We will concentrate on 2010 Q4, which coincides well with the Tunisian revolution. Three horizons are taken for the forecast period:i. H = 12, the Forecast Period: 2011Q1-2013Q4. ii. H = 8, the Forecast Period: 2012Q1-2013Q4. iii. H = 4, the Forecast Period: 2013Q1-2013Q4.

In general, the choice of a prediction comparison criterion, which may be decisive when comparing these models, depends mainly on its use, on its quantitative evaluation of the precision and also on the reliability of its prediction. In this way, we adopted the RMSE criterion for its high sensitivity, its current use, its explanatory power and its ease of implementation. This criterion allows us to compare forecasting performance.

The Root Mean Square Error :RMSE(e) = and MSE : the Mean Square Error :MSE(e) = e_i^2. The results are presented in Appendix 5. We found that:if pt=CPI or PPI

1-The multivariate approach outperforms the univariate approach for all horizons.The 3 inflation models (the mark-up model, the monetary model and Phillips curve) have the lowest RMSE compared to AR (1) and AR (2) RMSE.

2-In the case of estimation with standard VAR and VECM modeling, the markup model presents the lowest RMSE compared to the other models (monetary model and Phillips curve) (cost-push inflation).

3-In the case a Bayesian VAR and VECM estimation, the markup model presents the lowest RMSE compared to other models (the monetary model and phillips curve) and it is the lowest compared to the RMSE markup for non-bayesian VECM model.

VI. CONCLUSION

As the main objective of monetary policy of the Central Bank of Tunisia is to reduce inflation and maintain stability of the volatility of the exchange rate over the last decade, many experts are advocating the use of a monetary policy well determined to control inflation in Tunisia, due to the instability in the economic environment. In such situation, forecasting future inflation can help policy makers to formulate their strategies.

Factors that could explain inflation in Tunisia may include secondary supply factors, particularly cost-push inflation with transmission exchange rate effects during the last period and excessive borrowing by the government and the parallel market (CBT report 2014). In this context, this paper has focused on forecasts of inflation in the short term for Tunisia, while comparing two important modeling approaches: the standard VAR and Bayesian VAR applied to three inflation models (the Mark-up model, the monetary model and phillips curve).The empirical objective of this study was primarily to test the predictive ability of these econometric models. The validity of the model was tested using the RMSE evaluation criterion. The results of the study mayprovide decision-makers with strategies to predict inflation in the short-term and long-term in Tunisia and help themadopt appropriate strategies to contain inflation. Our results join those of the literature which indicate that the gains are better by a modeling based on Bayesian VAR models. We found that the BVECM for the mark-up model is best suited toforecast inflation in Tunisia (cost-push inflation). The results show also that forecasting with the mark-up model for the BVAR approach leads to a reduction in forecasting error compared to most other models. Although the standard and Bayesian VAR models have proven to be reliable tools for modeling and forecasting, they are always linear and they do not consider parameters change in time in our case. In this regard, as a future line of research, non-linear models can be applied,first like the switching-Markov models which employ transition probabilities, characterized by a Markov chain process, under the hypothesis that regime change is determined by an unobservable variable. Second, we mention the threshold models such as the model of smooth transition autoregressive (STAR) which implies a gradual adjustment. Third, we mention the approaches based on decompositions like decomposition in the frequency domain: the waves (WAVE).

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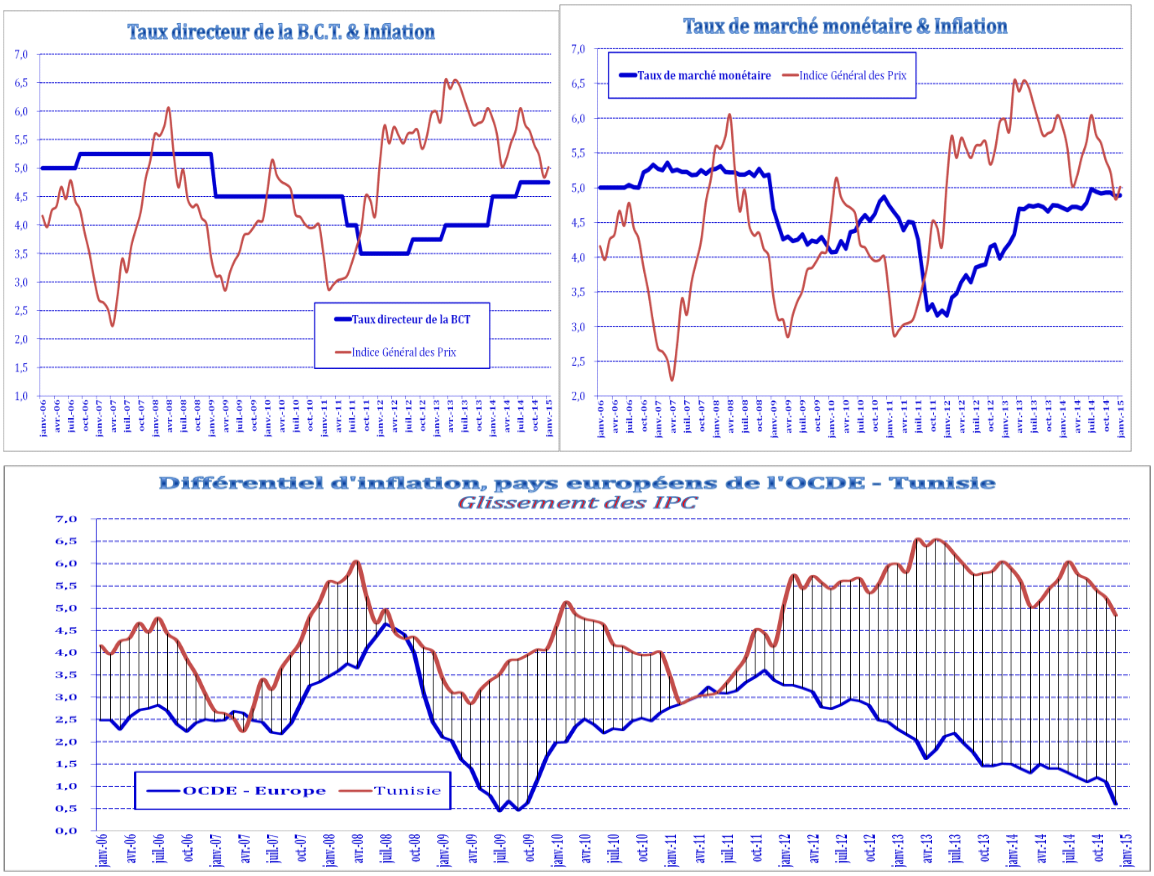
Appendixes

Appendix 1: Figure 2: Graphs of CPI and Interest Rates



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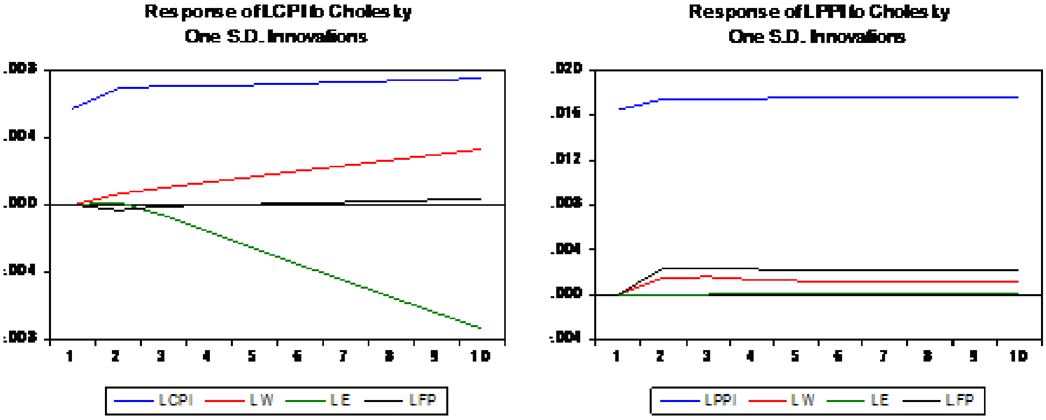
Appendix2: Figure 3: Impulse function for a standard VAR or VECM model

1-markup model :

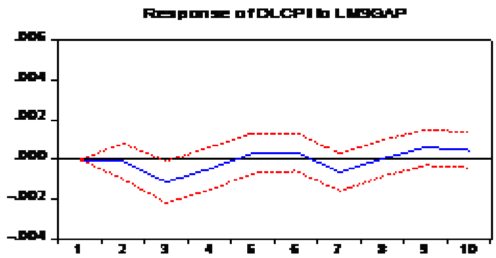
VECM DLCPI VECM DLPPI

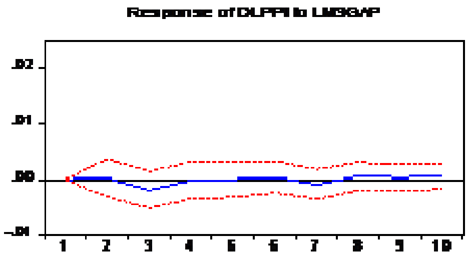


2-monetary model :

Response to Cholesky One S.D. Innovations ± 2 S.E.

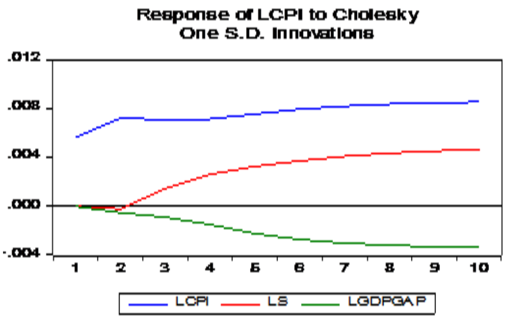
VAR DLCPI VAR DLPPI

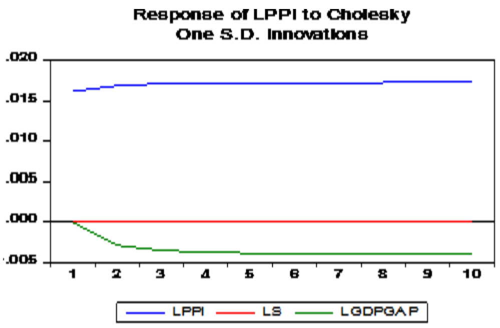




3-phillipscurve :

VECM DLCPI VECM DLPPI





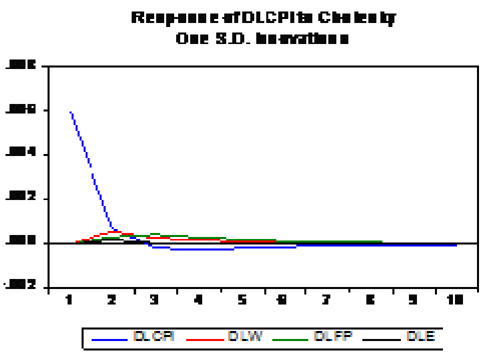
Sources: made by the author

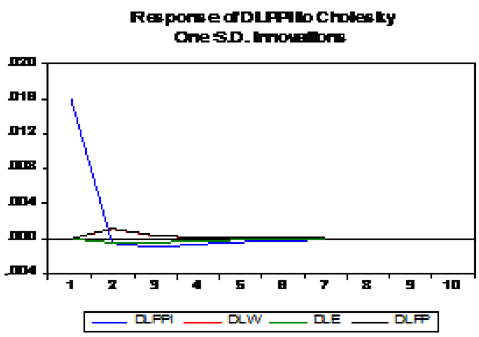
Appendix 3: Figure 4: posteriorimpulse function for a BVAR model or BVECM

***Posterior impulse response – Minnesota prior L1: 0.1**

1-markup model:

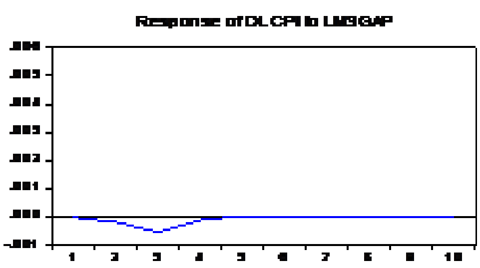
VECM DLCPI VECM DLPPI

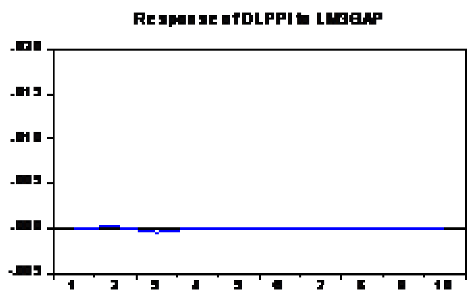




2-monetary model :

VAR DLCPI VAR DLPPI

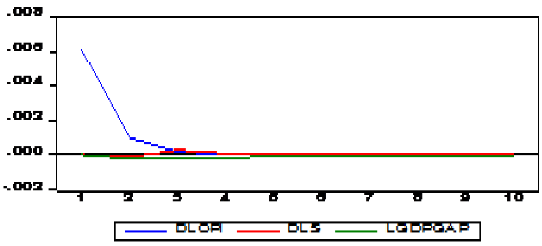


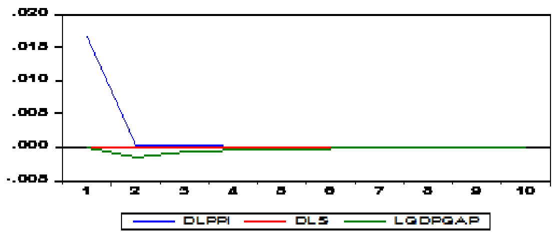


3-phillipscurve :

Response to Cholesky One S.D. Innovations ± 2 S.E.

VECM DLCPI VECM DLPPI



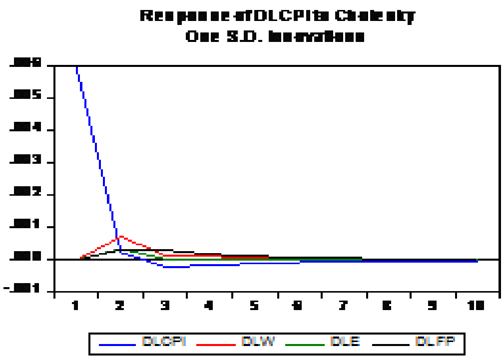


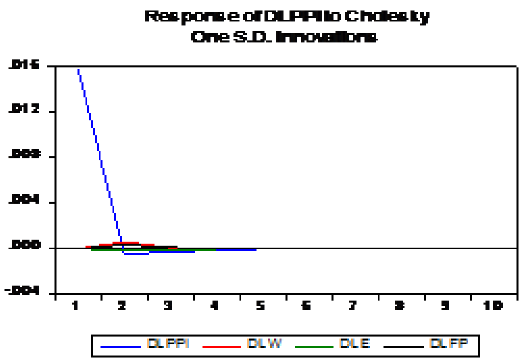
Sources: made by the author

2/ Posterior impulse response – normal wishart prior L1: 0.01

1-markup model:

VECM DLCPI VECM DLPPI

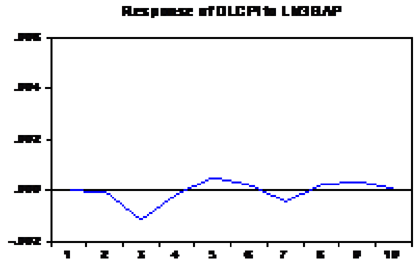


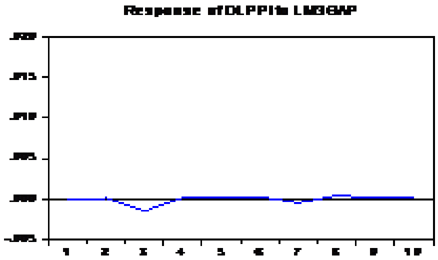


2-monetary model:

Response to Cholesky One S.D. Innovations ± 2 S.E.

VAR DLCPI VAR DLPPI



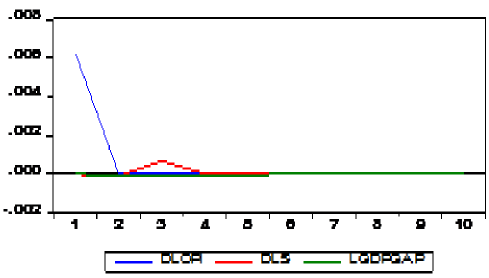


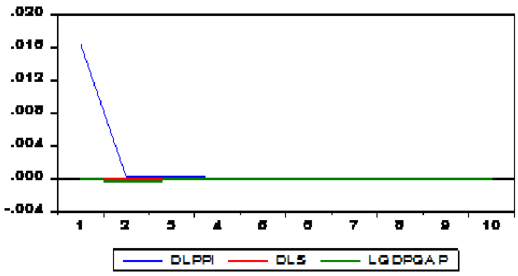
3-phillips curve:

Response of DLS to Cholesky
One S.D. Innovations

VECM DLCPI

VECM DLPPI





Sources: made by the author

Appendix 4: Test of Bai and Perron (1998, 2003)

The methodology of Bai and Perron (1998, 2003) consider the multiple structural breaks model with m breaks (m + 1 systems). The estimation method proposed by Bai and Perron (1998) and specified in Bai and Perron (2001) is based on ordinary least squares. To do this we use the algorithm developed in Bai and Perron (2003), based on the principle of dynamic programming to estimate the unknown parameters. In the general case, any m, tests are then used to determine the number of breakpoints. Taking this into account, the structural breaks was mainly discussed in the context of univariate autoregressive time series with a unit root in the line of work Perron (1989). For empirical obtaining different phases of the economy of Tunisia, we will apply the methodology of Bai-Perron (Bai and Perron (1998), Bai and Perron (2001b) and Bai and Perron (2001a)) to the variable of inflation which, in this context, is subject to forecast: The CPI (the index of consumer prices) and PPI (the index of producer prices).

Table 1: Breaks test of Bai and Perron (2003)

	Value of Statistic		Numbers of Breaks		Breaks dates	
Type of Statistic	CPI	PPI	CPI	PPI	CPI	PPI
Sequential F-statistic	5.426831	4.285566	5	5	1996Q1 2000Q1 2003Q3 2007Q1 2010Q3	1996Q4, 1999Q4, 2003Q1, 2006Q1, 2009Q1
UDmaxdetermined	13.01247	10.380235	2	2	1996Q1 2007Q2	2006Q1, 2009Q1
WDmaxdetermined	15.46357	12.015384	2	2	1996Q1 2007Q2	2006Q1, 2009Q1

Source: Author's estimations.

Appendix 5: comparison of forecasts

1/ 1st case: pt=CPI
Table 2: RMSE for univariateapproach

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
AR(1)	0,05077		0,08268		0,11482	
AR(1) bayesian	0,04556	10,262%	0,05711	30,926%	0,06615	42,388%
AR(2)	0,04751		0,06483		0,10118	
AR(2) bayesian	0,04170	12,230%	0,05381	16,998%	0,06418	36,568%

Table 3: RMSE for the model markup

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VECM	0,013813		0,020847		0,022116	
BVECM	0,004444	67,827%	0,004217	79,771%	0,006057	72,612%

Table 4: RMSE for the monetary model

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VAR	0,05853		0,05520		0,07777	
BVAR	0,007716	86,817%	0,007473	86,461%	0,007233	90,699%

Table 5: RMSE for the Phillips curve

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VECM	0,009191		0,011139		0,010717	
BVECM	0,004733	48,503%	0,005846	47,517%	0,006090	43,174%

2/ 2nd case: pt=PPI

Table 6: RMSE for univariateapproach

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
AR(1)	0,06166		0,07989		0,13561	
AR(1) bayesian	0,06103	14,025%	0,06205	22,330%	0,07654	44,558%
AR(2)	0,03514		0,05242		0,07613	
AR(2) bayesian	0,03006	14,456%	0,03118	41,518%	0,07230	20,885%

Table 7: RMSE for the model markup

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VECM	0,009921		0,007445		0,007173	
BVECM	0,005853	41,003%	0,005520	25,856%	0,002490	54,705%

Tableau 8 :RMSE forthe monetary model

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VAR	0,018921		0,019745		0,021733	
BVAR	0,005860	69,029%	0,006140	68,903%	0,007777	64,215%

Table 9: RMSE for the Phillips curve

	H=4		H=8		H=12	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
VECM	0,015906		0,013712		0,013784	
BVECM	0,007572	52,395%	0,005950	56,607%	0,006856	50,261%