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On the Influence of Oil Prices on Financial Variables

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Abstract

This paper investigates how oil price shocks interact with three key financial variables—implied stock market volatility, interest rate, and exchange rate—within a Bayesian VAR (BVAR) framework. By defining oil price as an endogenous variable and a shock, as in Hamilton (2003), our proposed model allows us to gauge the shock transmission among the system variables over time. We are also able to compare the conditional one-period-ahead forecasts produced by the BVAR model using different distributional priors. Our empirical findings show that the results of parameter estimates, impulse responses, and forecasts are insensitive to the choice of priors that provide similar findings. Moreover, of the three key financial variables, the volatility index is the most sensitive to oil price shocks. Further, shocks to these three variables have transitory impacts on oil price, with the longest impact deriving from changes in the exchange rate.

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1. Introduction

Numerous studies have shown that the Bayesian VAR (BVAR) model provides better forecasts than the standard VAR for most financial variables. The main desired feature is its ability to overcome over-parameterization when the number of variables in the VAR system increases. Furthermore, it allows for much comprehensive dynamics than the traditional VAR approach. Recent studies have also demonstrated that this model outperforms a variety of competing econometric techniques in forecasting financial variables.[1]

The literature includes studies that apply the BVAR model to economic and financial variables. Most of these studies deal with one or two variables, such as exchange rates and stock markets. However, there is a need for a BVAR-based study that deals with major variables such as oil, stock markets, exchange rates, and financial risks simultaneously. While oil price is a major source of instability in the world economy, it is not a measure of risk and fear, or a gauge of future economic health in financial markets. The S&P 500 equity CBOE measures volatility index (VIX) expectations of credit risk that oil price cannot measure. Including the credit risk in a BVAR model is important because of the mounting risks that plagued the financial markets.

In this paper, our objectives are threefold (i) examine the effects of oil shocks on financial variables including interest rate, exchange rate, and implied volatility; (ii) compare the shock effects induced by financial variables; and (iii) investigate six types of priors, of which three lead to analytical solutions for the posterior and predictive density and three require the use of a simulation algorithms.

Several influential studies investigate the impact of oil prices on financial variables. Jones and Kaul (1996) examine the effect of crude oil prices on real returns for the United States, Canada, United Kingdom, and Japan by employing time series regression models. They find that in all four countries, the oil price has a statistically significant and negative effect on real returns. Sadorsky (2001) and Boyer and Filion (2007) show that oil price increases positively affect stock returns of Canadian oil and gas companies. By using the standard VAR model, Park and Ratti (2008) find that oil price shocks have a statistically significant impact on real stock returns in the United States and 13 European countries. Also, for oil importing countries in Europe, they find few asymmetric effects on returns from positive and negative oil price shocks. Arouri and Nguyen (2010) investigate the links between oil prices and 12 stock

[1] A few examples are Dua and Ray (1995), Dua and Miller (1996), and Dua, Miller, and Smyth (1999). However, Krainz (2011) finds mixed results.

sectors in Europe. They show that the reaction of sector returns to changes in oil prices is significantly different across sectors, and that the inclusion of oil assets into a portfolio of sector stocks improves the portfolio's risk-return characteristics. Using a large database of macroeconomic, financial variables for 17 OECD countries, Abid et al. (2013) study the contagion effects on U.S key variables and housing markets over the sub-period of the subprime crisis. The authors compare different sizes of VAR models (a standard VAR estimated by OLS, and a MEDIUM and LARGE VARs estimated by a Bayesian shrinkage procedure). Their results show that the MEDIUM VAR is more successful than the LARGE VAR and the standard one. The main result is that the Bayesian shrinkage is a not neglecting alternative to the OLS when dealing with more than 10 variables. While the OLS is a robust estimation method, the Bayesian shrinkage gives qualitatively the same results and is more appropriate in the case of an international study. This finding has been confirmed in Abid and Kaabia (2013).

The remainder of this paper is structured as follows: Section 2 presents the empirical methodology. Section 3 describes the data and presents the results in terms of forecast and structural analysis. Section 4 summarizes the findings and presents conclusions.

2. Empirical Framework

We follow standard recommendations in the Bayesian literature and build on the results of De Mol et al. (2008) and Bańbura et al. (2010) by coping with the curse of dimensionality using Bayesian shrinkage via the imposition of priors. A VAR model with p lags, $\mathrm{VAR}(\mathrm{p})$, can be written as follows:

$$y_t = \alpha_0 + \sum_{j=1}^{p} A_j\, y_{t-j} + \varepsilon_t \qquad (1)$$

where y_t is a $k*1$ vector containing T observations on k time series variables, ε_t is a $k*1$ vector of residuals assumed to be $N(0,\Sigma)$, α_0 is a $k*1$ vector of intercepts, and A_j is a $k*k$ vector of parameters.

The above VAR model in Eq. (1) can be written in matrix form. Let's first define Y as the $kT*1$ vector that stacks all the T observations of the first endogenous variable, then all the T observations of the second endogenous variable, etc. Accordingly, we define E as the vector that stacks all errors ε in a manner conformable to that in y and Y.

Moreover, let $x_t = \left(1, y'_{t-1}, \dots, y'_{t-p}\right)$ and

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix}_{T*K}$$

where $K = kp + 1$. If $A = (\alpha_0, A_1, \dots, A_p)$, the matrix form of the VAR model in Eq. (1) is

$$Y = XA + E$$

or equivalently, $y = (I_k * X)\alpha + \varepsilon$ with $\varepsilon \rightarrow N(\Sigma \otimes I_T)$.

The likelihood function can be obtained from the sampling density $p(y/\alpha, \Sigma)$. This likelihood function includes the distribution of α given Σ, that is, $\alpha/\Sigma, y \rightarrow N(\widehat{\alpha}, \Sigma \otimes (X'X)^{-1})$, and another where Σ^{-1} has a Wishart distribution such that $\Sigma^{-1}/y \rightarrow W(S^{-1}, T - K - k - 1)$ and $\hat{\alpha} = vec(\hat{A})$, where $\hat{A}$ is the OLS estimate of A.

One important issue related to the estimation and inference in the VAR model is the choice of a good prior. Some priors we use in this paper, such as noninformative, Minnesota, and natural conjugate, lead to analytical results for the posterior and predictive densities, thus reducing the computational burden. Other priors such as independent normal-Wishart and stochastic search variable selection (SSVS)[2] require the use of Markov Chain Monte Carlo (MCMC) to carry out Bayesian inference.

The Minnesota prior suggests that Σ is a diagonal matrix and each element of the diagonal can be estimated by OLS. This assumption may be relaxed and Σ could be replaced by *S/T*, where *S* is the empirical variance-covariance matrix of errors. Even if the replacement of Σ by an estimate will reduce the computational burden, the method presents the risk of replacing Σ by a potentially poor estimate. This is considered the major drawback of the Minnesota prior.

The natural conjugate prior assumes that the priors, likelihood, and posterior come from the same family of distributions. With this prior, α/Σ is normal and Σ^{-1} follows a Wishart distribution. Similar to the noninformative and Minnesota priors, the natural conjugate prior provides analytical results and allows for Bayesian estimation and inference. However, it presents two major disadvantages. First, it requires the same number of variables in each of the VAR equations, rendering its application to restricted VAR inappropriate. Second, it restricts the prior covariance of the coefficients in any two equations to be proportional to one another.

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[2] SSVS was implemented by George, Sun, and Ni (2008).

Contrarily, the independent normal-Wishart and SSVS priors allow the VAR coefficients and error covariance to be independent, while requiring a posterior simulation algorithm such as the Gibbs sampler. In particular, the normal-Wishart prior is written as $p(\alpha, \Sigma^{-1}) = p(\alpha) * p(\Sigma^{-1})$, where $p(\alpha)$ is normal and $p(\Sigma^{-1})$ is Wishart. The SSVS prior has the following form:

$\alpha_j/\lambda_j \sim (1-\lambda_j)N(0, \sigma_{0j}^2) + \lambda_j N(0, \sigma_{1j}^2)$, where λ_j is a dummy variable taking the value 0 if α_j is drawn from $N(0, \sigma_{0j}^2)$ and 1 if α_j is drawn from $N(0, \sigma_{1j}^2)$.

3. Data Description

Our large international dataset is drawn from DataStream, Eurostat, and the Federal Reserve website, FRED - St. Louis Fed. The data consist of monthly US variables for the period January 1999–October 2012. Our dataset includes four variables: oil price, implied stock market volatility, interest rate, and exchange rate.

West Texas Intermediate (WTI) is a grade of crude oil used as a benchmark in oil pricing. This grade is described as light because of its relatively low density and sweet because of its low sulfur content. It is the underlying commodity of the New York Mercantile Exchange's oil futures contracts. The price of WTI is often referenced in news reports on oil prices, alongside the price of Brent crude from the North Sea. Other important oil markets include Dubai crude, Oman crude, Urals oil, and the OPEC Reference Basket.

The equity (VIX) is an index that measures volatility expectations of the S&P 500 index over the next 30-day period. It is calculated based on options on the S&P 500 equity index and quoted in percentage points. [3] VIX is referred to as the "fear index" in the equity market. An increase of VIX is usually associated with a decrease in the S&P 500 index. The VIX usually spikes as stocks go down and is more informative than spikes in other markets' fear indices, like the Merrill Lynch Option Volatility Estimate index (MOVE).

The exchange rate (EXCH) is a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners.

The interest rate (FRR) at which a depository institution lends funds maintained at the Federal Reserve to another depository institution overnight is the federal funds rate. It is generally only applicable to the most credit worthy institutions. The federal funds rate is one

[3] For example, if VIX is 50, one may infer that the index options markets would, with a 68% probability, expect that the S&P 500 should move up or down by $\frac{50\%}{\sqrt{12 \text{ months}}} = 14\%$ over the next 30-day period.

of the most influential interest rates in the U.S. economy since it affects monetary and financial conditions and thus has a bearing on key aspects of the broad economy, including employment, growth, and inflation. The Federal Open Market Committee (FOMC), which is the Federal Reserve's primary monetary policymaking body, telegraphs its desired target for the federal funds rate through open market operations.

All the data are seasonally adjusted and variables are measured at constant national prices. Furthermore, as in the literature, activity variables are logarithmic.

4. Results

On the supply side, oil is used as an input and feedstock in the production process; on the demand side, it is used in transportation and thus affects consumers' budgets. Higher oil prices may lead to higher inflation expectations, which in turn increase nominal interest rates (Fisher, 1930); thus, oil prices are expected to negatively impact discounted streams of cash flows and earnings. Friedman (1977) contends that increasing oil prices creates higher risks and uncertainty, and thereby distorts price signals and negatively affects financial variables. Huybens and Smith (1998, 1999) show that inflationary pressures contribute to credit market frictions, which have negative repercussions on the performance of financial markets. They also show that high inflation decreases the real return on all assets, including stocks. We also expect financial variables to have positive impacts on oil prices. Higher economic growth lifts all boats, including corporate earnings and demand for oil.

On the other hand, VIX is expected to have a positive relationship with oil price. It hit its historic high of 89.53 on October 24, 2008, only three months after oil price reached its all-time high. Moreover, VIX is expected to have a positive relationship with the U.S. dollar, because the greenback is considered a safe haven during crises.

Table 1: Posterior mean of VAR coefficients for two priors

	Minnesota				SSVS-VAR			
	Ex. $rate_t$	Vix_t	wti_t	i_t	Ex. $rate_t$	Vix_t	wti_t	i_t
intercept	-0.1922	0.4082	3.3834	0.6147	-0.0083	0.4415	0.1340	0.2567
Ex. $rate_{t-1}$	-0.1125	-0.0311	0.7844	-0.0165	-0.0171	-0.0023	0.1385	-0.0052
Vix_{t-1}	0.2411	0.7903	1.7704	-0.2959	0.0072	0.8303	0.5588	-0.0807
Wti_{t-1}	0.0025	0.0109	-0.1812	0.0191	0.0003	0.0049	-0.0794	0.0055
I_{t-1}	-0.0835	-0.0126	-1.0415	0.7927	-0.0044	-0.0010	-0.0502	0.8078
Ex. $rate_{t-2}$	0.0416	0.0619	0.4634	-0.0151	0.0054	0.0185	0.0340	0.0009

Vix_{t-2}	-0.0857	0.0266	-2.3932	0.0148	-0.0023	0.0096	-0.4624	-0.0058
Wti_{t-2}	0.0046	0.0022	0.1083	0.0047	-0.00006	0.0001	0.0678	0.0002
I_{t-2}	-0.0391	-0.0473	0.3070	0.3569	-0.0032	-0.0009	-0.0101	0.2995
Ex. $rate_{t-3}$	-0.1038	-0.0495	0.6082	-0.0367	-0.0116	-0.0065	0.0788	-0.0088
Vix_{t-3}	-0.2531	0.0303	-0.5366	0.0573	-0.0108	0.0078	0.0298	0.0013
Wti_{t-3}	0.0075	0.0061	-0.0196	-0.0014	0.0013	0.0072	-0.0038	0.0002
I_{t-3}	0.0934	0.0398	0.4580	-0.0620	-0.0005	0.0013	-0.0018	-0.0271
Ex. $rate_{t-4}$	-0.1356	-0.0300	1.5092	0.0089	-0.0306	-0.0004	1.2306	0.0016
Vix_{t-4}	0.1514	0.0104	0.3380	0.0241	0.0031	0.0044	0.0238	0.0020
Wti_{t-4}	-0.0084	-0.0026	0.0042	-0.0019	-0.0018	-0.0006	0.0028	-0.0004
I_{t-4}	0.0171	0.0233	0.1284	-0.1062	-0.0002	0.0015	-0.0002	-0.0952

The parameter estimates in Table 1 are rarely of interest in the VAR analysis since they are numerous and it is hard to interpret them. Nonetheless, Table 1 reports parameter estimates for two priors, namely, Minnesota and SSVS-VAR. It is worth noting that the results are similar, but SSVS-VAR is seen to shrink coefficients towards zero.

Forecasting economic and financial time series while accounting for their interdependencies, as is the case in VAR models, is of great importance for researchers and policymakers since their decisions are primarily based on anticipations and predictions. Table 2 reports the predictive results for an out-of-sample forecasting exercise based on the predictive density $p(Y_{T+1}/Y_1, Y_2, \dots, Y_T)$, where T refers to September 2012. The results show that forecasts are insensitive to the choice of priors. In fact, they are similar for all six choices of priors. Posterior predictive distribution is depicted in Figure 1.

Table 2: Predictive mean of y_{T+1}

	Ex. $rate_{T+1}$	Vix_{T+1}	WTI_{T+1}	i_{T+1}
Noninformative	-0.0885	2.9226	2.3260	0.1439
Minnesota	-0.0821	2.9218	2.3311	0.1312
Natural conjugate	-0.0831	2.9231	2.3021	0.1400
Indep. normal-Wishart	-0.0604	2.9249	2.1810	0.1182
SSVS-VAR	-0.0202	2.9386	1.0552	0.1123
SSVS	-0.0198	2.9323	1.1848	0.1064
True value	0.2327	2.8605	1.9469	0.1300

Figures 2–7 plot the impulse response functions issued from the estimated BVAR for all variables and shocks using the six priors considered in our paper. In these graphs, the posterior median is represented by a solid line, while the 10^{th} and 90^{th} percentiles are represented with dashed lines.

At first sight, we notice that responses do not change considerably according to the model specification. Also, it is important to stress that impulse responses are significant for all specifications. Moreover, the tight confidence bounds in all specifications indicate the precision of the response of VIX, exchange rate, and interest to oil price shock.

For all types of priors, the responses of VIX and interest rate confidence bounds are relatively large. It appears that impulse response functions of exchange and interest rates have a more realistic shape than what happened during oil shocks. We also notice that the key financial variables have been impacted by the oil shock.

When using noninformative, Minnesota, and natural conjugate priors, the VIX reacts significantly and positively to oil price shocks. The reaction lasts 4 months and then vanishes towards zero. Also, oil price shocks result in a rapid increase of its dynamics (1 month), and then a quick decrease (1 month) before reaching the zero-level equilibrium. However, the use of independent normal-Wishart, SSVS-VAR, and SSVS priors render the impact of oil price on VIX insignificant.

Moreover, oil price reacts significantly to shocks to exchange rate, VIX, and interest rate. In particular, an exchange rate shock has a positive effect on oil price for a period of four months. In addition, a shock to VIX has a positive impact on oil price for two months, whereas an interest rate shock induces a decrease in oil price for the same period.

Figure 8 depicts the impulse response paths of the simple VAR. It shows that shocks on financial variables including interest rate, exchange rate, and implied volatility are not exceeding two months. The estimated BVAR provides more plausible impulse response and hence faithfully reproduces the observed patterns over the studied period.

5. Conclusion

In this paper, we investigate the impact of oil price on three key financial variables—VIX, exchange rate, and interest rate—using BVAR modeling. The use of a BVAR model has several advantages compared to a standard VAR model; the most important is that it allows accounting for nonlinearities through the time varying feature of parameters. Second, this type of unconstrained model lets the data speak freely. Also, we used six priors that differ in two aspects. First, some priors provide analytical solutions to the likelihood function, inference, and predictive density (noninformative, Minnesota, and natural conjugate), while the others (independent normal-Wishart, SSVS-VAR, and SSVS) require the use of a simulation algorithm such as the Gibbs sampler. Second, the former are less computationally demanding.

Our findings are summarized as follows: (i) The results of parameter estimates, impulse responses, and forecasts are insensitive to the choice of priors. In fact, all priors provide similar findings. (ii) Of the three key financial variables considered in this paper, VIX is the most sensitive to oil price shocks. (iii) Shocks to the three variables have transitory impacts on oil price, with the longest impact deriving from changes in exchange rate.

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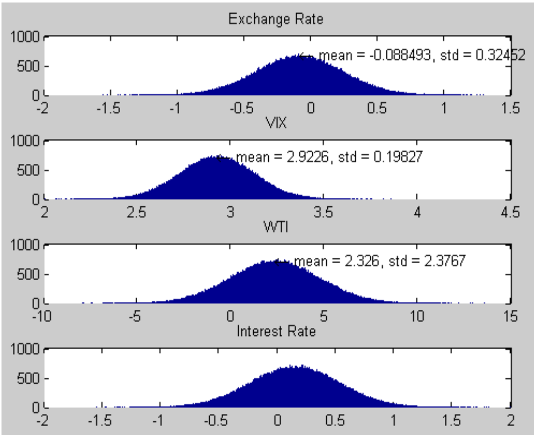
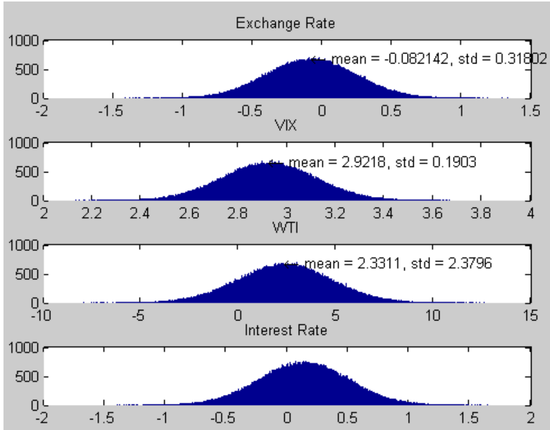
Figure 1: Posterior predictive distribution

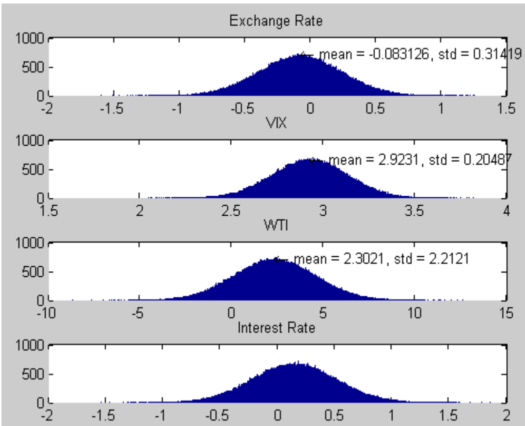
Noninformative prior



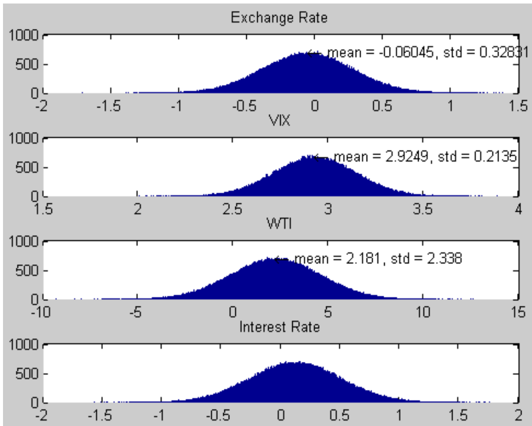
Minnesota prior



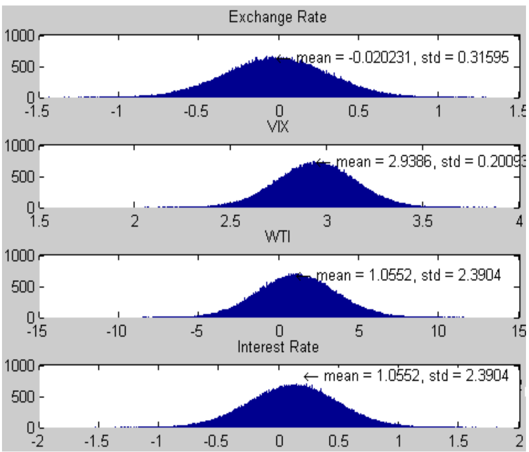
Natural conjugate prior



Independent normal-Wishart prior



SSVS-VAR prior



SSVS prior

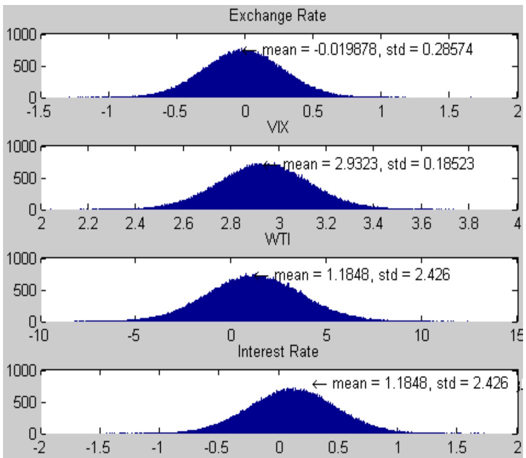


Figure 2: Posterior impulse response functions (Noninformative prior)

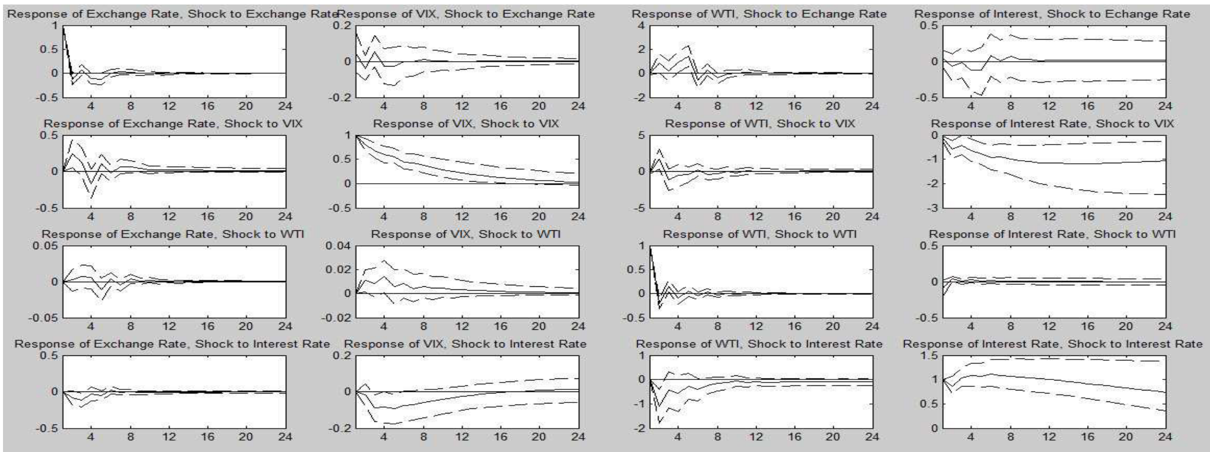


Figure 3: Posterior impulse response functions (Minnesota prior)

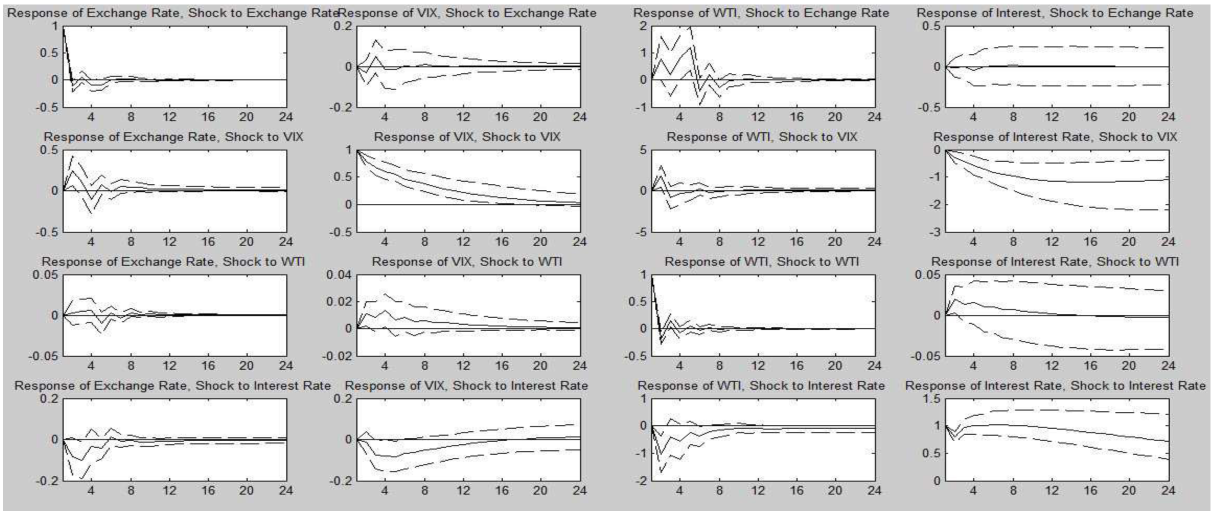


Figure 4: Posterior impulse response functions (Natural conjugate prior)

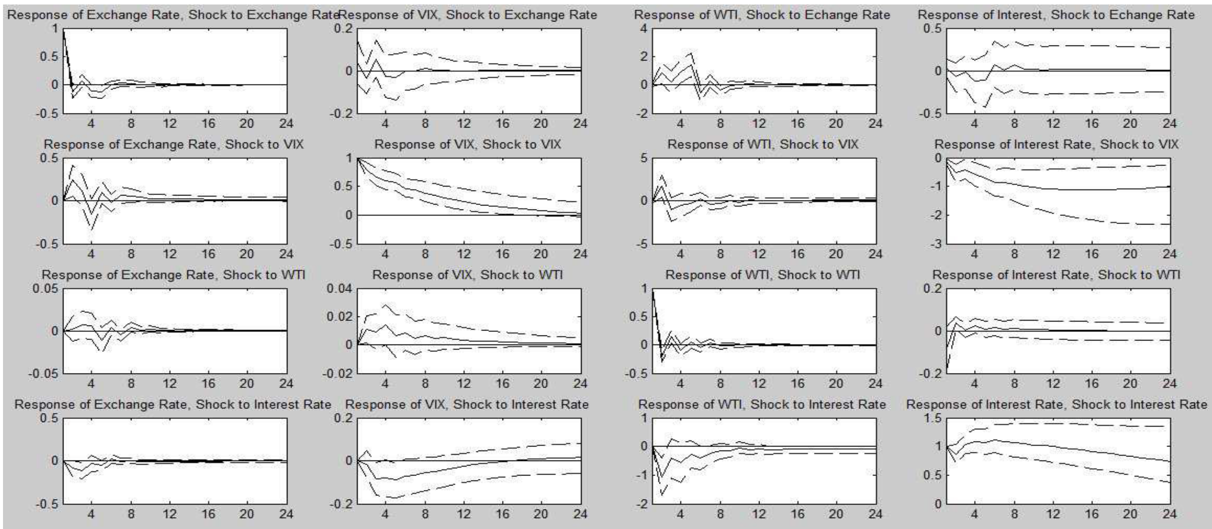


Figure 5: Posterior impulse response functions (Independent normal-Wishart prior)

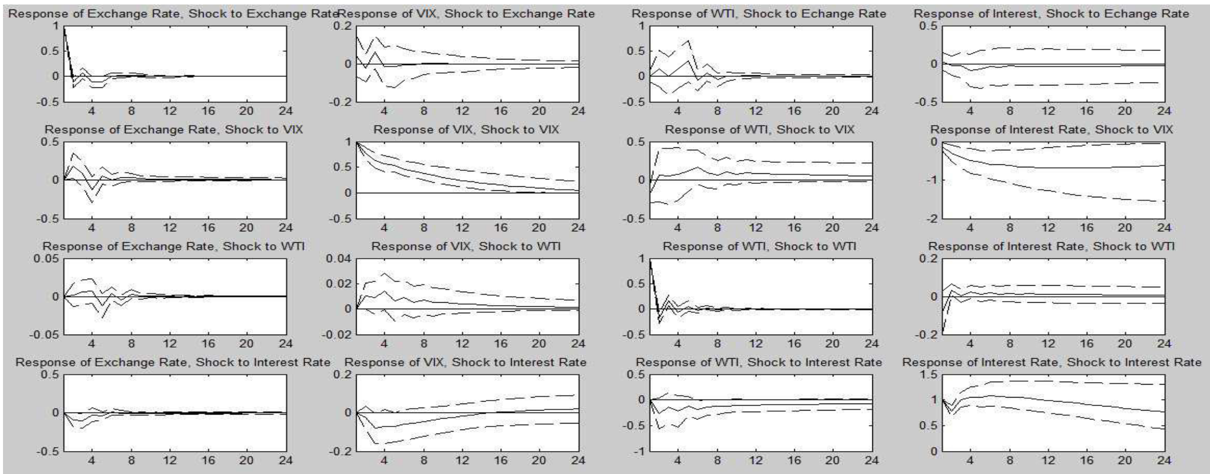


Figure 6: Posterior impulse response functions (SSVS-VAR prior)

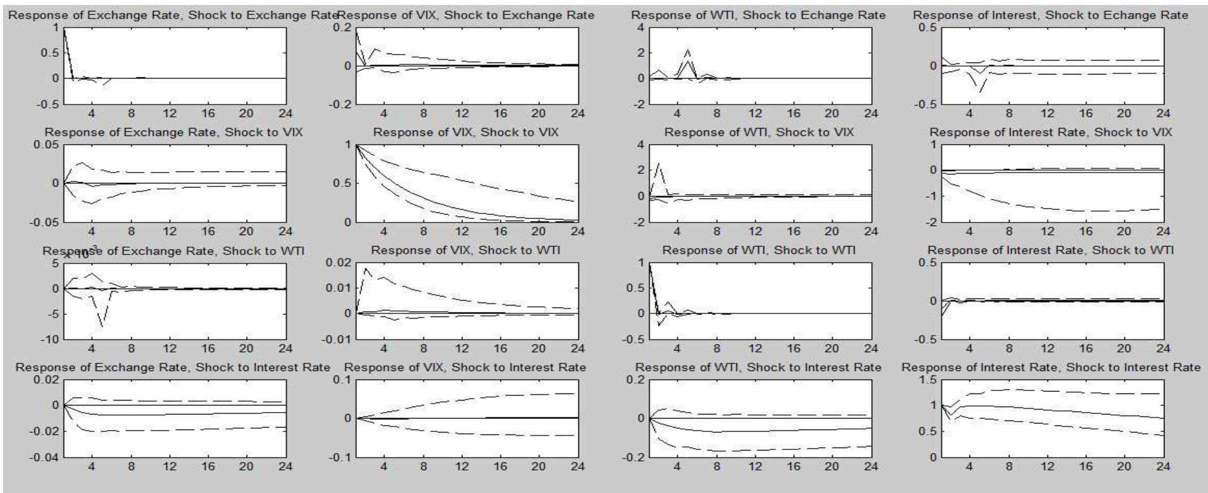


Figure 7: Posterior impulse response functions (SSVS prior)

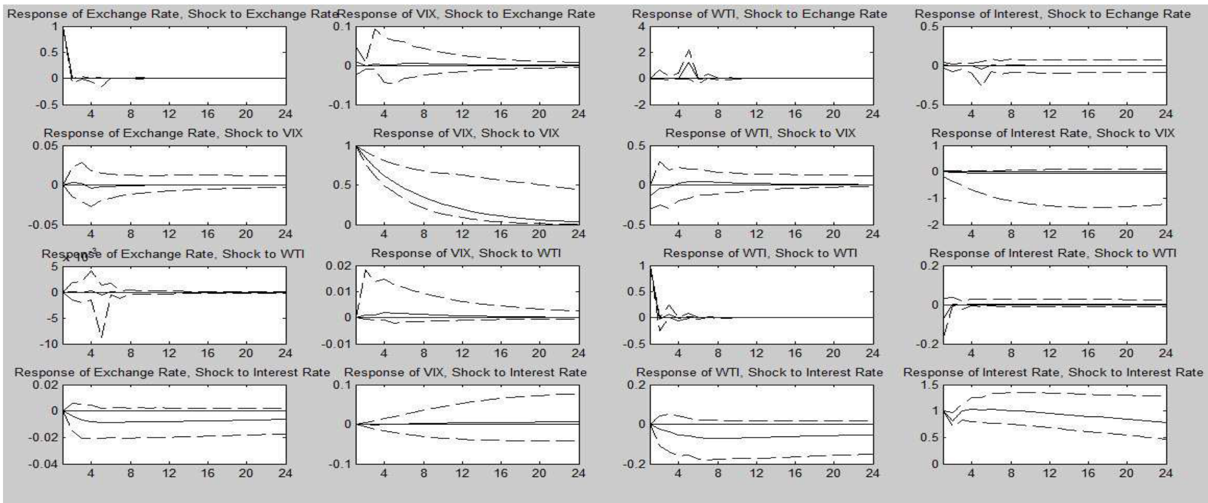


Figure 8: Standard VAR impulse response functions