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# The Effectiveness of Monetary Policy Transmission in a Dual Banking System: Further Insights from TVP-VAR Model

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## Abstract

Using a time-varying VAR model with drifting parameters and stochastic volatilities, this paper attempts to empirically investigate the monetary policy transmission in Saudi Arabia, as well as the role of Islamic banks in this transmission and the interactions between Islamic and conventional banks over a period of approximately 25 years. The findings provide empirical evidence of the dependence of Islamic banking activity on oil revenues, and suggest that, in practice, there are few differences between the Islamic banks' modus operandi and the methods used by conventional banks. However, the results do not provide clear evidence that Islamic banks are more stabilizing than conventional banks, even though the sensitivity of the non-oil economic activity to Islamic bank financing seems to be relatively less volatile than its sensitivity to conventional bank credits.

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## 1. Introduction

In 1933, Ragnar Frisch dissociated the analysis of the dynamics of economic fluctuations into impulse processes and propagation processes. Impulses occur irregularly, but when they occur, a propagation process transmits their effects through the economic system. Contemporary economists replace "impulse" with "shock" and "propagation" with "transmission" (Meltzer 1995) and define the monetary policy transmission mechanism as "*the process through which monetary policy decisions are transmitted into changes in real GDP and inflation*" (Taylor 1995).

Central Bank indirect control of interest rates is the monetary policy regime currently used in most countries. There is therefore an inconsistency between one of the main principles of Islamic finance, i.e. the prohibition of  $riba^1$ , and the conduct of monetary policy within a conventional framework. Although the literature on monetary policy transmission mechanisms in conventional finance is abundant, the study of the role of Islamic banks in monetary policy transmission has been the subject of very few empirical investigations (e.g. Di Mauro et al. 2013; Ben Amar et al. 2015; Hamza and Saadaoui, 2018), despite the rapid growth of the Islamic banking industry. Therefore, the purpose of this paper is to empirically investigate the role of Islamic banks in the monetary policy transmission process in Saudi Arabia.

The results found in the empirical literature on the transmission of monetary policy in Saudi Arabia are concordant and suggest that interest rate and bank lending channels appear to play an important role in the transmission process of monetary policy (e.g. Prasad and Khamis 2011; Cevik and Teksöz 2012; Espinoza and Prasad 2012; Westelius 2013).<sup>2</sup> However, they do not provide empirical evidence of the dynamic structure of the underlying economy. Thus, to analyze the transmission channels of monetary policy in Saudi Arabia, we use a time-varying VAR model with drifting parameters and stochastic volatilities (Primiceri, 2005), which enables us to capture possible nonlinearities in the underlying structure of the Saudi economy and provides us a diagnosis on the persistence of shocks as well as their variance.

The rest of the paper is organized as follows. Section 2 presents the empirical strategy. Section 3 outlines results and their economic interpretation. Finally, section 4 highlights the main conclusions and practical recommendations.

## 2. Empirical strategy

Since Primiceri's (2005) TVP-VAR model with stochastic volatility allows both changes in the structure of the economy and the volatility of shocks to be taken into account, it has been included in several empirical studies (e.g. He and Lin, 2018; Avouyi-Dovi et al. 2017; Baumeister et al. 2008; Gambetti et al. 2008; Nakajima, 2011; Bijsterbosch and Falagiarda, 2014; Carriero et al. 2015; Canova and Pérez Forero, 2015). Thus, to analyze the transmission channels of monetary policy in Saudi Arabia, we use the Primiceri's (2005) methodology of time-varying vector structural autoregressive models (TVP-VAR) with stochastic volatility.

<sup>&</sup>lt;sup>1</sup> While it is accepted in conventional finance, the interest rate is prohibited in Islamic finance. More precisely, what is condemned in Islam is the *riba*. This prohibition is the fundamental characteristic of Islamic finance and the major, if not unique, breaking point with conventional finance. However, the term *riba* is broader than interest and usury: any prefixed return in all types of transactions is *riba* and therefore prohibited. It refers to any benefit, whether monetary or not, other than the principal amount, to be paid to the lender as a condition for granting a loan or extending its repayment period.

 $<sup>^{2}</sup>$  These results are somehow expectable since the effectiveness of the bank lending channel requires banks to play an important role as a source of external funding for the private sector (Bernanke and Gertler, 1995), a condition which, *a priori*, is likely to be verified in emerging and developing economies with underdeveloped capital markets.

A standard structural autoregressive vector of order s [VAR(s)] is defined as:

$$Ay_{t} = F_{1}y_{t-1} + \dots + F_{s}y_{t-s} + u_{t}, \text{ with } t = s + 1, \dots, n$$
(1)

where  $y_t = (y_{1t}, ..., y_{kt})'$  is the  $k \times 1$  vector of endogenous variables,  $F_1, ..., F_s$  are  $k \times k$  matrices of coefficients, and A is the  $k \times k$  matrix of the simultaneous relations of the structural shock. The disturbance  $u_t$  is a  $k \times 1$  vector of orthogonal structural shocks, with  $u_t \sim N(0, \Sigma)$  and  $\Sigma$  a diagonal matrix.

The most common practice (e.g. Sims, 1980; Primiceri, 2005) is to assume the matrix A lower-triangular, normalize its diagonal to one and impose a recursive structure on it. By premultiplying model (1) by  $A^{-1}$  we obtain the following reduced form VAR model:

$$y_t = B_1 y_{t-1} + \dots + B_s y_{t-s} + A^{-1} \Sigma \varepsilon_t, \quad \varepsilon_t \sim N(0, I_k) \text{ and } B_i = A^{-1} F_i \text{ for } i = 1, \dots, s$$
 (2)

Stacking the elements in the rows of the  $B_i$ 's to form  $\beta$ , a  $k^2 s \times 1$  vector, and defining  $X'_t = I_k \bigotimes [y'_{t-1}, ..., y'_{t-s}]$ , the model (2) can be written as:

$$y_t = X_t \beta + A^{-1} \Sigma \varepsilon_t \tag{3}$$

Coefficients and parameters in model (3) are time-invariant. To extend it to a TVP-VAR model, the coefficients  $\beta$  and the parameters  $A^{-1}$  and  $\Sigma$  must be allowed to change over time, such that:  $y_t = X_t \beta_t + A_t^{-1} \Sigma_t \epsilon_t$ , with t = s + 1, ..., n (4)

Following Primiceri (2005) and Nakajima (2011), let  $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, ..., a_{kk-1})'$  be a stacked vector of the lower-triangular elements in  $A_t$  and  $h_t = (h_{1t}, ..., h_{kt})'$  the vector of the diagonal elements of the matrix  $\Sigma_t$  with  $h_{jt} = \log \sigma_{jt}^2$ , for j = 1, ..., k and t = s + 1, ..., n.

The parameters in (4) are assumed to follow a random walk process. Thus, the dynamics of the TVP-VAR model is specified by:

$$\beta_{t+1} = \beta_t + u_{\beta_t}$$
;  $a_{t+1} = a_t + u_{a_t}$ ;  $h_{t+1} = h_t + u_{h_t}$ 

where  $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$ ,  $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$  and  $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$ , for t = s + 1, ..., n.<sup>1</sup> All innovations in the model are assumed to be normally distributed, such as:

$$\begin{pmatrix} \epsilon_{t} \\ u_{\beta_{t}} \\ u_{a_{t}} \\ u_{h_{t}} \end{pmatrix} \sim N \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_{a} & 0 \\ 0 & 0 & 0 & \Sigma_{h} \end{pmatrix}$$

where  $\Sigma_{\beta}, \Sigma_a$  and  $\Sigma_h$  are diagonal matrices, and I an identity matrix of size k.

The estimation of TVP-VAR models with stochastic volatility requires the use of numerical methods to overcome the problem of over-identification (Koop and Korobilis, 2010). Indeed, although stochastic volatility makes the estimation difficult because the likelihood function becomes intractable, this type of non-linear state space models can be estimated using an MCMC (Monte-Carlo by Markov Chain) algorithm in the context of a Bayesian inference (Nakajima, 2011). The goal of the MCMC method is to assess numerically the joint posterior distribution of the parameters of interest (*i.e.* the unobserved states B, A and  $\Sigma$ ) and the hyper-parameters of the variance-covariance matrix (*i.e.*  $\Sigma_{\beta}$ ,  $\Sigma_{a}$  and  $\Sigma_{h}$ ) without computing the normalizing constant.

<sup>&</sup>lt;sup>1</sup> It is to note that parameters in s + 1 should be normally distributed around parameters in s.

Let  $y = \{y_t\}_{t=1}^n$  and  $\omega = (\Sigma_{\beta}, \Sigma_a, \Sigma_h)$ .  $\pi(\omega)$  is the prior probability density for  $\omega$ . Given the data y, samples are drawn from the posterior distribution,  $\pi(\beta, a, h, \omega|y)$ , by the following algorithm<sup>1</sup>:

- 1. Initialize  $\beta$ , a, h and  $\omega$ .
- 2. Sample  $\beta | a, h, \Sigma_{\beta}, y$ .
- 3. Sample  $\Sigma_{\beta}|\beta$ .
- 4. Sample  $a|\beta, h, \Sigma_a, y$ .
- 5. Sample  $\Sigma_a | a$ .
- 6. Sample  $h|\beta, a, \Sigma_h, y$ .
- 7. Sample  $\Sigma_h$ |h.
- 8. Go to (2)

For the i-th diagonals of the covariance matrices, we assume the following priors distributions:

$$\begin{cases} \left( \Sigma_{\beta} \right)_{i}^{-2} \sim \Gamma(40, 0.02) \\ (\Sigma_{a})_{i}^{-2} \sim \Gamma(4, 0.02) \\ (\Sigma_{h})_{i}^{-2} \sim \Gamma(4, 0.02) \end{cases}$$

As we have no information on the initial state of the time-varying parameters, we set, like Nakajima (2011), flat priors, such as  $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$ , and  $\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0} = 10 \times I$ .

## **3.** Settings and empirical results

#### 3.1. Data and settings

We estimate three models, and each includes four types of variables: (i) monetary policy control variable, (ii) transmission variables, (iii) monetary policy target variables, and (iv) an information-control variable. Let  $y'_t = [TGV'_t \ TRV'_t \ COV_t \ OP_t]$  the vector of endogenous variables, with  $TGV'_t[=P_t \ GDP_t]$  is the vector of the monetary policy target variables (*i.e.* the non-policy block),  $TRV'_t$  is the vector of transmission variables,  $COV_t[=T3MAS_t]$  is the control variable of monetary policy, and  $OP_t$  is the oil price. Table 1 illustrates the structure of each of the three models.

Transmission Channel	Control variable	Transmission variable	Target variables	$\mathbf{y}_{\mathbf{t}}'$	
Model 1 Benchmark Model		М		$[P_t GDP_t M_t T3MAS_t OP_t]$	
Model 2	T3MAS	$CBD \Leftrightarrow IBD$	$\text{GDP} \Rightarrow \text{P}$	$[P_t GDP_t CBD_t IBD_t T3MAS_t OP_t]$	
Model 3		$CBC \Leftrightarrow IBC$		$[P_t GDP_t CBC_t IBC_t T3MAS_t OP_t]$	

Table 1: Models' structure and identification restrictions

\* P stands for the Consumer Price Index, GDP for the private sector non-oil GDP, M for the broad money supply (M3), CBD for the deposits at conventional banks, IBD for the deposits at Islamic banks, CBC for the credit granted by conventional banks, IBC for the Islamic bank financing, T3MAS for the three-months interest rate and OP for the oil price.

The price of oil provides information on recent economic developments in the world and Saudi Arabia, and on the evolution of the scope of monetary policy in Saudi Arabia's total activity<sup>2</sup>.

<sup>&</sup>lt;sup>1</sup> For more details on the methods used to estimate the parameters and the smoother simulation algorithms used to accelerate the convergence of Markov chains, see De Jong and Shephard (1995), Shephard and Pitt (1997), Durbin and Koopman (2002), Watanabe and Omori (2004) and Nakajima (2011).

 $<sup>^{2}</sup>$  All other things being equal, the rise (respectively fall) in oil prices improves (worsens) the fiscal balance and, thereby, reduces (increases) the share of total GDP that is sensitive to monetary policy.

Thus, it reacts contemporaneously to every structural shock (Canova and Pérez Forero, 2015). The money demand equation is derived from the quantitative money equation. Thus, within the period money demand react to shocks on  $P_t$  and (GDP<sub>t</sub>). As for monetary policy, it reacts systematically and contemporaneously to shocks on  $P_t$  and GDP<sub>t</sub> (monetary policy response function). This equation will allow us to understand to what extent the monetary authority uses the interest rate to regulate the economic cycle (response to GDP shocks) and thereby control inflation (response to inflation shocks): any change in the interest rate that is not explained by this reaction function would be an exogenous shock of monetary policy (Kilian 2013)<sup>1</sup>. The interest rate is also used as a tool for controlling the money supply ( $M_t$ ). Empirical literature that examines the transmission mechanisms of monetary policy assumes that target variables (i.e. the non-policy block) do not react contemporaneously to shocks to control variables. Thus, the lower-triangular recursive structure of A assumes that target variables, non-oil private sector GDP, and inflation respond to monetary policy and information shocks with some time lag (Bernanke and Blinder, 1992; Canova and Pérez Forero, 2015; Pérez Forero, 2017)<sup>2</sup>.

To take into account the role of Islamic banks in the monetary policy transmission process, as well as the interactions between Islamic and conventional banks, we assume that money demand is sensitive not only to non-oil private output and prices, but also to the nature of the banks that make up the banking system. Thus, Model 2 distinguishes between conventional and Islamic banks deposits in order to capture the nature of interactions that may occur between Islamic and conventional banks following monetary policy shocks, and the extent to which they contribute to the transmission of those shocks. As in Bijsterbosch and Falagiarda (2014) and Gambetti and Musso (2017), among others, Model 3 aims to study the role of credit supply shocks on economic cycles. As credits make deposits, models 2 and 3 are expected to produce very similar results. Table 2 summarizes the definitions, frequency, and sources of the data.

	Table 2: Selected variables: definition, frequency and sources					
Variable	Definition	Frequency	Sources			
М	Broad money supply (M3)	Quarterly	SAMA Quarterly			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	Statistics			
TBD	Total bank deposits	Quarterly	SAMA Quarterly			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	Statistics			
IBD	Deposits at Islamic banks	Quarterly	Thomson One Banker /			
IDD	(in Saudi riyals / current price)	[1990:4 – 2017:2]	Author's calculations			
CBD	Deposits at conventional banks	Quarterly	Author's calculations			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	CBD = TBD - IBD			
TBC	Total bank credit	Quarterly	SAMA Quarterly			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	Statistics			
IBC	Islamic bank financing	Quarterly	Thomson One Banker /			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	Author's calculations			
CBC	Credit granted by conventional banks	Quarterly	Author's calculations			
	(in Saudi riyals / current price)	[1990:4 – 2017:2]	CBC = TBC - IBC			
Р	Consumer Price Index	Quarterly	International Financial			
	(2010=100)	[1990:4 – 2017:2]	Statistics (IMF)			
T3MAS	Nominal three-month interbank rate	Quarterly	SAMA Quarterly			
	Nommar unce-month interbark rate	[1990:4 – 2017:2]	Statistics			
OP	Oil price	Quarterly	International Financial			
	(in Saudi riyals / current price)	[1990:4 - 2017:2]	Statistics (IMF)			
GDP	Private sector real non-oil GDP	Quarterly	SAMA Quarterly			
	(in Saudi riyals / 2010=100)	[1990:4 - 2017:2]	Statistics			

Table 2: Selected variables: definition. frequency and sources

<sup>&</sup>lt;sup>1</sup> Such shocks may occur, for example, from de-correlation between the Saudi and American cycles, or they may reflect discretionary monetary policy responses to idiosyncratic events that are not captured by standard reaction rules.

<sup>&</sup>lt;sup>2</sup> Given the recursive structure of A, the simultaneous relations between the target variables are not modelled.

The data cover a period of approximately 25 years from 1990/Q1 to 2017/Q2. In addition to the alternating phases of stability (1990/Q14-1999/Q1), rise (1999/Q1-2008/Q3 and 2009/Q1-2014/Q2) and fall in oil prices (2008/Q3-2009/Q1 and 2014/Q2-2015/Q3), this period is characterized by other events likely to influence the Saudi economy: the second Gulf War (August 1990); the Asian crisis (July 1997); the terrorist attacks of September 11; the stock market crash of 2001-2002; the third Gulf War; the financial crisis; the stock market crash in China (June 2015); the establishment of three Islamic banks (Al-Inma [2008], Al-Jazeera [Islamic from 2002] and Al-Bilad [2004]).

As in Canova and Pérez Forero (2015), all the variables are expressed in annual rate changes, *i.e.*  $z_t = \log(y_t) - \log(y_{t-4})$ , except for the interest rate, and standardized, *i.e.*  $y_t^* = (z_t - E(z_t))/\sigma(z_t)$ , to have all the variables on the same scale.<sup>1</sup> The number of lags retained for each of the three VAR models is one.<sup>2</sup> Figure 1 shows the plot of the transformed data.

#### **3.2.** Empirical results

To compute the posterior estimates, we draw E = 20,000 samples after the initial 2,000 samples are discarded in the burn-in period. Table 3 report the MCMC algorithm estimation results for selected parameters for the three TVP-VAR models: the posterior means, the standard deviations, the 95% credible intervals, the convergence diagnostic (CD) of Geweke (1992), and the inefficiency factors (IF) of Geweke (1992). The convergence diagnostic (CD) of Geweke (1992) shows that the null hypothesis of the convergence of the parameters towards their posterior distributions is not rejected at the 5% significance level. The inefficiency factors are quite low which indicates that the MCMC algorithm produces posterior draws efficiently.

Parameter*	Mean	Std-dev	95% interval**	CD	IF
(a) Model 1					
$(\Sigma_{\beta})_{1}$	0.0225	0.0026	[0.0181, 0.0281]	0.274	6.26
$(\Sigma_{\beta})_{2}^{\dagger}$	0.0229	0.0026	[0.0185, 0.0288]	0.099	5.54
$(\Sigma_a)_1$	0.0883	0.0812	[0.0404, 0.2355]	0.336	38.09
$(\Sigma_a)_2$	0.0695	0.0216	[0.0399, 0.1239]	0.578	32.26
$(\Sigma_h)_1$	0.5657	0.1696	[0.2953, 0.9612]	0.214	54.48
$(\Sigma_{\rm h})_2$	1.3032	0.3451	[0.6512, 2.0367]	0.439	71.72
(b) Model 2					
$(\Sigma_{\beta})_{1}$	0.0228	0.0026	[0.0183, 0.0285]	0.729	6.82
$(\Sigma_{\beta})_{2}$	0.0232	0.0027	[0.0186, 0.0292]	0.524	6.86
$(\Sigma_a)_1^2$	0.0911	0.0662	[0.0396, 0.2500]	0.282	38.61
$(\Sigma_a)_2$	0.0744	0.0280	[0.0400, 0.1447]	0.268	40.15
$(\Sigma_{\rm h})_1$	0.6323	0.1749	[0.3485, 1.0219]	0.557	36.13
$(\Sigma_{\rm h})_2$	1.3391	0.3259	[0.7932, 2.0585]	0.216	66.41
(d) Model 3					
$(\Sigma_{\beta})_{1}$	0.0225	0.0026	[0.0181, 0.0281]	0.274	6.26
$(\Sigma_{\beta})_{2}$	0.0229	0.0026	[0.0185, 0.0288]	0.099	5.54
$(\Sigma_a)_1^2$	0.0883	0.0812	[0.0404, 0.2355]	0.336	38.09
$(\Sigma_a)_2$	0.0695	0.0216	[0.0399, 0.1239]	0.578	32.26
$(\Sigma_{\rm h})_1$	0.5657	0.1696	[0.2953, 0.9612]	0.214	54.48
$(\Sigma_{\rm h})_2$	1.3032	0.3451	[0.6512, 2.0367]	0.439	71.72***

Table 3: Estimation results of selected parameters in the TVP-VAR model

\* The estimates of  $\Sigma_{\beta}$  and  $\Sigma_{a}$  are multiplied by 100; \*\* In Bayesian inference, the uncertainty of the parameters is given by "credible intervals", instead of "confidence intervals" in the frequentist approach; \*\*\* For  $(\Sigma_{h})_{2}$ , the inefficiency factor is about 72 in models 1 and 3, and 67 in model 2, which implies that we obtain about E/72 = 278 uncorrelated samples in models 1 and 3, and E/67 = 298 uncorrelated samples in model 2. It is considered to be sufficient for the posterior inference.

<sup>&</sup>lt;sup>1</sup> All the standardized variables are stationary. Unit root (ADF and PP) and stationarity (KPSS) tests results are available on request.

<sup>&</sup>lt;sup>2</sup> To choose the lag order for each of the selected VAR models, we have used the Bayesian information criterion.

### **3.2.1.** Estimation results for the benchmark model (Model 1)

Figure 2 plots the posterior estimates of stochastic volatility ( $\sigma_{it} = \exp(h_{it}/2)$ ), as well as the simultaneous relation ( $\tilde{a}_{it}$ ) that are specified by the lower triangular matrix ( $A_t$ ).

Stochastic volatility of inflation (P) exhibits a spike around 1990 due to the second Gulf War (August 1990 - February 1991) and remains at a relatively high level until the late 1990s. Since then, it shows a bearish trend, with a cyclical peak around 2009/2010, following the rise in domestic demand and the exogenous increase in food prices. The decline in the stochastic volatility of inflation during the first half of the 2000s can be explained by the low (and relatively stable) inflation experienced by the Saudi economy during this period, which is in line with the SAMA's price stability objective. Stochastic volatility of output (GDP) shows two peaks: the first, around 2007/2008, when the global financial crisis began, and the second, around 2010, is due to the hike in oil prices. Stochastic volatility of money supply (M), although showing a slightly upward trend during the 2000s due to the significant increase in bank lending to the economy, remains broadly stable. Stochastic volatility of the interest rate (T3MAS) decreased significantly in the mid-1990s when the U.S. Federal Reserve reduced its policy rate from 8 to 3%. It fell and stabilized towards the end of the 2000s when the Fed, and mechanically the SAMA, reduced its key rate to a level close to zero. Stochastic volatility of the oil price (OP), although relatively high throughout the sample period considered, exhibits some cyclical ups and downs. The increase in stochastic volatility in the late 1990s is mainly due to the 40% collapse in oil prices between November 1997 and the end of 1998 after OPEC's production increased and the Asian crisis erupted. In August 2005, the price of crude oil reached \$70 the barrel, mainly because of geopolitical instability (Iraq war, social unrest in Venezuela and Nigeria) and natural disasters that hit oil installations in the Gulf of Mexico. Driven by the decline in U.S. stocks, the price of a barrel went beyond \$147 on July 11, 2008. In December 2008, the price dropped to \$32 following the subprime crisis and the decline in consumption. In response to the suspension of the Libyan production, the oil price reached a peak of \$127 on March 11, 2011. Since the summer of 2014, and because of the decline in global demand (especially Chinese) and the increase in supply, the price of black gold has fallen sharply.

Figure 2.b plots the posterior estimates of the free elements in  $A_t^{-1}$ , denoted  $\tilde{a}_{it}$ , i.e. the simultaneous response of other variables to one unit of the structural shock based on the recursive identification. The simultaneous relation of the output to the inflation shock ( $P \rightarrow$ PIBNP) stays negative and remains almost constant over the sample period. The instantaneous relations of the output to the inflation shock ( $P \rightarrow PIBNP$ ) is negative and broadly constant over the entire period studied. The instantaneous relations of the money supply to the inflation shock  $(P \rightarrow M)$  is positive and shows an upward trend, which means that the SAMA's money supply policy is not an inflation prevention policy. It is therefore an empirical proof of the lack of credibility of the SAMA with respect to its price stability objective. The instantaneous relations of the money supply to the output shock (PIBNP  $\rightarrow$  M), although positive over most of the period studied, shows a downward trend until 2010, before stabilizing at a level very close to zero thereafter. This can be explained, on the one hand, by the instability of the velocity of money and, on the other, the relative stability of inflation until the mid-2000s. We note however that the instantaneous relations of the interest rate to the inflation shock ( $P \rightarrow T3MAS$ ) and to the monetary shock ( $M \rightarrow T3MAS$ ) is low, which can be explained by the fact that the SAMA's interest rate policy is not autonomous.

The impulse response is a basic tool to study the potential over time of the macroeconomic dynamics captured by the estimated TVP-VAR models. For TVP-VAR models, the impulse responses can be computed at all points in time (i.e. 1990/Q4-2017/Q2) using the estimated

time-varying parameters. Thus, the TVP-VAR model allows to simulate impulse responses in several ways: either set the horizon and introduce a shock at each point in time or set the date and introduce shocks at different horizons. As in Nakajima (2011), we calculate the impulse responses by setting an initial shock size equal to the time-series average of stochastic volatility over the sample period and using simultaneous relations at each point in time. Then, the estimated time-varying coefficients are used to compute the response of a variable to shocks on other variables. We thus obtain impulse response trajectories for specified horizons.

Figure 3 shows the responses of the macroeconomic variables to structural shocks identified by Model 1 at each point in time and over different horizons (one, two and three years horizons). In other words, it tracks the possible evolving nature of macroeconomic dynamics between the variables in the model, thus allowing us to analyze the response of the target variables to a shock on the control variable whose size is equal to the average of stochastic volatility over the sample period. The impulse responses of output to a positive inflation shock ( $\epsilon_P \rightarrow PIBNP$ ) are negative between the 1990s and the beginning of the 2000s and become positive from the mid-2000s onwards. Economic theory suggests that an inflation shock negatively affects activity over the medium to long term, which is consistent with the negative impulse responses observed in the first half of the sample period. The positive impulse responses observed in the second half of the sample period imply the possibility of a mutual reinforcement between inflation and growth. Indeed, starting in the early 2000s, the oil price rose at a steady pace to reach almost \$150 per barrel in the second quarter of 2008. As Saudi Arabia is a net oil exporting country, the increase in oil prices has stimulated the economy. At the same time, there was, in 2007/2008, an episode of speculation in favor of the rival which caused capital inflows whose effects were inflationary. In the aftermath of the economic crisis, the Kingdom's external and, consequently, fiscal balances were quite affected. From 2008 onwards, the slowdown in domestic demand, added to imported disinflation, caused inflation to fall from 10 to 5% between 2008 and 2009. Thus, the positive impulse responses observed at the end of 2010 imply the possibility of a mutual reinforcement between the slowdown in the price rises (largely imported disinflation) and the economic growth. The impulse responses of inflation to a positive output shock  $(\epsilon_{PIBNP} \rightarrow P)$ , although declining steadily between the early 1990s and the mid-2000s and remaining broadly stable thereafter, are positive over the entire sample period, which is in line with economic theory. Nevertheless, the downward trend in the impulse response until the mid-2000s can be explained by the recurrence of episodes of political instability (the second Gulf War [August 1990] and the third Gulf War [March 2003]) and economic turbulence (the Asian crisis [July 1997], the terrorist attacks of 11 September and the subsequent stock market crash) which characterized that period, and which resulted in a slowdown in economic activity and in inflation.

We note that, until the early 2000s, positive interest rate shocks ( $\varepsilon_{T3MAS}$ ), reflecting restrictive monetary policy, led to a decrease in inflation (P). This effect gradually fades to near zero by the late 2000s, when the short-term rate become almost zero. As for the sensitivity of the transmission variable to the control variable, we see that, until the mid-2000s, positive shortterm interest rate shock ( $\uparrow \varepsilon_{T3MAS}$ ) affects the money supply negatively ( $\downarrow$  M). This sensitivity declined gradually thereafter: it remains around zero between the mid of the 2000s and the beginning of the 2010s, and slightly positive towards the end of the period studied. This disconnection between control and transmission variables can be explained by the SAMA's recourse, on several occasions, notably from the second half of the 2000s onwards, to more direct instruments (e.g. the increase in the coefficient on minimum reserves) to regulate domestic liquidity and counter inflationary pressures. Moreover, the impulse responses of the short-term interest rate to a positive money supply shock ( $\varepsilon_{M} \rightarrow T3MAS$ ) remain negative over the whole sample period. As for the impulse responses of output to positive shocks on the transmission variable ( $\epsilon_M \rightarrow \text{PIBNP}$ ), they exhibit a standard pattern: over the sample period, positive money supply shock has a positive impact on economic activity, with a slight decline between the mid-1990s and the early 2000s, a period of political and economic instabilities that probably reduced the effectiveness of the bank credit channel.

### 3.2.2. Interactions between Islamic and conventional banks

To make our vision clearer, we need to examine the possible interactions between Islamic bank financing and conventional bank credit. To analyze these interactions and their role in the transmission of monetary policy, we include deposits at conventional banks (CBD) and deposits at Islamic banks (IBD) as transmission variables in Model 2, and credit granted by conventional banks (CBC) and financing provided by Islamic banks (CBI) as transmission variables in Model 3. Figure 4 plots the posterior estimates of stochastic volatility ( $\sigma_{it}$ ), as well as the simultaneous relation ( $\tilde{a}_{it}$ ) of Models 2 and 3.

From posterior estimates for stochastic volatility of the structural shock of Model 2 (Figure 4.a) we note that the stochastic volatilities of inflation, output, interest rates, and oil prices seem to be broadly consistent with the previous analysis. As for the volatility of bank deposits, it behaves differently depending on whether they are conventional bank deposits or Islamic bank deposits. The stochastic volatility of Islamic bank deposits (IBD) exhibits three peaks. The first occurred in 2001/2002 following the terrorist attacks of 11 September and the subsequent stock market crash, and the transformation in 2002 of Al-Jazeera bank (established in 1976) into a fully-fledged Islamic bank. The second occurred in 2004 after the establishment of the Islamic bank Al-Bilad. The third took place in the late 2000s in response to the fall in oil prices from \$150 in the second quarter of 2008 to \$50 in the first quarter of 2009 and the establishment of Al-Inma Islamic bank in 2008. Indeed, the plunge in oil prices was accompanied by a decline in the volume of Islamic and, less mechanically, conventional bank deposits. Symmetrically, the stochastic volatility of Islamic bank financing (Model 3) reached a peak in the late 2000s. This can be considered as an empirical evidence of the dependence of Islamic banking activity on oil revenues. Regarding the stochastic volatility of conventional bank deposits (CBD), although it behaves similarly to the money supply (M) in Model 1,<sup>1</sup> two major hikes are recorded. The first, which occurred in the early 1990s, may be explained by political instability in the region (second Gulf War) and the resulting economic uncertainty. The second spike, more persistent,<sup>2</sup> observed since the early 2000s, can be explained by the massive repatriation of Saudi assets abroad (after the September 11 attacks), the sustained rise in the price of crude oil since the beginning of the 2000s (which have boosted domestic liquidity), the establishment of three fully-fledged Islamic banks (Al-Jazira [2002]; Al-Bilad [2004]; Al-Inma [2008]), the Chinese stock market turbulence (June 2015-February 2016), and the drop in oil prices (which affected domestic liquidity).

Figure 5 plots the results of simultaneous relations  $(\tilde{a}_{it})$  for Models 2 and 3. The results obtained show that, for models 2 and 3, the free parameters  $\tilde{a}_{it}$  of  $A_t^{-1}$ , i.e. the simultaneous responses of other variables to one unit of the structural shock based on the recursive identification, behave broadly in a similar way. Given the lower triangular structure of the contemporaneous relations matrix, the order of variables in the vector  $y_t$  assumes that the Saudi interest rate respond contemporaneously to the target variables (P and GDP), that the target variables have contemporaneous impact on both the credit granted by conventional banks ( $a_{31} \neq 0$ ;  $a_{32} \neq$ 0) and the financing provided by Islamic banks ( $a_{41} \neq 0$ ;  $a_{41} \neq 0$ ), and that Islamic bank financing respond contemporaneously to conventional bank credit ( $a_{43} \neq 0$ ).

<sup>&</sup>lt;sup>1</sup> This result is quite natural given that, over the period examined, conventional bank deposits account, on average, for 72% of the broad money.

<sup>&</sup>lt;sup>2</sup> By persistent, we mean the fact that stochastic volatility remained at a relatively high level until the mid-2010s.

We note that the effects of inflation and output on conventional bank deposit ( $P \rightarrow DBC$  and PIBNP  $\rightarrow$  DBC, respectively) are broadly consistent with the simultaneous relations found in the previous specification, i.e. the simultaneous relation of the money supply to shocks on the target variables, which is quite natural given the weight of conventional banks' deposits in the broad money (around 72% on average over the sample period). As for the simultaneous effects of inflation on the Islamic banks' deposits ( $P \rightarrow DBC$ ), although it was largely stable and close to zero in the first half of the 1990s, it reveals a growing trend between the late 1990s and the late 2000s before reversing thereafter. This result can be interpreted as empirical evidence of the existence of trade-offs between conventional and Islamic banks' deposits. Indeed, since most of the Islamic banks' deposits are subject to profit and loss sharing agreements, a positive change in the general price level implies an enhancement of the value of Islamic banks' assets and, hence, of their result, which will subsequently be shared among shareholders and depositors. Furthermore, conventional banks' deposits give the depositors the right to a fixed and contractually determined money income. Stable inflation is therefore likely to improve the profitability of Islamic bank deposits relative to conventional bank deposits, thereby providing an incentive for non-financial agents to increase their balances with Islamic banks. For this reason, the simultaneous response of Islamic bank deposits to inflation shocks shows an upward trend between the late 1990s and the late 2000s, while over the same period the simultaneous response of conventional bank deposits to inflation shocks is broadly stable. Moreover, when inflation becomes unstable and uncertain, as has been the case since the late 2000s, nonfinancial agents tend to reduce their deposits at Islamic banks and increase their deposits with conventional banks in order to limit the impact of this uncertainty on the nominal return of their funds. It should also be noted that conventional and Islamic banks' deposits react simultaneously in the same way to cyclical fluctuations: the simultaneous response of bank deposits (conventional and Islamic) to shocks on non-oil private GDP, although generally positive over the entire sample period, dropped considerably towards the end of the 2000s because of the fall in oil prices, which affected both economic activity and domestic liquidity. As regards direct simultaneous interactions between conventional and Islamic banks, they differ according to whether we are on the liability side (Model 2) or on the asset side (Model 3). On the liabilities side (i.e. DBC $\rightarrow$ DBI), they vary between the early and late 1990s and become widely stable, at a level slightly above zero, from the early 2000s onwards. This can be explained by the evolution of the Islamic banking sector which, until the end of the 1990s, contained only one Islamic bank, and was consolidated during the 2000s. On the asset side (i.e.  $CBC \rightarrow CBI$ ), the sensitivity of Islamic bank financing to conventional bank credit shocks is negative over the whole period examined. The low significance of the instantaneous interaction between conventional and Islamic banks is probably due to the specific operating mode of Islamic banks. In other words, although Islamic banks reacts to changes in conventional banks' credit supply, this response is not instantaneous, but phased gradually. Indeed, to reduce reputational risk without increasing "displaced commercial risk",<sup>1</sup> Islamic banks exhibit relative "temporary insensitivity" to changes in the conventional bank credit supply: they tend to be in line with changes in conventional credit, but with some delay.<sup>2</sup>

Figure 6 plots the impulse responses of estimation results for models 2 and 3. It shows, on one hand, the response of target variables (GDP and P) to a shock on the short-term interest rate and on the transmission variables, and, on the other hand, the interactions between Islamic and conventional banks.

<sup>&</sup>lt;sup>1</sup> "In dual financial systems, displaced commercial risk, which is specific for Islamic banks, may be defined as the risk of incurring losses resulting from both the volatility of investment accounts returns and the willingness of Islamic banks to ensure a competitive return to the holders of those accounts" (Ben Amar, 2018).

<sup>&</sup>lt;sup>2</sup> These results are very similar to those of Azad et al. (2018) and Ben Amar (2018).

The impulse responses between inflation, output, interest rate and oil prices are similar to the previous specification, i.e. Model 1. Regarding the impulse responses to money supply shocks, they differ significantly depending on whether the supply comes from conventional or Islamic banks. Although, over the sample period, the increase in the money supply results in an overall improvement in economic activity, the time-varying impulse responses are more volatile when this increase comes from conventional banks. Can this result be considered as an empirical evidence that Islamic banks are more stabilizing than conventional banks? In part yes, because, in Islamic finance, most of bank deposits are subject to profit and loss sharing agreements, and any financial transaction must be systematically backed by a real asset, which is, in theory, likely to improve the synchronization between financial cycles and real cycles. It should also be added that the size of the Saudi Islamic banking system is marginal compared to that of the conventional banking system. Thus, it is not surprising that the sensitivity of the economic activity to Islamic bank financing is relatively less volatile than its sensitivity to conventional bank credits. The results also show that, in the medium term (after 2 and 3 years), conventional bank credit and Islamic bank financing respond in the same way to interest rate shocks. This result shows that, despite the "nominal" application of the Shari'a rules, there are few differences on the asset side between the Islamic banks' modus operandi and the methods used by conventional banks.

We also notice that the effect of positive conventional banks' money supply shocks on economic activity progressively weakens between the early 1990s and the early 2000s, then gradually increases until the mid-2000s to a level around which it stabilizes until the mid-2010s. Moreover, from the early 2000s onwards, the rise of the impulse responses of output to positive Islamic banks' money supply shocks was relatively strong. This can be explained by the emergence of new Islamic banks since the early 2000s. In addition, positive cyclical shocks result in an increase in both conventional bank credit and Islamic bank financing. We also find that conventional and Islamic banks react to each other, but in opposite directions. This asymmetry may be explained, in our opinion, by the relative size of each of these two sectors. Indeed, despite the development of the Saudi Islamic banking sector, it remains marginal compared to the conventional one. Thus, the increase in conventional bank deposits has been achieved at the cost of a decrease in Islamic bank deposits. Therefore, the unexpected positive shocks on CBD result in a decline in Islamic bank deposits. In contrast, the increase in Islamic bank deposits is only the consequence of a general increase in the liquidity rate, which is why shocks in the supply of money by Islamic banks are reflected in an increase in conventional bank deposits.

## 4. Concluding remarks

Using the Primiceri's (2005) methodology of time-varying vector structural autoregressive models with stochastic volatility, this paper attempts to empirically investigate the monetary policy transmission in Saudi Arabia, as well as the role of Islamic banks in this transmission and the interactions between Islamic and conventional banks. The results obtained provide empirical evidence of the dependence of Islamic banking activity on oil revenues. They also indicate that, in the medium term, conventional and Islamic banks respond in the same way to interest rate shocks, which suggest that, in practice, there are few differences between the Islamic banks' modus operandi and the methods used by conventional banks. However, they do not allow us to clearly conclude whether Islamic banks are more stabilizing than conventional banks. Indeed, as the size of the Saudi Islamic banks is marginal compared to that of the conventional banks, it is not surprising that the sensitivity to conventional bank credits.

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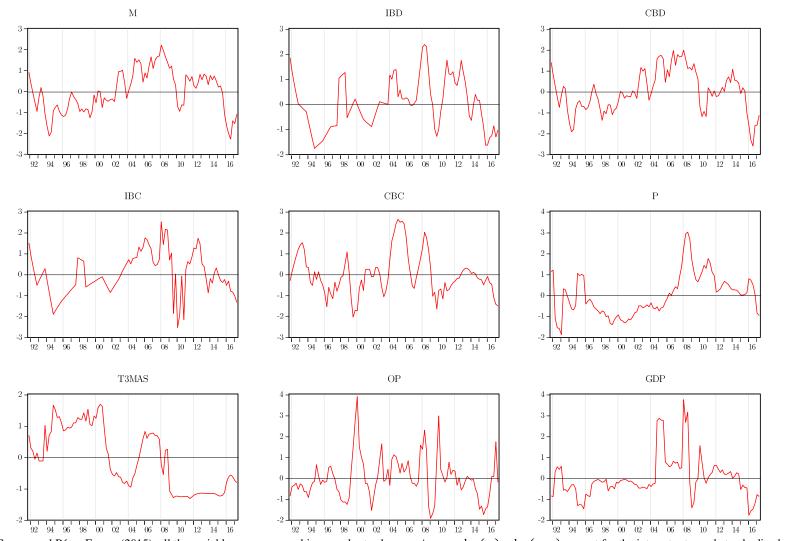
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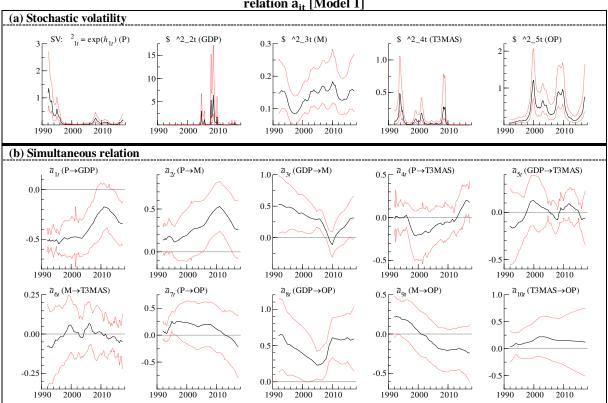
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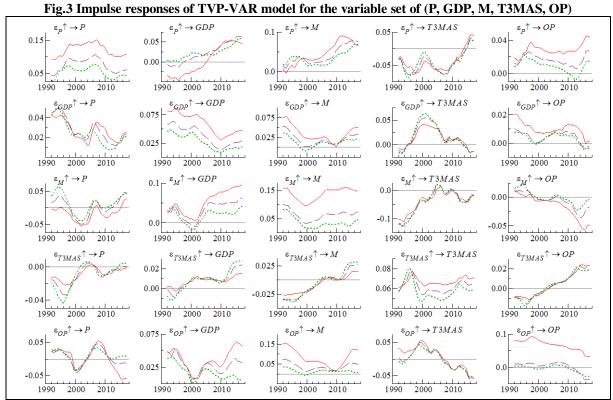
Fig.1 Transformed variables



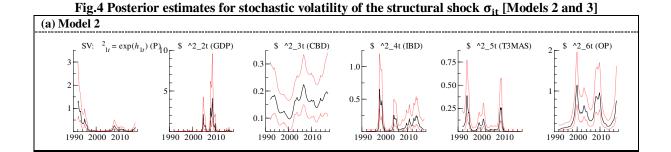
Note: As in Canova and Pérez Forero (2015), all the variables are expressed in annual rate changes, *i.e.*  $z_t = \log(y_t) - \log(y_{t-4})$ , except for the interest rate, and standardized, *i.e.*  $y_t^* = (z_t - E(z_t))/\sigma(z_t)$ , to have all the variables on the same scale.

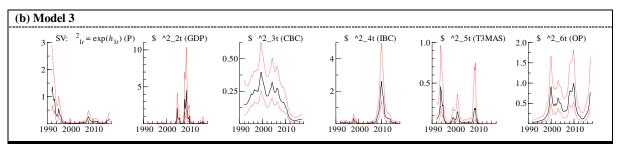


Note: Posterior mean (black line) and 95% credible intervals (red line).

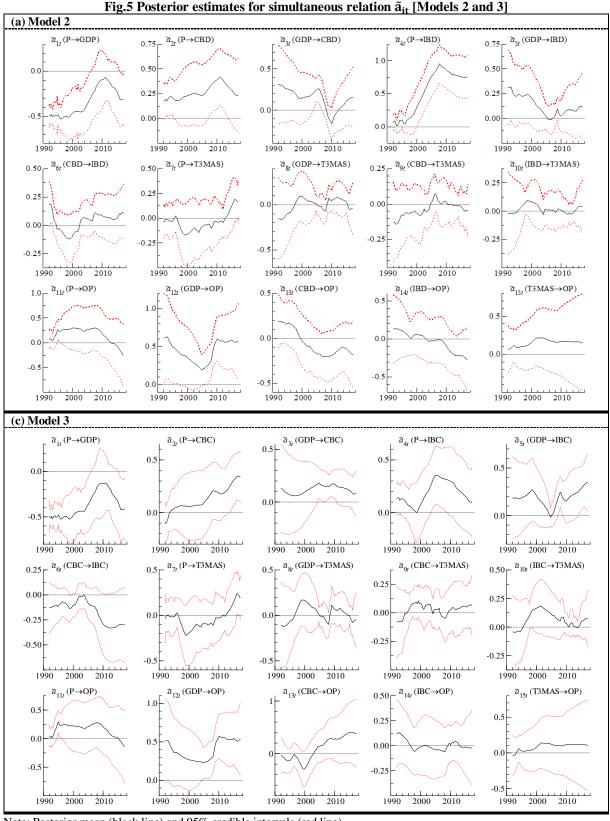


Note: Time-varying responses for one-year (red), two-year (purple), and three-year (green) horizons.

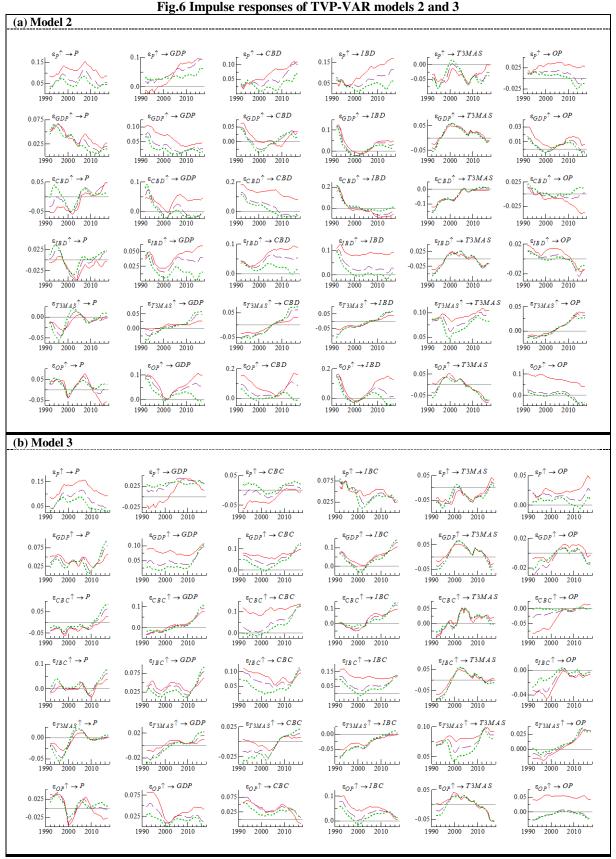




Note: Posterior mean (black line) and 95% credible intervals (red line).



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