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Monetary Policy Shocks and Economic Growth in Morocco: A Factor-Augmented Vector Autoregression (FAVAR) Approach

Marouane Daoui[1], Bouchra Benyacoub[2]
[1]*(Faculty of Law, Economics and Social sciences - Fez /University Sidi Mohamed Ben Abdellah, Morocco)*
[2]*(Faculty of Law, Economics and Social sciences - Fez /University Sidi Mohamed Ben Abdellah, Morocco)*

Abstract:
In response to the empirical anomalies relating to the use of VAR models in analysing the impact of monetary policy shocks, the Factor-Augmented VAR (FAVAR) models attempt to provide a practical solution. Moreover, these models, based on dynamic factor models (DFM), make it possible to summarize the information present in a large database into a small number of factors common to all the variables. In this paper, we analyse the effects of monetary policy shocks on economic growth using the FAVAR model on a large number of Moroccan macroeconomic time series (117 quarterly time series from 1985Q1 to 2018Q4). First, we present the econometric framework of the FAVAR model, then the data used and their necessary transformations. Next, we determine the number of factors before estimating the model. Then, we focus on the analysis of the impulse response functions of some indicators of economic growth in Morocco. The results of the analysis indicate that, the overall decline in GDP in response to monetary policy shocks suggests that they have a clearly negative impact on economic growth.

Key words*: Monetary policy shocks; Economic growth; Dynamic factor model; FAVAR; Morocco*

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I. Introduction

Currently, macroeconomic and financial data are increasingly available both in terms of number and length of series. The conduct of monetary policy by central banks takes place in an information-rich environment. In terms of econometric tools, the methods used in the analysis of monetary policy shocks generally refer to standard VAR models or their variants such as VECM (vector error-correction models) or SVARs (structural VAR models). However, it is known that the use of large amounts of information in these models is accompanied by dimensionality problems. In this paper we propose an approach in terms of FAVAR models (factor augmented VARs).

Bernanke et al. (2005), among others, recognize significant strengths in VAR models in their classical form. They note that VAR models provide empirical responses of economic variables to a monetary policy shock that are consistent with the relative simplicity of the model, which is its main strength. However, Bernanke et al. (2005) also point out some limitations associated with the use of VAR models to analyze monetary policy shocks. A first shortcoming is the disagreement over the most appropriate strategy for identifying shocks. A second limitation arises from the small number of variables used to maintain sufficient degrees of freedom for model estimation. Similarly, the limited number of variables used in the VAR model is far from covering the hundreds of variables tracked by economists and this fact can lead to two difficulties. First, the responses of the variables to shocks may be biased because of the absence of a large number of variables containing information used in decision making. Second, an inevitable consequence of VAR models is that the number of observable responses is constrained by the reduced number of variables in the model. However, we may be interested in the responses of variables not included in the model for reasons of degree of freedom.

To correct the weaknesses of VAR models, Bernanke et al. (2005) propose new information-rich econometric models. These models allocate Factor Augmented Autoregressive Vectors (FAVARs) based on the dynamic factor models (DFM) or diffusion indixes used by Stock and Watson (2005). Dynamic Factor Models are considered the tool for "big data" in macro-econometrics. These models apply to many contexts where econometricians seek to synthesize a large number of heterogeneous time series. They allow the common dynamics of a large number of macroeconomic variables to be summarized as a relatively small number of latent variables called factors. These models have proven to be very useful tools for shock analysis and economic forecasting.

In this paper, we will use the FAVAR model to analyze the impact of monetary policy shocks on economic growth in Morocco. The model used has allowed us to obtain impulse response functions for all indicators in the macroeconomic data set used (117 quarterly series from 1985: Q1 to 2018: Q4) in order to have a more realistic and complete representation of the impact of monetary policy shocks on the Moroccan economy. However, in our analysis, we were interested only in the main indicators of economic growth in Morocco.

II. Econometric framework of the FAVAR model

2.1 Dynamic and static forms:

Bernanke et al. (2005) mention that the factors will allow us to model certain concepts that are difficult to identify using one or two variables. Indeed, we will consider a number M of observable variables contained in the vector Y_t and K "factors" contained in the vector f_t, the dynamics of the economy is modelled by the following vector augmented factor model (FAVAR) :

$$\begin{bmatrix} f_t \\ Y_t \end{bmatrix} = \gamma(L) \begin{bmatrix} f_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t \quad : \forall\, t = 1, \dots, T \qquad (1)$$

This Where $\gamma(L)$ is a polynomial matrix including P lags and ν_t is a vector of $[(K+M) \times 1]$ containing the statistical innovations of null mean. The factors f_t, representing aggregate economic concepts, are by definition non-observable. However, we can consider a panel of N observable and informative economic series included in the X_t vector where $N \gg K$ and $N \gg M$ such that :

$$X_t = \lambda_f(\mathrm{L}) f_t + \lambda_Y Y_t + e_t \quad : \quad \forall\ t = 1, \dots, T \qquad (2)$$

Where $\lambda_f(\mathrm{L})$ is a polynomial matrix including S lags and e_t is a $[N \times 1]$ vector containing the statistical innovations of mean zero. The observable series of X_t, which can number in the tens or hundreds, share a common component described by the factors of f_t and Y_t and an idiosyncratic part represented by the residuals e_t. The factors of f_t and Y_t are considered orthogonal to the residuals of e_t. The residuals can be temporally correlated with the residuals of other variables, but the correlation should be limited. Under this assumption, the form of the FAVAR is called "approximated" (Stock and Watson, 2005). The aim is therefore to observe the responses of certain macroeconomic variables contained in X_t to structural shocks associated with the variables in Y_t. However, in order to estimate the factors, we must first transform the dynamic form into a static form.

As noted by Stock and Watson (2005), every FAVAR model has a static representation in which there are R static factors contained in the F_t vector that represent the present and past values of the K dynamic factors. In other words, if $\lambda_f(\mathrm{L})$ in the equation (2) has S lags, then there will be $R = K \times (S+1)$ static factors such as $F_t = [f_t f_{t-1} \dots f_{t-s}]$. Based on equations (1) and (2), the static form of the FAVAR model is described by the following two equations:

$$X_t = \Lambda_F F_t + \Lambda_Y Y_t + E_t \quad : \quad \forall\ t = 1, \dots, T \qquad (3)$$

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Gamma(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + V_t \quad : \forall\, t = 1, \dots, T \qquad (4)$$

Where F_t is a vector of size $[R \times 1]$ containing the R static factors and $\Gamma(L)$ a polynomial matrix with L lags. The residuals E_t and V_t are zero means.

To summarize, the dynamics of the economy and the transmission mechanisms are modelled by the FAVAR model of the equation (4). This FAVAR model allows the use of observable series contained in Y_t. These series are considered observable factors because they intervene directly in the dynamics of the economy to impact all economic variables. These series are supplemented by the non-observable factors F_t modelling economic concepts plus "diffuse". The equation (3) indicates that many of the economic series included in X_t are influenced by these factors, which represent the common component shared by the variables in X_t. This last equation will allow us to estimate the non-observable factors.

2.2 Estimation and identification of shocks:

Although the static factors F_t are not observable, the equation (4) will allow us to estimate them. Two estimation methods are generally used: the first is based on principal component estimation (PCA), the second is based on Bayesian likelihood estimation. However, the two-step PCA method has the non-negligible advantage of being non-parametric. Bernanke et al. (2005) propose to estimate unobservable factors in two steps. The first step is to estimate the non-observable factors from the equation (3). The second step consists in estimating the FAVAR of the equation (4).

Concerning the identification of structural shocks, the aim is to observe the responses of variables X_t to shocks associated with observable factors Y_t. However, the VAR model residuals of the equation (4) represent statistical innovations and not structural shocks. To identify the latter, let us write the structural form of the VAR model of equation (4):

$$\Phi \begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Theta(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + U_t \quad \forall\, t = 1, \dots, T \qquad (5)$$

Where U_t is a vector that contains the structural shocks such that their variance covariance matrix is equal to I; the unit matrix. From VAR models (equations 1 and 4), we can deduce:

$$U_t = \Phi V_t \qquad \forall\ t = 1, \dots, T \qquad (6)$$

To compute Φ, we will apply a Cholesky decomposition to the variance covariance matrix Σ of the residuals V_t is equal to : $\Sigma = E(V_t V_t') = \Phi^{-1} E_t(U_t U_t') \Phi^{-1\prime} = \Phi^{-1}\Phi^{-1\prime}$. The latter allowing us to retrieve a lower triangular matrix Φ^{-1}.

From equations (3), (4) and (6), we can calculate the moving average representation of X_t which is:

$$X_t = \Lambda[I - \Gamma(L)]^{-1}\Phi^{-1} U_t + E_t \qquad \forall\ t = 1, \dots, T \qquad (7)$$

From this representation, we will be able to study the responses of the variables X_t to a structural shock U_t.

III. Empirical application

3.1 Data and transformations:

As mentioned above, our database consists of 117 quarterly time series from 1985:Q1 to 2018:Q4. The variables used come mainly from monetary reports and statistics from Bank Al-Maghrib (BM), statistics from the Office of the High Commissioner for Planning (HCP), the Exchange Office (OC), the Casablanca Stock Exchange (BVC) and the International Financial Statistics of the International Monetary Fund (IMF). The different series are listed by category in Table (1), the full list of which is presented in Appendix. Due to the unavailability of certain variables at a quarterly frequency, the annual series have been quarterlyized, as have the monthly series.

Table 1: Time series in the database by categories

#	Categories	Number of series	Frequency	Source
1	Gross Domestic Product by Industry, base 2007	21	A: [1985 - 2006] Q: [2007Q1 - 2018Q4].	HCP
2	Domestic production by industry, base 2007	16	A: [1985 - 2018]	HCP
3	Gross National Disposable Income, base 2007	7	A: [1985 - 2006] Q: [2007Q1 - 2018Q4].	HCP
4	Gross National Expenditure	4	A: [1985 - 2018]	BM
5	Final consumption expenditure	9	A: [1985 - 2018]	IMF HCP
6	Investments	7	A: [1985 - 2018]	BM HCP
7	Currency	19	M: [1985M1 - 2018M12].	BAM
8	Stock market indicators	3	A: [1985 - 2001] M: [2002M1 - 2018M12].	BVC
9	Gross national savings, base 2007	3	A: [1985 - 2018]	HCP
10	Inflation, Consumer Price Index	5	Q: [1985Q1 - 2018Q4].	IMF
11	Industrial Producer Price Index	2	Q: [1985Q1 - 2018Q4].	IMF
12	Unemployment rate	1	A: [1985 - 1995] Q: [1996Q1 - 2018Q4].	IMF
13	Exchange rates	6	Q: [1985Q1 - 2018Q4].	IMF
14	Interest rates	4	Q: [1985Q1 - 2018Q4].	IMF
15	Foreign trade	10	A: [1985 - 1997] M: [1998M1 - 2018M12].	IMF OC
	Total	**117**		

-Notes: A: Annual - Q: Quarterly - M: Monthly
-Source: Authors**.**

The data have undergone four preliminary transformations. First, in the DFM, the theory associated with these models assumes that the variables are second order stationary. For this reason, each series has been transformed to be approximately zero-order integrated. Decisions regarding these transformations were guided by unit root tests (ADF and Phillips Perron tests) combined with visual examination and/or a priori economic judgment. Second, for each series, outliers were detected and statistically corrected based on the interquartile range (IQR). Third, following Stock and Watson (2012), the long-term mean of each series was removed using a double-weighted filter with a bandwidth of 100 quarters. Fourth, after these transformations, the series were normalized to have a unit standard deviation and to make them comparable on the same scale. Similarly, estimating the FAVAR model using the two-step principal component method (PCA) requires prior normalization of the variables.

The use of the FAVAR model also requires dividing the sample into two groups, fast and slow variables, according to their speed of response to shocks. Monetary aggregates, stock market indicators, interest rates, and exchange rates are considered fast variables. In contrast, the remaining variables are considered slow variables.

3.2 Determination of the number of factors:

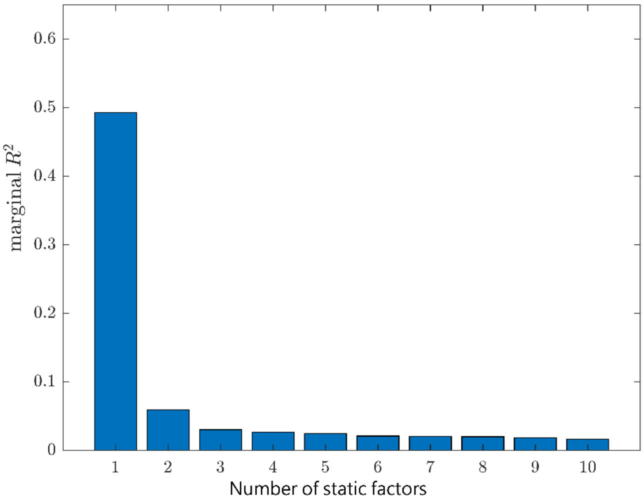
An important step before estimating the FAVAR model is to determine the number of static factors in the complete database. Indeed, we will use the criteria of Bai and Ng (2002) and Ahn and Horenstein (2013) respectively. Table (2) summarizes the factor number statistics: the marginal R^2 of the factors (the numerical values corresponding to the bars in figure (1) showing the scree of eigenvalues), the IC_{p2} information criterion of Bai and Ng (2002) and the eigenvalue ratio of Ahn and Horenstein (2013).

Table 2: Estimation of the number of static factors

Number of static factors	Trace R^2	Marginal trace R^2	BN-ICp2	AH-ER
1	0,493	0,493	-0,603	**8,286**
2	0,553	0,060	**-0,651**	1,961
3	0,583	0,030	-0,645	1,144
4	0,609	0,027	-0,634	1,065
5	0,634	0,025	-0,623	1,184
6	0,655	0,021	-0,606	1,021
7	0,676	0,021	-0,591	1,029
8	0,696	0,020	-0,578	1,088
9	0,714	0,018	-0,564	1,129
10	0,731	0,016	-0,546	1,072

- Notes: BN-ICp2 refers to the ICp2 information criterion of Bai and Ng (2002). AH-ER is the ratio of Ahn and Horenstein (2013) which is the ratio between the i^{th+1} and the i^{th} eigenvalue. In each column, the minimum value of BN-ICp2 and the maximum value of the Ahn-Horenstein ratio, which are shown in bold, represent the respective estimates of the number of factors.
- Source: Authors' calculations.

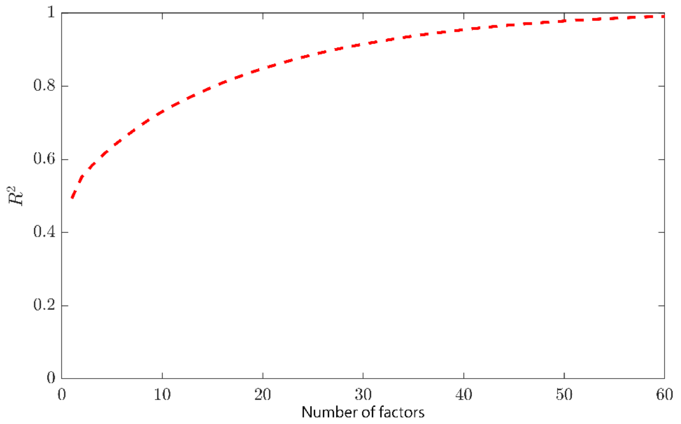
Figure 1: Eigenvalue scree plots for all data sets



Source: Authors' simulations.

As shown in figure (1), the dominant contribution to the trace of R^2 of the 117 aggregates comes from the first factor which fully explains 49.3% of the variance of the 117 time series. Nevertheless, there are potentially significant contributions to R^2 from the second and third factors: the marginal R^2 of the second factor over the whole sample is 6%, that of the third factor is 3%. The total R^2 of the first four factors is 61%, a significant increase from the 49.3% explained by the first factor alone. The IC_{p2} criterion of Bai and Ng (2002) estimates two factors, while the ratio of Ahn and Horenstein (2013) estimates only one factor. Similarly, figure (2) shows how the trace of R^2 increases with the number of principal components (for a maximum of 60 principal components). This ambiguity is often encountered, in which case a judgment has to be made depending on the purpose for which the DFM is used. For the forecasting of economic growth, the sampling error associated with a large number of factors could exceed their predictive contribution. However, we can use more factors for structural analysis using DFMs because it is important that factor innovations cover the space of structural shocks and that the large number of factors capture variation.

Figure 2: Cumulative R^2 as a function of the number of factors



Source: Authors' simulations.

In principle, there are at least two possible reasons why there could be more than one factor. The first possible reason is that there could be a single dynamic factor that manifests itself as multiple static factors. The number of dynamic factors can be estimated from the number of static factors. Then, applying the test of Amengual and Watson (2007) to the data set, with four static factors, it is estimated that there are only two dynamic factors (Table 3). However, the contribution to the R^2 trace of possible additional dynamic factors remains significant in the economic sense, so the estimate of two dynamic factors is suggestive but inconclusive.

Table 3: Amenguel-Watson's estimate of the number of dynamic factors: BN-ICpi values

Number of dynamic factors	Number of static factors									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	-0,382	-0,375	-0,369	-0,362	-0,362	-0,361	-0,361	-0,364	-0,361	-0,364
2		**-0,399**	**-0,393**	**-0,383**	**-0,388**	**-0,387**	**-0,386**	**-0,388**	**-0,388**	**-0,382**
3			-0,380	-0,373	-0,379	-0,375	-0,376	-0,377	-0,378	-0,372
4				-0,360	-0,362	-0,356	-0,355	-0,356	-0,359	-0,355
5					-0,338	-0,332	-0,331	-0,334	-0,339	-0,337
6						-0,309	-0,308	-0,312	-0,317	-0,315
7							-0,287	-0,291	-0,297	-0,296
8								-0,272	-0,279	-0,278
9									-0,257	-0,257
10										-0,236

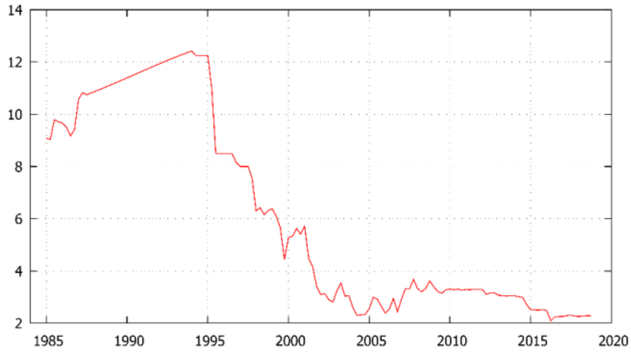
- **Notes:** The values of BN-ICp2 are calculated using the covariance matrix of the residuals of the regression of the variables on the lagged values of the number of static factors in the column, estimated by the principal components.
- **Source:** Authors' calculations.

The second possible reason is that these series vary in response to multiple structural shocks and that their responses to these shocks are sufficiently different that innovations to their common components cover the space of more than one aggregate shock.

3.3 Empirical results:

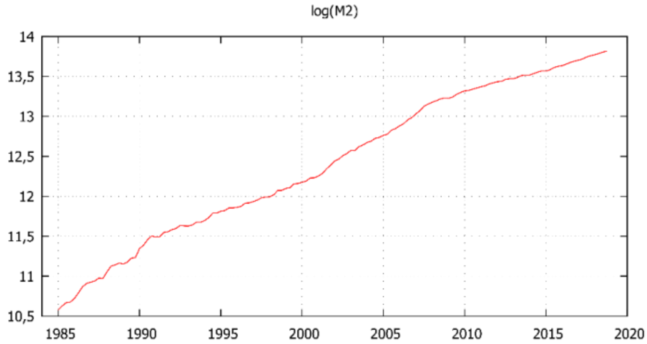
Using the FAVAR model of equation (4), as Bernanke et al. (2005) and Boivin et al. (2010) do, the aim is to observe the responses of certain macroeconomic variables contained in X_t to structural shocks associated with the variable contained in Y_t. Indeed, this FAVAR model offers us the possibility to study the responses of all the variables contained in X_t, *i.e.* 117 impulse response functions. However, we are only interested in the main indicators of economic growth. In order to choose the global number of lags of a FAVAR model, we will usually use the traditional information criteria. These criteria, calculated on our FAVAR model, for Y_t represents the money market interest rate (MMIR), allow us to retain an optimal lag of 2. However, for the FAVAR model where Y_t represents the money supply (M2) the optimal lag found is 4. The evolutions of these two variables, MMIR and M2, are presented respectively in figures (3) and (4).

Figure 3: Money Market Interest Rates in Morocco



Source: Authors, based on data from BAM.

Figure 4: M2 Money Supply in Morocco (in logarithm)



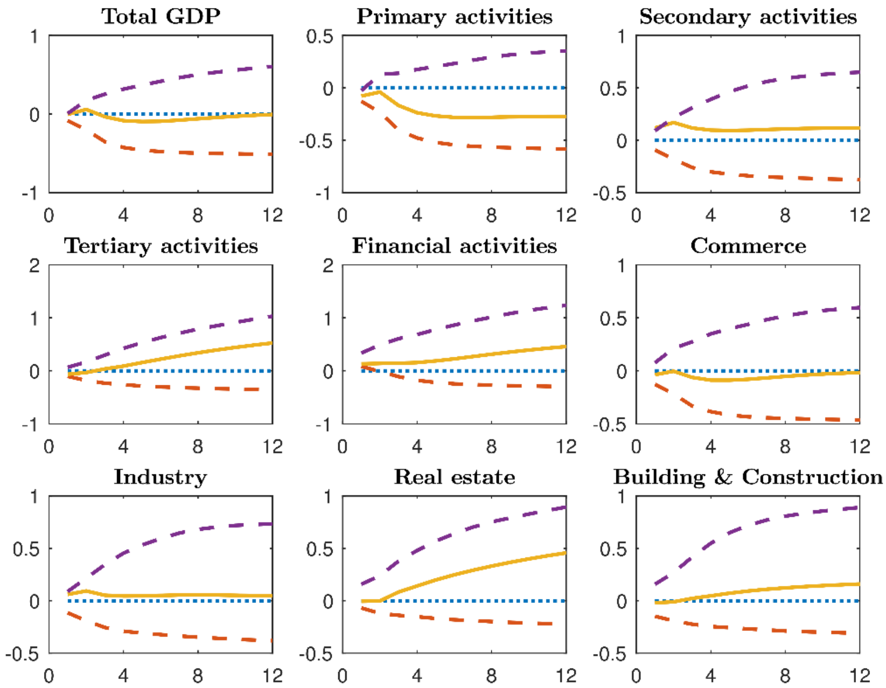
Source: Authors, based on data from BAM.

In fact, we have chosen this number of lags so that the residues of our FAVAR model can be considered as white noise. Our first FAVAR model therefore has 2 lags, 2 non-observable factors and only one observable factor (normalized first-difference money market interest rate). However, in our second model, where Y_t represents M2, there are 4 lags, 2 unobservable factors and only one observable factor (the money aggregate M2 in log first-difference and normalized). We therefore simulate the effects of a 25-basis-point increase in the money market interest rate (MMIR) and then in the monetary aggregate M2 (money supply shock) on Moroccan economic growth as measured by the few indicators of GDP by industry.

The impulse responses of variables representative of economic growth, by branch of activity, to these two types of restrictive monetary policy shocks are presented respectively in figures (5) and (6) with 95% confidence intervals. We adopt the boostrap procedure of Kilian (1998) which takes into account the uncertainty of the factor estimates in order to obtain more precise confidence intervals for the response functions of the variables. Indeed, the impulse responses show no significant anomaly.

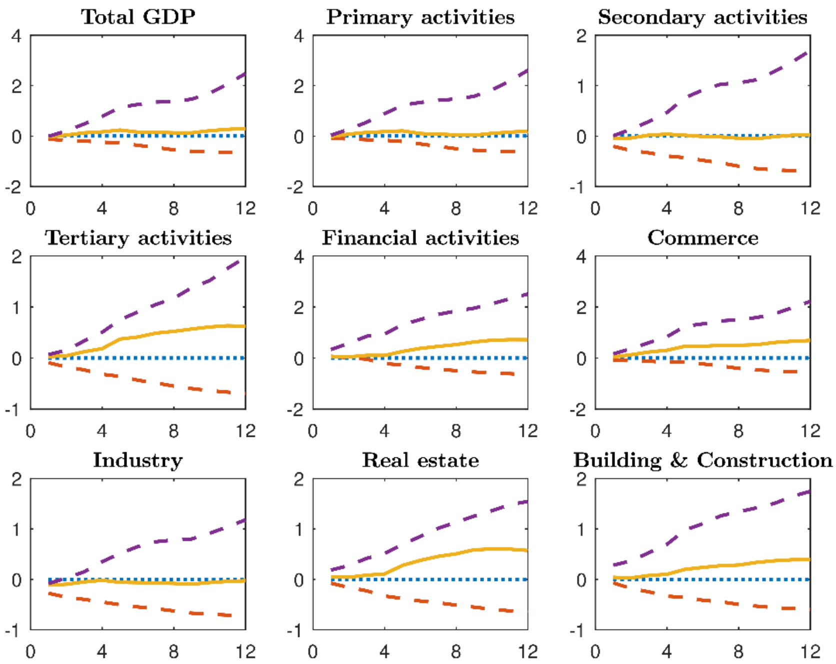
From figure (5), we observe that the shock of restrictive monetary policy (an increase in the money market interest rate) causes a slight decrease in total GDP and trade GDP, while it causes a remarkable decrease in GDP relative to tertiary activities as early as the second quarter following the shock. The fall in total GDP and trade GDP gradually weakens from the 8th quarter onwards to return to its initial state. However, the other GDP indicators studied show an almost negligible increase.

Figure 5: Responses of Economic Growth Indicators to a Money Market Interest Rate Shock



Source: Authors' simulations.

Figure 6: Responses of Economic Growth Indicators to an M2 Shock



Source: Authors' simulations.

Moreover, in figure (6), the money supply shock (M2 shock) essentially causes a very slight decrease in industrial GDP . On the other hand, we observe a gradual increase in real estate GDP and GDP of financial activities from the 4th quarter onwards. We find almost the same behavior with respect to the GDP for construction and public works, but in a less strong way. The remaining variables do not show strong reactions to this category of monetary policy shock.

Tables (4) and (5) present, respectively for a TIMM and M2 shock, the results of the variance and R^2 decomposition for the economic growth indicators previously illustrated in figures (5) and (6). For each type of shock, the money market interest rate (MMIR) and the money supply (M2), the first column shows the contribution of the monetary policy shock to the variance of the forecast error at a 12-quarter horizon. The second column contains the R^2 of the common component for each of the variables studied.

Table 4: Analysis of the decomposition of variance and R^2 of a TIMM shock

Variable	Variance decomposition	R^2
Total GDP	0,0135	0,8269
Primary activities	0,0325	0,7955
Secondary activities	0,0184	0,7424
Tertiary activities	0,0312	0,653
Financial activities	0,0332	0,5692
Commerce	0,0124	0,4475
Industry	0,0083	0,6029
Real estate	0,0374	0,3400
Building & Construction	0,0103	0,1976

- **Notes:** The column entitled "variance decomposition" shows the fraction of the variance of the forecast error, at the 12-quarter horizon, explained by the monetary policy shock. R^2 refers to the fraction of the variance of the variable explained by the common factors.
- **Source:** Authors' calculations.

Table 5: Analysis of the decomposition of variance and R^2 of a M2 shock

Variable	Variance decomposition	R^2
Total GDP	0,0144	0,8239
Primary activities	0,0119	0,8124
Secondary activities	0,0056	0,7079
Tertiary activities	0,0332	0,6358
Financial activities	0,0278	0,6376
Commerce	0,0445	0,4490
Industry	0,0172	0,5921
Real estate	0,0419	0,3912
Building & Construction	0,0307	0,2120

- **Notes:** The column entitled "variance decomposition" shows the fraction of the variance of the forecast error, at the 12-quarter horizon, explained by the monetary policy shock. R^2 refers to the fraction of the variance of the variable explained by the common factors.
- **Source:** Authors' calculations.

Indeed, the contribution of the money market interest rate shock (MMIR) to the variance of the forecast error is between 1.03% and 3.74%. In particular, this shock explains respectively 1.35%, 3.32% and 3.74% of the forecast error of total GDP, GDP of financial activities and real estate GDP. On the other hand, the contribution of the M2 shock is between 0.56% (GDP of secondary activities) and 4.45% (GDP - trade). This suggests that the effects of these two monetary policy shocks on economic growth are relatively small.

The R^2 analysis indicates that the R^2 of GDP construction, GDP real estate and GDP trade are particularly low, suggesting that we should have less confidence in the estimates of the impulse response of these variables. However, the variance of the factors estimated in the FAVAR model explains a large percentage of the variance of the remaining variables.

IV. Conclusion

The use of the FAVAR models is all the more relevant because of the use of a rich database, which allowed us to analyze the responses of some representative indicators of economic growth to monetary policy shocks (money market interest rate and money supply shocks) in Morocco.

Overall, the FAVAR model simulations show that monetary policy shocks influence the evolution of the main indicators of economic growth. Indeed, the analysis of impulse responses shows that the effect of a tightening of monetary policy (money market interest rate shock) leads, in the second quarter following the shock, to a decline in total GDP, GDP of primary activities, GDP of tertiary activities, and GDP of trade. On the other hand, the money supply shock (M2 shock) essentially leads to a decrease in GDP Industry. The overall decline in GDP in response to these two types of monetary policy shocks, in the short run, therefore suggests that they have a clearly negative impact on economic growth.

Finally, there is one area for improvement that deserves to be studied. This involves combining the FAVAR models and the time-varying parameter approach (Time-Varying FAVAR) in order to shed light on the question of whether the transmission mechanism of monetary policy shocks in Morocco has changed over time and, if so, how.

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Appendix: Data Description

The database is composed of 117 time series at quarterly frequency from 1985:Q1 to 2018:Q4. “Fast” variables are denoted with an asterisk (*), the remaining block of variables is considered “slow”. The transformation of the variables to make them stationary is done according to the transformation codes (TC) below:

- No transformation: $X_{it} = Y_{it}$
- First difference: $X_{it} = \Delta Y_{it}$
- Second difference: $X_{it} = \Delta^2 Y_{it}$
- Logarithm $X_{it} = \log Y_{it}$
- First difference of logarithm: $X_{it} = \Delta \log Y_{it}$
- Second difference of logarithm: $X_{it} = \Delta^2 \log Y_{it}$

#	Mnemonic	Description	TC
Gross Domestic Product by branch of activity, base 2007 (MMAD)			
1	TGDP	Gross Domestic Product (Total)	5
2	GDPFIA	GDP: Financial and insurance activities	5
3	GDPPA	GDP: Primary Activities	5
4	GDPGPASS	GDP: General public administration and social security	5
5	GDPSA	GDP: Secondary activities	5
6	GDPONFS	GDP: Other Non-Financial Services	5
7	GDPTA	GDP: Tertiary activities	5
8	GDPBPW	GDP: Building and Public Works	5
9	GDPT	GDP: Trade	5
10	GDPEGW	GDP: Electricity, gas and water	5
11	GDPEHSA	GDP: Education, Health and Social Action	5
12	GDPEP	GDP : excluding primary	5
13	GDPHR	GDP: Hotels and restaurants	5
14	GDPEI	GDP: Extraction industry	5
15	GDPRERBS	GDP: Real estate, rentals and business services	5
16	GDPMI	GDP: Manufacturing industry	5
17	GDPTPS	GDP: Taxes on products net of subsidies	5
18	GDPPT	GDP: Post and telecommunications	5
19	GDPTI	GDP: Total Industries	5
20	GDPT	GDP: Transportation	5
21	GDPNA	GDP: non-agricultural AV	5
National production by branch of activity, base 2007 (MMAD)			
22	NPTBL	NP: Total business lines	5
23	NPGPASS	NP: General Public Administration and Social Security	5
24	NPFIA	NP: Financial and Insurance Activities	5
25	NPPA	NP: Primary Activities	5
26	NPONFS	NP: Other Non-Financial Services	5
27	NPBPW	NP: Building and Public Works	5
28	NPT	NP: Trade	5
29	NPEGW	NP: Electricity, gas and water	5
30	NPEHSA	NP: Education, Health and Social Action	6
31	NPHR	NP: Hotels and Restaurants	5
32	NPEI	NP: Extraction Industry	5
33	NPRERBS	NP: Real Estate, Rental and Business Services	6
34	NPMI	NP: Manufacturing Industry	5
35	NPPT	NP: Post and Telecommunications	5

36	NPRPOEP	NP: Refining of Petroleum and Other Energy Products	2
37	NPT	NP: Transportation	5
Gross National Disposable Income, base 2007 (In million MAD)			
38	FCE	Final consumption expenditure	5
39	FCEGG	Final consumption expenditure general government	5
40	HFCE	Household final consumption expenditure	2
41	GNI	Gross National Income	2
42	GNDI	Gross National Disposable Income	2
43	NPIES	Net property income from external sources	2
44	NCTA	Net current transfers from abroad	5
Gross National Expenditure			
45	GNED	Gross national expenditure deflator	2
46	GNECU	Gross national expenditure (units of local currency in current)	5
47	GNECO	Gross national expenditure (local currency units in constant dollars)	5
48	GNEGDP	Gross national expenditure (% of GDP)	2
Final consumption expenditure			
49	FCECU	Final consumption expenditure (current MAD)	5
50	FCECO	Final consumption expenditure (constant MAD)	5
51	HDCCU	Household final consumption at current prices	5
52	FCEHNGDP	Final consumption expenditure of households and NPISHs (% of GDP)	2
53	FCENNCU	Final consumption expenditure, nominal, national currency	5
54	FCENGDP	Final consumption expenditure, nominal, ratio to GDP, percentage	2
55	FCEPSN	Final consumption expenditure, private sector, nominal, MAD	2
56	FCEGDP	Final consumption expenditure (% of GDP)	2
57	FCEPS	Final consumption expenditure, public sector, MAD	5
Investments			
58	INVR	Investment rate	2
59	GIR	Gross investment rate	2
60	FDINI	Foreign direct investment, net inflows (% of GDP)	2
61	FDINO	Foreign direct investment, net outflows (% of GDP)	2
62	GFCFGR	Gross fixed capital formation (% growth)	2
63	GFCFCO	Gross fixed capital formation (constant MAD)	5
64	GFCFCU	Gross fixed capital formation (current MAD)	5
Currency (In MMAD)			
65	M1*	M1	5
66	M2*	M2	5
67	M3*	M3	5
68	ORA*	Official reserve assets	2
69	BCC*	Banknotes and coins in circulation	5
70	TACVB*	Term accounts and cash vouchers with banks	2
71	SAB*	Savings accounts with banks	4
72	FCIR*	Fiduciary Circulation	5
73	NRBAM*	Net receivables from BAM	2
74	REC*	Receivables	2
75	DDEP*	Demand deposit	2
76	SDBAM*	Sight deposits with BAM	2
77	SDBKS*	Sight deposits with banks	2
78	DDEPTR*	Demand deposits with the Treasury	2
79	CBKS*	Cash at banks	2
80	COMM*	Commitments	2
81	SINV*	Sight Investments	5
82	NIRES*	Net International Reserves	2
83	OMASS*	Other monetary assets	2
Stock market indicators			
84	SETUR*	Stock exchange turnover (In MMAD)	2
85	MCAP*	Market capitalization (in millions of MAD)	2
86	DIVD*	Dividends (In Millions of MAD)	5
Gross national savings, 2007 base (in millions of Moroccan dirhams)			
87	GNS	Gross national savings	2
88	GDS	Gross domestic savings	2
89	EXTS	External savings	2
Inflation, Consumer Price Index			
90	INFGDP	Inflation, GDP deflator (in %)	2
91	INFCP	Inflation, consumer prices (in %)	1
92	CPI	Consumer Price Index (2010 = 100)	4
93	CPIPY	CPI, Corresponding period of the previous year (in %)	2
94	CPOPP	CPI, Previous period (in %)	1
Industrial producer price index			
95	IPPIMAN	Industrial producer price index, manufacturing	2
96	IPPIMIN	Industrial producer price index, mining	2
Unemployment rate			

97	UMPR	Unemployment rate	2
Exchange rates			
98	ILTREGFE*	International Liquidity, Total reserves excluding gold, foreign exchange, SDR (Million)	2
99	ILTREGFC*	International Liquidity, Total reserves excluding gold, foreign currencies, US dollars. (Million)	2
100	ERMADSDR*	Exchange rate, MAD per SDR, average for the period	2
101	ERMADEUR*	Exchange rates, MAD per euro, Average for the period	1
102	ERMADUSD*	Exchange rate, MAD per US Dollar, average for the period	2
103	NEERI*	Exchange rate, Nominal effective exchange rate, Index	2
Interest rates			
104	IRDEP*	Interest rate, Deposit,	2
105	IRDIS*	Interest rate, discount	2
106	MMIR*	Interest rate, money market	2
107	IRGBYSMT*	Interest rates, government bond yields, short and medium term % %.	2
Foreign trade			
108	EBGS	External balance of goods and services (% of GDP)	2
109	TRAGDP	Trade (% of GDP)	2
110	EGSCU	Exports of goods and services (current MAD)	2
111	EGSCO	Exports of goods and services (constant MAD)	2
112	EGSGDP	Exports of goods and services (% of GDP)	2
113	IMPGSCU	Imports of goods and services (current MAD)	2
114	IMPGSCO	Imports of goods and services (constant MAD)	2
115	IMPGSGDP	Imports of goods and services (% of GDP)	2
116	EXTBGSCU	External balance in goods and services (current MAD)	2
117	EXTBGSCO	External balance in goods and services (constant MAD)	2

- **Source:** Authors.

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