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Hajer Ben Romdhane
Central Bank of Tunisia

Nahed Ben Tanfous
Central Bank of Tunisia

Chemin Eugène-Rigot 2
P.O. Box 136
CH - 1211 Geneva 21
Switzerland

THE GRADUATE INSTITUTE GENEVA

INSTITUT DE HAUTES ÉTUDES INTERNATIONALES ET DU DÉVELOPPEMENT
GRADUATE INSTITUTE OF INTERNATIONAL AND DEVELOPMENT STUDIES

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Abstract

The aim of this paper is to compute the conditional forecasts of a set of variables of interest on future paths of some variables in dynamic systems. We build a large dynamic factor models for a quarterly data set of 30 macroeconomic and financial indicators.

Results of forecasting suggest that conditional FAVAR models which incorporate more economic information outperform the unconditional FAVAR in terms of the forecast errors.

Key words: FAVAR, Conditional FAVAR, Conditional Forecast.

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1. Introduction

Understanding the transmission mechanism of structural shocks is important for identifying the best policy response to national developments. In emerging countries which have experienced a steady increase in goods, capital and financial markets integration, this aspect of the transmission mechanism has become an essential ingredient for the policy discussion.

Most empirical studies on the international transmission of shocks are based on small scale vector autoregressive (VAR_s), and impulse responses can be observed only for the included variables which generally constitute only a small subset of the variables that the policy makers care about. Unfortunately, inclusion of additional variables in standard VAR is severely limited by degrees of freedom problems.

Therefore, this small number of variables is unlikely to span the information sets used by actual central banks. Despite VAR's models common use, relatively small number of macroeconomic variables that cannot capture all the necessary information and might cause omitted variables.

Stock and Watson (2002) employed a factor models which beneficially adapt large of information sets to the analysis by providing convenient tool to reduce dimensions and to extract information. Factor analysis is a statistical approach that can be used to analyze relationships among a large number of variables and explain these variables in terms of their common underlying dimensions. In particular, it condenses the information, contained in a number of time series observations into a smaller set of dimensions with a minimum loss of information.

Therefore, the factors can be considered as an exhaustive summary of the information contained in a large dataset. Indeed, these factors capture fluctuations in unobserved potential output, which reflect theoretically motivated concepts such as "economic activity", "price pressures" or "credit conditions".

There are two types of factor analysis: the first one is "the common factor analysis", which this technique used an estimate of common variance among the original variables to generate the factor solution, where the solution is used to identify the structure underlying such variables and to estimate score to measure latent factors themselves. The second approach is the Principal component analysis, initiated by Stock and Watson (2002). Stock and Watson (2002) designed a method for forecasting of a single time series of length T, using a large number N of predictor series, where $N \geq T$.

The recent macroeconometric literature has seen an increasing interest in the application of factor-augmented vector autoregressive (FAVAR) models for forecasting and evaluating the mechanism transmission of the monetary policy.

Bernanke and al. (2005) combine factor models with VAR to be able to use both large information sets and explain the effects of monetary shocks on various indicators. These are known as Factor Augmented VAR (FAVAR) model. In fact, the FAVAR approach allows us to characterize the response of all data series to macroeconomic disturbances, such as monetary policy shocks or oil price shocks.

Central Bank of Tunisia (CBT) rely its policy decision not only on the information about the aggregate economy but also examine the monetary policy shock on disaggregate level of prices. And for this reason, we include in our database the disaggregate levels of prices such as commodity prices and prices of other sectors.

Usually, the forecast algorithms considered up to now are unconditional multivariate forecasts, where only unconditional forecasts with no conditions on the future variables or future structural shocks are used in this approach. But, the forecasters are interested in question that how do forecasts of other macroeconomic variables change if the some variables as fiscal variables or economy growth rate in the next, two to three years follows different paths? In the framework of FAVAR models, these questions require to impose conditions prior to forecast, on the future values of certain endogenous variables. These forecasts are known by "conditional forecasts".

Also, it's sometimes desirable to obtain forecasts of some variables in the system conditional of knowledge of the future path of other variables in the system. For example, when forecasting macroeconomic variables using quarterly data from a FAVAR model, it may happen that some of the future values of certain variables in the FAVAR model are known, because data on others variables are released earlier than data on the other variables in the system. So when we work with a FAVAR model, we will often want to compare model predictions under a variety of different assumptions regarding the path of (exogenous variables). Several application Methods of conditional forecasts have been developed by Doan, Letterman (1984) that they exploit the covariance matrix structure in a VAR to account for the impact of conditioning on post-sample values for some variables in their models.

Wagoner and Zha (99) used Bayesian methods to compute to exact finite sample distribution of conditional forecasts in both structural and reduced form of VAR accounting for the uncertainty in the parameters. Their methodology involves drawing the paths of reduced form which are compatible with the conditioning path on the observables. It argues that to the extent that leading information is available, relevant and reliable, conditioning on it may reduce the uncertainty in the endogenous variables and thereby improve the forecasting performance of a FAVAR model without necessarily having to change its structure. Conditional forecasts are very useful for policy simulations: (effects of an increase of interest rate, or a government spending), for the assessment of risk (currency depreciation or oil price shocks).

This paper is organized as follows. Section 2 describes the theory of a VAR model. Section 3 describes the theory and empirical estimation of the FAVAR model. We consider both a one- step method, which makes use of Bayesian Likelihood method and Gibbs sampling to estimate the factors and the FAVAR simultaneously; and a two -step estimation method, in which factors are estimated by principal components prior to the estimation of the factor augmented VAR. Section 4 applies the conditional FAVAR methodology relative to the three different scenarios and revisits the evidence on the effect of monetary policy on wide range of disaggregate level prices. Section 5, consists to compare the performance unconditional forecasting with conditional forecasting in FAVAR model. Section 6, concludes. An appendix provides more detail concerning the application of the Gibbs sampling procedure to FAVAR estimation and conditional FAVAR.

2. A Basic VAR model

In This section we introduce the basic VAR model and discuss problems with a small scale VAR models. A model VAR consists of $t = 1, ...T$ observations on a set of n endogenous macroeconomic variables $Y_t = (y_{1t}, y_{2t}, ...y_{nt})'$, such that Y_t is a $(n \times 1)$ vector containing T observations on n time series.

The $VAR(p)$ process with p lags is then defined as:

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + \varepsilon_t \qquad (1)$$

Where:

- The A_i are $(n \times n)$ coefficients matrices for $i = 1, ...p$.
- c is a $(n \times 1)$ vector of intercepts ; and
- $\varepsilon_t = (\varepsilon_{1t}, \ \varepsilon_{2t}, ...\varepsilon_{nt})'$ is an unobservable, n-dimensional vector error with $E(\varepsilon_t) = 0$ and time invariant (constant) , positive definite variance-covariance matrix $\mathrm{cov}(\varepsilon_t) = E(\varepsilon_t \varepsilon_t')$ = $\sum$ (white noise), such that $\varepsilon_t \sim N(0, \sum)$.

In this model, there are lots of coefficients to estimate. In fact, the number of parameters to be estimated is equal to $n \times (np + 1)$, and unrestricted OLS estimates of the coefficients are often not very well determined (in the sense of imprecise) in a finite set of data.

For this reason, many alternative methods for estimating the coefficients have been developed (with a common then being “shrinkage”).

As alternative method, we consider the following (SVAR (1)) with GDP, inflation and interest rate, such that $Y_t = (y_t, \pi_t, R_t)$

3. Factor-augmented VAR (FAVAR)

In This section we introduce the FAVAR model, discuss its estimation, and compare it to its related approaches.

3.1 The FAVAR model

The factor augmented VAR builds on the dynamic factor model structure and allows identifying monetary policy shocks. This methodology of the FAVAR is an interesting strategy to deal with the "curse of dimensiality" (Bernanke (2005)). This approach consists of two equations:

The $(M \times 1)$ vector, Y_t, of observable economic variables and the small $(k \times 1)$ vector of unobserved factors, F_t, are combined in a transition equation :

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \qquad (1)$$

Where $\phi(L)$ is a conformable lag polynomial of finite order. Setting $Z_t = (F_t, Y_t)'$ can be identified as VAR (p) where:

$$Z_t = \theta(L) Z_{t-1} + v_t \qquad (2)$$

$$= c + \sum_{i=1}^{p} A_i Z_{t-i} + v_t$$

Estimation of factors can proceed in two ways:

- Either a two-step (semi parametric) method, in which the factors, F_t are estimated by principal components prior the estimation of the factor-augmented VAR given by (2).
- Fully parametric one step method, which makes use of Bayesian likelihood methods and Gibbs sampling to estimate the factors, F_t, and the dynamics simultaneously in a state space model.

Bernanke, et al. (2005) illustrate their FAVAR methodology and underline the importance of considering a long list of informational variables in the context of a simplified Rundebush and Svensson (99) model of monetary policy. Their set of informational time series, X_t, consists of a balanced panel of 120 monthly stationary US macroeconomic time series .

Therefore, the division of variables between F_t and Y_t in (1) depends on which variables are assumed to be directly observed. The authors assume that the most realistic description of the information structure is that the Central Bank observes only the policy instrument (the nominal interest rate), i.e., $Y_t = FFR_t$ (the federal funds rate) as well as a large set of noisy macroeconomic indicators, X_t in particular the financial variables, commonly denoted as "fast moving " variables. Moreover, it's likely that the nominal interest rate is contemporaneously related to some subset of variables in X_t, in particular the financial variables, commonly denoted as "fast-moving "variables.

In this paper we use two methodologies:

- ✓ The first one is based on Gibbs sampling techniques. In fact, the Gibbs sampling approach provides empirical approximation of the marginal posterior densities of the factors and parameters via an iterative sampling procedure, which factors are sampled conditional on the most recent draws of the model parameters, and then the parameters are sampled conditional on the most recent draws of the factors. As the statistical literature has shown, this Bayesian approach, by approximating marginal likelihoods by empirical densities, helps to circumvent the high-dimensionality problem of the model. Moreover, the Gibbs-sampling algorithm is guaranteed to trace the shape of the joint likelihood, even if the likelihood is irregular and complicated.
- ✓ The second approach consists to remove the correlation of interest rate with some of the fast moving variables. In this way, we follow these steps:
  - We estimate F_t as above using the principal components estimator,
  - Then we estimate $F_{slow,t}$ using only variables in X_t that are slow-moving macroeconomic variables.
  - In the next step, we calculate $F_{new,t} = F_t - IR_t \times B$, where IR_t is the interest rate, B is the coefficient on interest rate in the regression: $F_t = \alpha + D \times F_{slow,t} + B \times IR_t + \varepsilon_t$, and then,
  - We estimate the FAVAR (p) in (2) using $F_{new,t}$ and IR_t.

Therefore, the monetary policy shock is identified using Choleski decomposition with ordering $F_{new,t}$, IR_t meaning that interest rate does not affect $F_{new,t}$, contemporaneously. For this reason, we can then calculate the impulse responses of $F_{new,t}$ and IR_t.

3.2 Estimating the FAVAR

We consider two approaches to estimate a FAVAR model using Tunisian Data over the period 2000Q1 to 2015Q4. The first one is a one-step method which makes use of Bayesian Likelihood method and Gibbs sampling to estimate simultaneously the factors and the FAVAR. The second method is the two-step method, in which factors are estimated by principal components prior to the estimation of the factor augmented VAR.

A one step- Gibbs sampling Method

We use 30 Macroeconomic and Financial time series to estimate and predict inflation. (Real GDP, Real Consumption, Government Consumption, Real Exports, Real Imports, commodity prices, consumer prices index, components of prices index, Nominal exchange rates and Monetary market rate) (Table 1 provides the details of the data).

Table1: Variables in FAVAR model

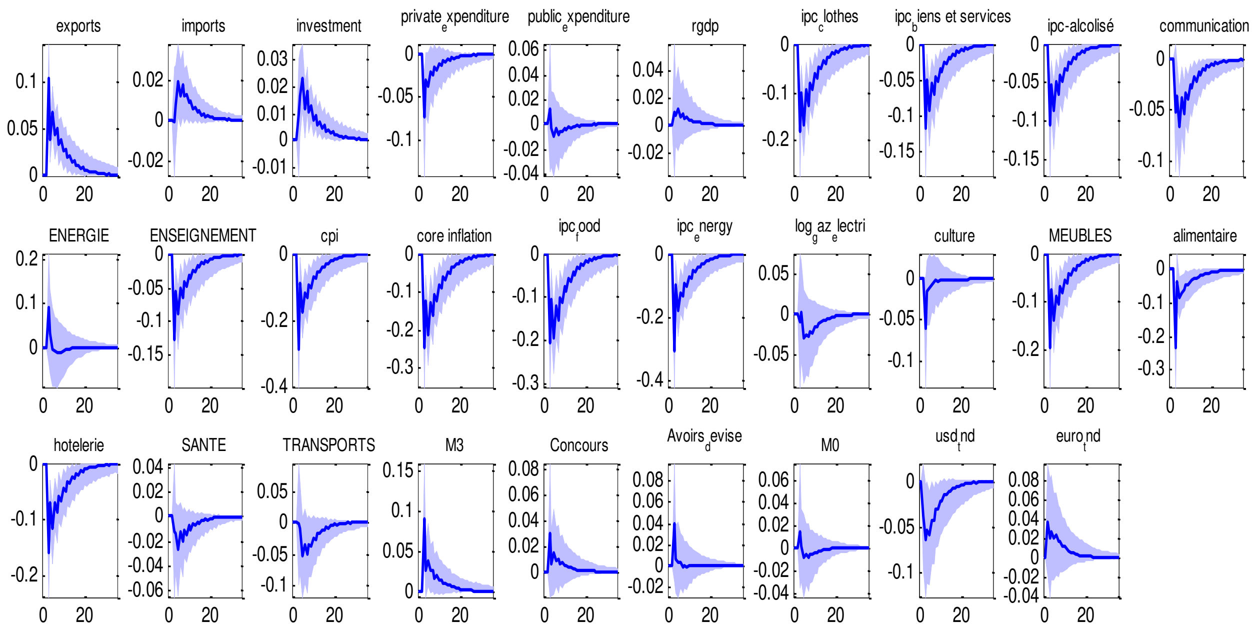
Category	Variables
Real activity measures	Real exports(sa), Real imports(sa), investment(sa), Private consumption(sa), Governement consumption(sa), RGDP(sa), index prices_clothes, index prices_goods_services, index prices_communication,
Infaltion components	index prices _energy, index prices_education, consumer prices index_all, consumer prices without food, core inflation, consumer prices without energy, prices_culture, prices_health, prices_hotel, prices_transports.
Monetary Indicators	Monetry aggregates(M3)(sa), credit to economy(sa), foreign assets, Reserve money(sa), interest rate.
Exchange rates	Euro/TND, USD/TND.
Note:"sa" refers to seasonally adjusted series.	

The series that were not already available in seasonally adjusted form are seasonally adjusted using the Census X13 method. Variables showing a non –stationary behavior are made stationary through differencing. Most series enter in differences of their logarithms except for interest rates, ratios enter in levels.

The number of factors can be determined by a combination of prior knowledge, visual inspection of a scree plot and the use of information criteria developed by Bai and Ng (2002). Bai and Ng (2002) adopts some information criteria to select the number of factors, this latter method is based on the observation that the eigenvalue –eigenvector analysis of the variance-covariance matrix solves the least square method.

In our case, we followed the method used by Bernanke and al (2005) when we increase K factors until there's no change in the impulse response functions, and then we find that the first three principal components do a good job in summarizing the information in our dataset. We also use a subjective measure such the proportion of variance explained by three factors.

Figure 1: Impulse responses of variables



The figure (1) reports the impulse response of real and financial variables. After an unexpected increase in interest rate the index prices consumer items decrease temporarily. The impulse responses then turn to zero after three to five years. The exception is signaled to commodity prices that's related to the energy products, which increase to **0,08%** higher on impact. One possible explanation of this discrepancy between the findings for the commodity prices is that energy products are administered products and any unexpected adjustment can generate a budgetary bias and reduce the impact of interest rate on inflation.

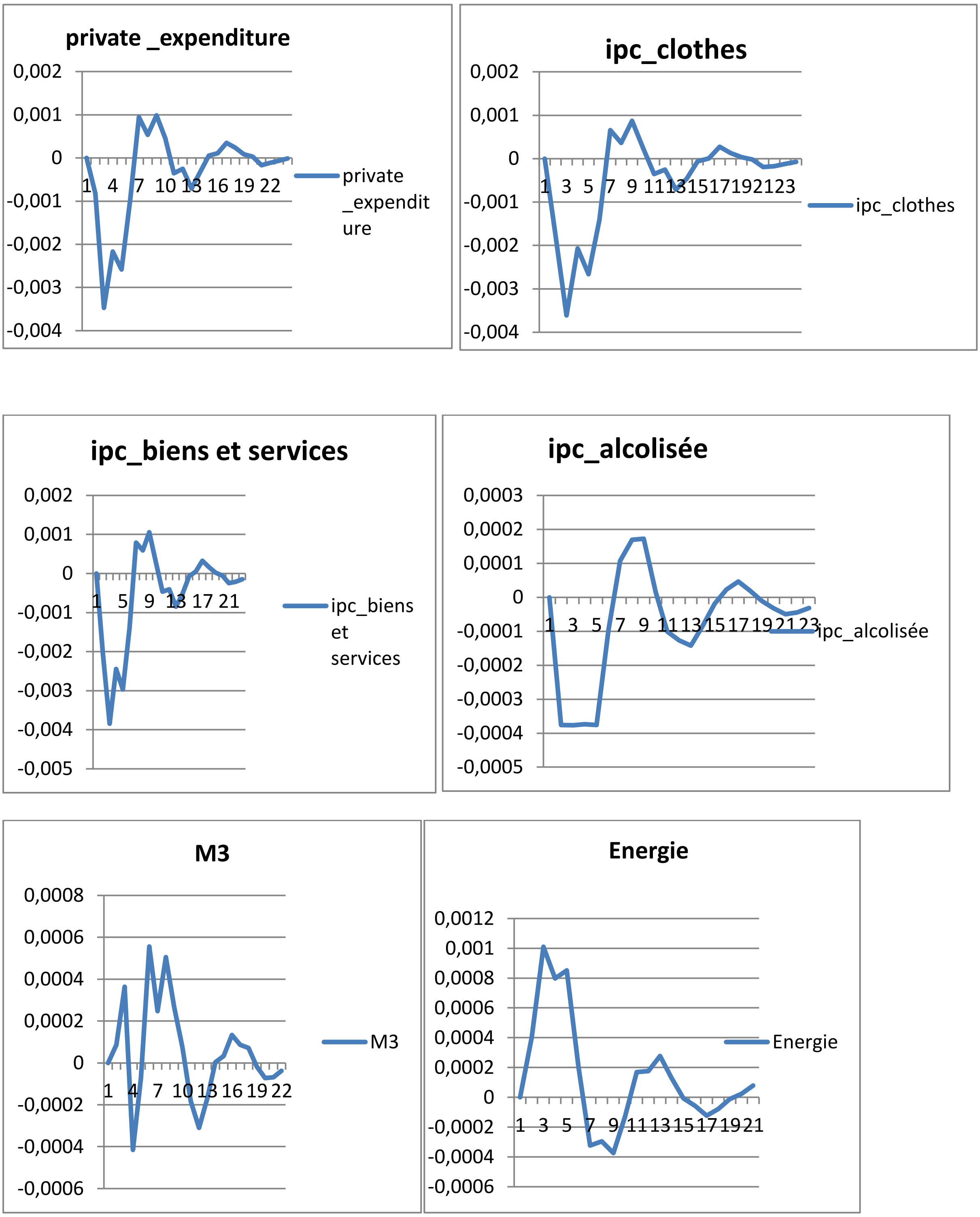
A two-step of Principal components

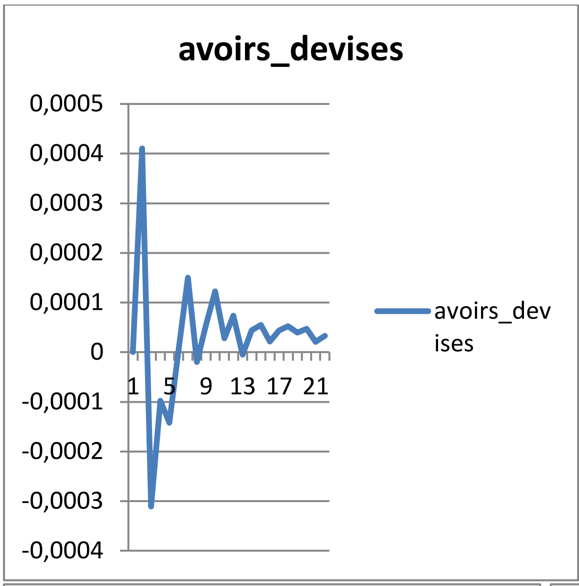
We use the same 30 Macroeconomic and Financial time series to estimate and predict inflation. (Real GDP, Real Consumption, Government Consumption, Real Exports, Real Imports, commodity prices, consumer prices index, components of prices index, Nominal exchange rates and Monetary market rate). The table 2 provides the details of the correlation coefficients between the Principal components and the dataset of variables.

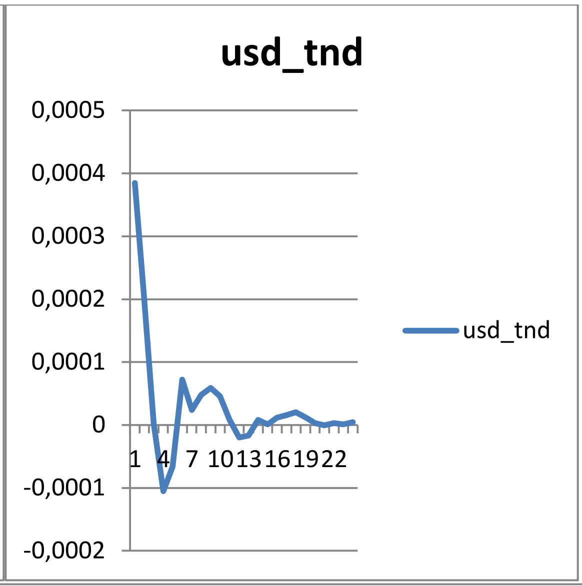
Table 2

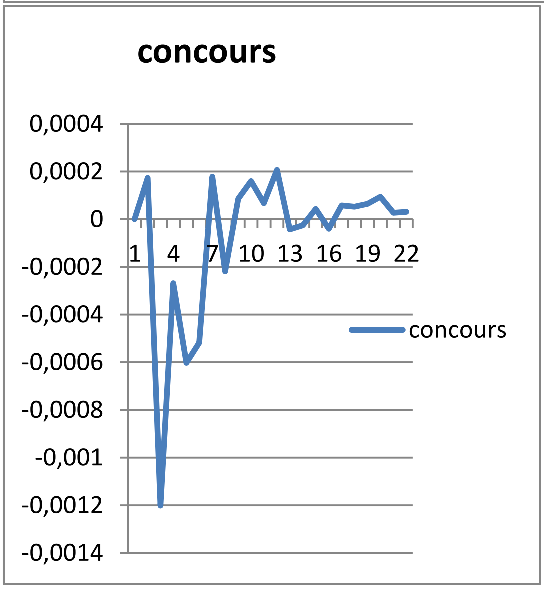
	Coefficients of Correlation coefficients		
Principal Components	**Variables**	**Correlations**	**Bloc**
PC1	CPI_inflation	0.36	**Inflation components**
	Core_inflation	0.36	
	IPC_food	0.36	
	IPC_Energy	0.35	
	IPC_Meubles	0.29	
	IPC_alimentaires	0.2	
	ipc hotelerie	0.24	
	ipc _clothes	0.24	
PC2	exports	0.42	**Real activity economy**
	imports	0.42	
	investment	0.42	
PC3	M3	0.46	**Monetary indicators**
	M0	0.49	

<u>Figure 2: impulse responses of variables</u>




avoirs_devises
0,0005
0,0004
0,0003
0,0002
0,0001
0
-0,0001
-0,0002
-0,0003
-0,0004
1 5 9 13 17 21
avoirs_devises


usd_tnd
0,0005
0,0004
0,0003
0,0002
0,0001
0
-0,0001
-0,0002
1 4 7 10 13 16 19 22
usd_tnd


concours
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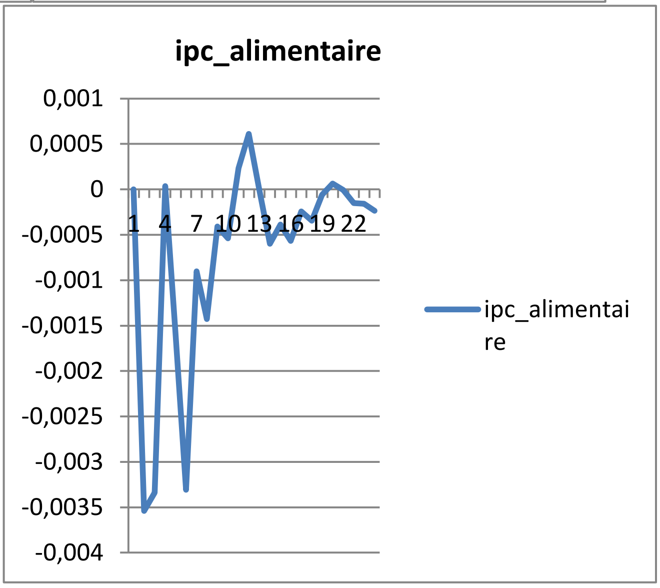
0,0002
0
-0,0002
-0,0004
-0,0006
-0,0008
-0,001
-0,0012
-0,0014
1 4 7 10 13 16 19 22
concours


ipc_alimentaire
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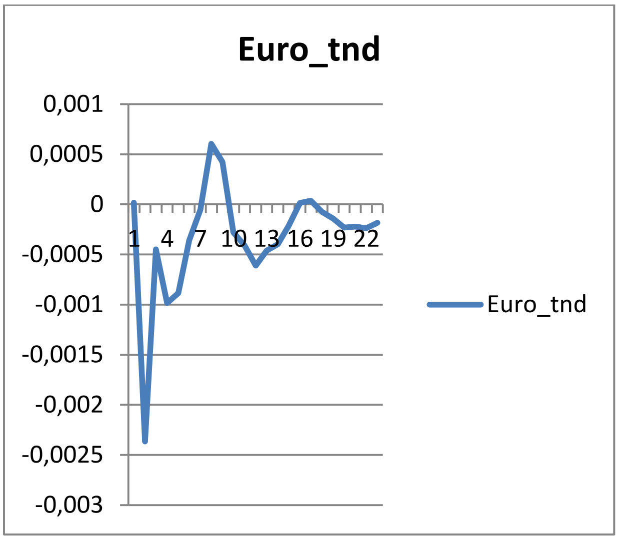
0,0005
0
-0,0005
-0,001
-0,0015
-0,002
-0,0025
-0,003
-0,0035
-0,004
1 4 7 10 13 16 19 22
ipc_alimentaire


Euro_tnd
0,001
0,0005
0
-0,0005
-0,001
-0,0015
-0,002
-0,0025
-0,003
1 4 7 10 13 16 19 22
Euro_tnd

The results show that for an increase of interest rate, real activity variables decline temporarily and the impulse responses turn to zero after two to three years, depending on the activity measure consistent with real long-run neutrality of monetary policy.

These approaches (one step and two steps) differ in various dimensions and it’s not clear a priori that one should be favored over the other. The results of these two approaches produce qualitatively similar results, but the two step approach tends to produce more “plausible” responses.

4. Conditional forecasts

4.1. Theoretical Model of Unconditional forecast:

In many cases forecasts of macroeconomic variables that are conditioned on fixed paths of others variables is required, that's relevant to central bank applications. One may want to forecast credit and money growth assuming that inflation and GDP growth follow future paths fixed at the official central bank forecast. Waggoner and Zha (1999), provide a convenient framework to calculate not only the conditional forecasts but also the forecast distribution using Gibbs sampling algorithm.

Consider forecasting from a VAR (1) model:

$$y_t = c + \sum_{l=1}^{P} \phi_l \; Y_{t-l} + C\varepsilon_t \;,\; \varepsilon_t \sim i.i.d.N(0,1) \qquad (1)$$

Where y_t denotes a $T \times N$ matrix of endogenous variables, ε_t are the uncorrelated shocks and $A_0 A_0^{'} = \sum$ where $\sum$ denotes the variance of reduced form VAR residuals.

Before discussing conditional forecasts and forecast revisions, the first step is to write down a formula for a multi-step ahead unconditional forecast of y. To simplify the derivation, we rewrite the VAR in terms of $z_t = y_t - \mu$ deviations of y_t from the central level μ defined as:

$$\mu = (I - \sum_{l=1}^{P} \phi_l)^{-1} c \qquad (2)$$

In the case of stationary VAR processes, μ is an unconditional mean. While, μ cannot be computed when the root of the VAR process is exactly unity because the matrix in equation (2) is not invertible.

The VAR in the companion form is:

$$\tilde{z}_t = F\tilde{z}_{t-1} + G\tilde{\varepsilon}_t \qquad (3)$$

Where

$$F_{pn \times pn} = \begin{pmatrix} \phi_1 & \cdots & \phi_P \\ I & & 0 \\ & & \end{pmatrix}, G = \begin{pmatrix} C & 0 \\ 0 & 0 \end{pmatrix}, \; \tilde{z}_t = \begin{pmatrix} z_t \\ \vdots \\ z_{t-p+1} \end{pmatrix}, \tilde{\varepsilon}_t = \begin{pmatrix} \varepsilon_t \\ \vdots \\ 0 \end{pmatrix}$$

Take $\tilde{z}_{S+h}$ and using equation (3) and we substitute recursively $\tilde{z}_{S+h-1}$, $\tilde{z}_{S+1,}$ in the first rows way obtain z_{s+h} expressed in terms of data up to S and subsequent errors

$$z_{s+h} = F^{h}_{(1\ldots N)} \tilde{z}_S + C\varepsilon_{S+h} + \psi_1 C\varepsilon_{S+h-1} + \ldots + \psi_{h-1} C\varepsilon_{S+1} \qquad (4)$$

Where ψ_j is the upper left $N \times N$ block of F^j (F to the power j). $\psi_j C$ is the matrix of orthogonalized impulse responses after j periods. $F^h_{(1,..,N)}$ is the matrix composed of the first N rows of F^h. The stacked vector of $z_{S+1},....z_T$ can be written as:

$$\begin{pmatrix} z_{S+1} \\ \cdots \\ z_T \end{pmatrix} = \begin{pmatrix} F_{(1..N,.)} \\ \cdots \\ F^{T-s}_{(1..N,.)} \end{pmatrix} \tilde{z}_S + \begin{pmatrix} C & 0 & 0 \\ \psi_1 C & C & 0 \\ \psi_{t-S+1} C & ..\psi_1 C & C \end{pmatrix} + \begin{pmatrix} \varepsilon_{s+1} \\ \cdots \\ \varepsilon_T \end{pmatrix} \qquad (5)$$

Or:

$$\text{z=H}\tilde{\text{z}}_S + R\varepsilon \qquad (6)$$

The above derivation is standard for stationary VAR and follows Hamilton (1994, pp.258-260).

4.2 The conditional forecast:

Scenario analysis

In this section, we perform a scenario analysis to assess the effects of positive development in real GDP represented by a 2.5% percentage point stronger growth (on impact). We compute the effects of the scenario by using our framework to produce conditional forecasts. Specifically, we estimate our model on the whole sample and generate two forecasts: an unconditional forecast for $T+1,............T+h$ given the sample 1,2,.........T which provides "baseline scenario"), and a conditional forecast in which the real GDP in $t+1$ is set to the value of its unconditional forecast plus 2.5 percentage points and all of the remaining variables are unconstrained.

In this section, we are planning to produce conditional forecasts from the FARVAR model developed in section (1), conditional on different paths for GDP. In fact, there are two methods to do this. These methods depend on our assumptions concerning the paths of GDP.

If we assume that GDP is an observed factor so that we have a VAR for the factor plus GDP and potentially the interest rate. Then we just use standard techniques to conditionally forecast the factors from the VAR assuming a certain path for GDP and then using the factor loadings, we can forecast the monetary aggregate (M3).

However, if we suppose that GDP does not enter the VAR for the factors we can use an algorithm based on Kalman filtering techniques to compute the conditional forecasts. The Kalman filter works recursively, i.e. period by period (Clarida and Coyle (1984)) and it reduces significantly the computational for longer forecast horizons and is particularly well suited for empirical approaches.

In this case, we consider a $(T-S)$-step ahead forecast of z in some of the periods. The total length of z is $k \equiv N(T-S)$, of which q elements are known and the remaining $k-q$ are unknown. The fact that q elements are known implies that we have q restrictions on ε, given by rows k of equation (6).

In the case of the factor model, structural shocks, $\eta_t = (\eta_{1,t}, \ldots\ldots\ldots, \eta_{r,t})'$, $E(\eta_t \eta'_t) = I_r$ are linear combinations of the shocks to the factors . We know that $u_t = \Gamma \eta_t = \gamma_1 \eta_{1,t} + \cdots \gamma_r \eta_{r,t}$, where Γ contains the contemporaneous responses to the shocks and $\Gamma \Gamma' = Q$. I f we are interested in obtaining the scenario based only on the last $r-s$ shocks, and then it is sufficient to replace Q with $\tilde{Q} = \gamma_{s+1} \gamma_{s+1}' + \ldots + \gamma_r \gamma_r'$.

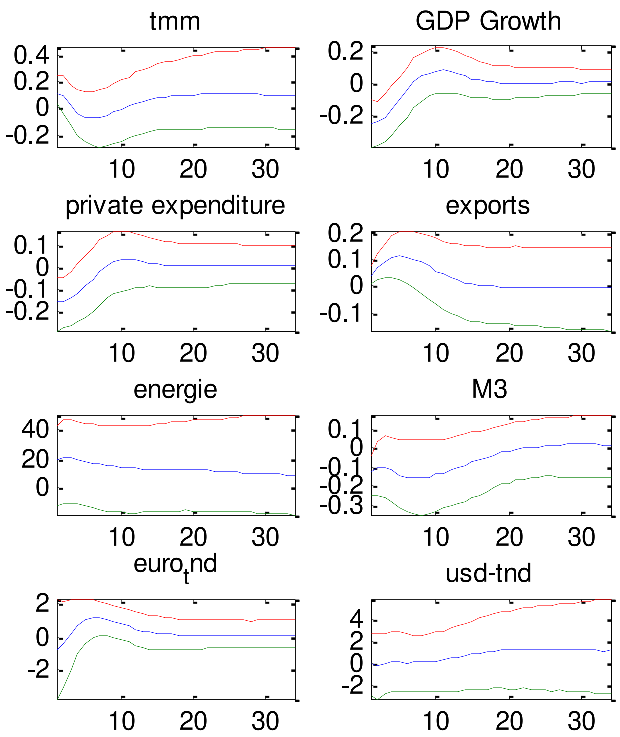
Another observation is that the conditional forecast framework can be used to obtain impulse response functions for VAR with recursive identification schemes. In this case Γ is lower triangular, and the impulse response function to a shock $\eta_{i,t}$ is obtained as:

$$
\begin{aligned}
&IRF_j^i = E(Y_{t+j} / \varepsilon_{1,t} = 0, \cdots, \varepsilon_{i-1,t} = 0, \varepsilon_{i,t} = \gamma_{ii}; Y_{t-1}, \ldots., Y_{t-p}) \\
&-E(Y_{t+j} / Y_{t-1}, \ldots, Y_{t-p}), \qquad (7)
\end{aligned}
$$

Empirical results

Our data set includes 30 macroeconomic variables. In fact, the sample covers the period from 2000Q1 to 2015Q4. We estimate a VAR (2) model for factors, GDP growth plus TMM (interest rate) and we use the estimated VAR to forecast M_3 assuming GDP growth remains fixed at 0,1% over the forecast horizon . As shown in Waggoner and Zha (99), the choice of identifying restrictions (the structure ofA_0) does not affect the conditional forecast which depends on the reduced form VAR. Therefore, it's convenient to use the Choleski decomposition to calculateA_0. The conditional forecast is calculated by simulating the VAR using the restricted shocks.

Figure 4: impulse responses for variables

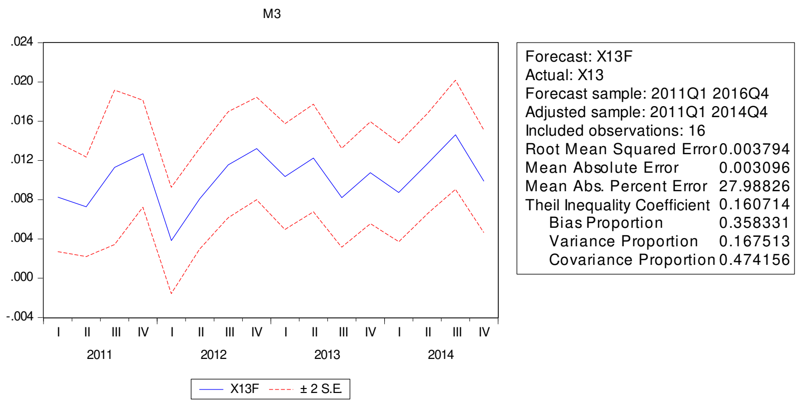


This figure shows the responses of some selected variables of the model function to an increase in TMM (-0.2%), as assumed in the scenario assumption. Considering the scenario analysis, the top left panel reports the decrease in TMM of 0.2% on impact. The real economy (GDP, exports, imports and private investment) keep on increasing for the first year, and then tends to drop back to the level prevailing before the initial increase. Consumer prices are also higher, reaching a peak after about two years. Credit aggregates; follow the same path as GDP and the monetary aggregates decreases on impact.

5. Comparison to conditional forecasts of M3

We generate forecasts of **M3** from the model conditional on the realized paths of the following variables: real GDP and the short-term interest rate. We consider the estimation of **Conditional FAVAR** model using quarterly data Tunisia from **2000Q1 to 2010Q4 (training sample)**. New forecasts are obtained **until 2015Q4. Out of sample forecast accuracy is measured in terms of RMSE**.

Figure 4: RMSE for individual models



	h=1	***h=2***	***h=3***	***h=4***
Individual Model Forecasts				
Random walk	2.07	1.18	1.2	1
SARIMA	0.96	0.99	1.27	1.38
FAVAR	0.73	0.79	0.81	0.9
TVP	0.64	0.74	0.79	1.11
FAVAR_conditionnal	0.59	0.66	0.65	1.05

The gains are clearly evident for the conditionnel FAVAR compared to others approaches. **Also,** forecast **1 quarter and 2-quarter** ahead M3 are better compared to **3 and 4 quarters ahead.**

6. Conclusion

In this paper, we have used two approaches to analyze the dynamic interactions among a large dataset of macroeconomic and financial indicators, as FAVAR and conditional FAVAR. We find that both classes produce accurate unconditional forecasts and meaningful scenarios (the robustness and reliability of dynamic factor models for analyzing large macroeconomic datasets has been established for Tunisia in relation to forecasting and impulse response function analysis.

In addition, the conditional FAVAR describe how scenarios analysis can be implemented and the findings of the study illustrate that conditional dynamic factor model, incorporating more economic information, perform better than individual models as TVP, SARIMA and RW in terms of reducing forecast errors.

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Appendix

A FAVAR model application

The **FAVAR model** used in this section is based on quarterly dataset of 30 macroeconomic variables, spanning the period **2000Q1 to 2015Q4**. The underlying data in quarterly growth rates are divided into "slow moving " and "fast moving "variables, where the latter generally refer to asset prices. They are called fast-moving variables as they adjust contemporaneously to changes in the monetary policy. The program follows these steps;

- **The step 1** of the program consists to read data on Eviews workfile.
- **The second step** creates a group called "gall" out of all variables, with the exception of the interest rate. It also converts the group consisting of individual series into a matrix called data.
- **The third step** extracts three principal components called PC_1, PC_2 and PC_3 from the entire dataset of **29 macroeconomic variables**. We used the option 'cor' when calculating principal components. This forces Eviews to use the correlation matrix to extract the principal components and implies that the data does not need to be standardized. The eigenvectors (eigenvalues) are saved in a matrix called ***m1 (v1***). Looking at the output, we can see that the first three principal components explain slightly more than **60%** percent of the variation in the entire dataset.