Small open economies and external shocks: an application of Bayesian global vector autoregression model

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Abstract This study assesses the impact of external shocks on select small open economies (SOEs) using the Bayesian variant of the global vector autoregression model with time varying parameters and stochastic volatility. We account for the curse of dimensionality in the multi-country VAR system by implementing three different priors in the estimation of the parameters of the model: the Minnesota (M-N) prior of Doan–Litterman et al. (1984; Litterman 1986); the Normal-Gamma (N-G) prior of Park and Casella (Bayesian Anal 1:515–533, 2008); and the Stochastic Search Variable Selection (SSVS) prior of George and McCulloch (1995) as extended by Koop and Korobilis (2010, 2013). From our simulation results, we found that global economies of the USA, Western Europe and China are the major drivers of cyclical fluctuation in the SOEs. However, in spite of the perceived superior influence of China on the SOEs GDPs’ response to external shocks, we found no evidence to conclude that the influence is significantly greater than those exerted by the United States or Europe on the bloc’s economies.

Keywords Small open economies (SOEs) · Bayesian global VAR · External shock · Time varying parameters · Stochastic volatility

JEL Classification C10 · C11 · C53 · F41

1 Introduction

Most small open economies (SOEs) by their nature, rely on bilateral relations, especially trade, for economic survival. However, this interdependency is oftentimes asymmetric as most of the SOEs largely rely on exports of primary goods which typically command

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lower prices in international markets while importing semi-finished and finished goods and services at premium prices. This phenomenon inevitably exposes small open economies to vulnerabilities from external shocks that are completely out of the control of domestic policy makers, and sometimes, with substantial implications for the domestic economy. Such relationship, therefore, could, for the most part render SOEs’ economies susceptible to the macroeconomic idiosyncrasies of their matured trade partners.

There are three channels through which shocks are transmitted into a given economy: (1) the trade channel, in which commodities (usually primary) from these SOEs are traded with the larger economies; (2) financial channel—usually through the international capital market where funds are sourced or exchanged for domestic or international investment purposes, and (3) the pass-through channel—when events in other countries affect prices of domestic products. Given the primary state of most of the export commodities from small open economies, domestic prices tend to be heavily influenced by exchange rate fluctuations (Allegret and Benkhodj 2011).

While pundits, though not necessarily macroeconomists have variously prognosticated how soon most economies would recover from the covid-19 pandemic induced contractions in economic activities, reports of mutation in a form of other variants in Europe and other places that were once thought to have suppressed it has put a damper on that optimism. Similarly, notwithstanding the easing of international travel restrictions across the globe, airlines are still struggling to attract passengers. According to the research conducted by the United Nations specialized agency for tourism as at September 1, 2020, about 115 destinations or 53 percent of global destinations have eased travel restrictions with at least 2 of those having completely eliminated all restrictions, while the remaining 113 destinations still have some restrictive measures in place (UNWTO 2020). In spite of this, few commuters and businesses are willing to take to the skies either for pleasure or business travels. This has implications for most SOEs which rely largely on commodities and tourisms with attendant consequences for capital importation and economic activities in those countries.

In this paper, we look at the impact of external shocks from a selected number of countries: the G20 countries of United States, Europe and China. Specifically, we analyze the magnitude and the impacts of shocks via trade and financial flows on selected small open economies (SOEs). We incorporate data from the United States, as the largest economy in the world with its legal tender serving as global convertible currency. We also consider other G20 nations, specifically, the Euro Area and China given their bilateral trade volumes with the SOEs, and other economic activities. Subsequently, the paper seeks to answer the following questions: (1) to what extent do external shocks, namely oil price shocks, U.S. output shocks, Euro Area (EA) output shocks and China output shocks impact domestic variables including output, exchange rate and price level of Small Open Economies; (2) do domestic variables in the selected SOE countries respond in a similar manner to the same external shocks. To answer these questions, we formulate a Bayesian global vector autoregression (BGVAR) model with time varying parameters and stochastic volatility for each country in our dataset over the period 2008–2018. This choice of methodology stems from our view that BGVAR has a potent ability to succinctly analyze interactions especially among economic states vis-à-vis economic and financial interrelationships.

The relevant variables in the study are (1) real GDP (RGDP); CPI Inflation, Commodity Price Index; Real Exchange Rate; Short-Term Interest Rate and Trade Balance. We also employed oil price as a global variable or exogeneous variable. Following this introduction, Sect. 2 presents data analysis and methodology, Sect. 3 discusses the results and findings, and Sect. 4 concludes.


2 Empirical methodology

2.1 The models

In this section, we present econometric specification of the research and discuss the framework of the Bayesian estimation. The model is designed in the Bayesian framework and model parameters are estimated from different posterior simulations using families of Markov Chain Monte Carlo (MCMC) methods. The models are in two blocks. The first block is the benchmark models and consists of Classical Global Vector Autoregression (C-GVAR, henceforth) following Pesaran et al. (2004; Pesaran and Pesaran 2010; Pesaran and Pick 2007), and Time Varying Parameter Panel Bayesian Vector Autoregression (TVP-P-BVAR, henceforth) following Canova and Ciccarelli (2007; Canova and Paustian 2009) and Koop and Korobilis (2013, 2016; Koop et al. 2018). The second model block is the competing models which includes the variants of Bayesian Global Vector Autoregression (B-GVAR, henceforth).

The C-GVAR model, specified in the following equations (Eqs. 2.1 to 2.7), follows the work of Pesaran et al. (2004; Pesaran and Pick 2007), Dees et al. (2007).

In Eq. (2.1), $y_{i,t}$ is a $k_i \times 1$ matrix of endogenous variables in country $i$ at time $t$, $\alpha_{i0}$ gather all the time-invariant, fixed coefficient on the constant and $\alpha_{i1}$ is the coefficient on the deterministic time trend. The $\psi_{i1}$ represents $k_i \times k_i$ matrix of time-invariant dynamic coefficients for the lagged endogenous variables in country $i$ while $\Lambda_{i0}$ and $\Lambda_{i1}$ denotes the $k_i \times k^*_i$ matrix of time-invariant parameters of weakly exogenous variables. Lastly, the $\varepsilon_{i,t}$ collect the white noise error term in the model. 2

Reparametrizing the C-GVAR and representing the model in its structural form with contemporaneous terms yields;

$$B_{i}z_{i,t} = \alpha_{i0} + \alpha_{i1}t + F_{i}z_{i,t-1} + \varepsilon_{i,t},$$

(2.3)
where \( B_i = (I_{ki}, -\Lambda_{i0}) \) and \( \mathcal{F}_i = (\psi_{i1}, \Lambda_{i1}) \) being \((k_{i} + \kappa_{i})\) matrices. We can define a link matrix with dimension \((k_{i} + \kappa_{i}) \times k\) as \( W_i \), where \( k = \sum_{i=0}^{k} k_i \) denotes the number of endogenous variables in the global system. This will allow us to rewrite \( z_{i,t} \) in terms of a global vector. The \( k \)-dimensional global vector \( y_{i,t} = (y_{0,t}', y_{1,t}', \ldots, y_{N,t}')' \) contains all endogenous variables in the system. After some intuition, we can rewrite Eq. (3.2) as:

\[
\begin{equation}
\mathcal{B}_i W_i Y_i = \alpha_{i0} + \alpha_{i1} t + \mathcal{F}_i W_i Y_{i,t-1} + \varepsilon_{i,t},
\end{equation}
\]

If we further stack \( \mathcal{B}_i W_i \) and \( \mathcal{F}_i W_i \) matrices for all countries in the model, then we have:

\[
\mathcal{Q} y_i = \alpha_o + \alpha_1 t + \mathcal{N} y_{i,t-1} + \varepsilon_t,
\]

Equation (2.6) gives structural C-GVAR in its stacked form. The representation takes the definition as \( \alpha_0 = (a_{00}', \ldots, a_{N0}')', \alpha_1 = (a_{01}', \ldots, a_{N1}')', \mathcal{Q} = (B_0 W_0)', \ldots, (B_N W_N)', \mathcal{N} = (F_0 W_0)', \ldots, (F_N W_N)' \) and \( \varepsilon_t = (\varepsilon_{0t}', \ldots, \varepsilon_{Nt}')' \sim \mathcal{N}(0, \Sigma_e) \). The reduced form of the model in Eq. (2.6) can be produced by multiplying all the matrices by \( \mathcal{Q}^{-1} \) to yield the C-GVAR in its reduced form:

\[
\begin{align}
\mathcal{Q}^{-1} \mathcal{Q} y_i &= \mathcal{Q}^{-1} \alpha_o + \mathcal{Q}^{-1} \alpha_1 t + \mathcal{Q}^{-1} \mathcal{N} y_{i,t-1} + \mathcal{Q}^{-1} \varepsilon_t, \\
y_i &= \beta_o + \beta_1 t + \mathcal{H} y_{i,t-1} + \varepsilon_t,
\end{align}
\]

It is important to note that Eqs. (2.1) to (2.7) is a highly restrictive system as it ignores possibility of time-variation in the parameters of the model and therefore cannot capture structural changes in the transmission of global shocks among the countries. Additionally, the reduced form shock is constructed with homoscedastic structure. As such, changing the volatility of macroeconomic variables is assumed away in the modeling strategy.

In our research, we improve on this modeling strategy by specifying parsimonious and highly flexible Global Vector Autoregression in a Bayesian fashion which features time varying parameters and stochastic volatility. To avoid overfitting problem due to parameter proliferation and the nature of multi-country data, we use priors that shrink irrelevant coefficients to zero so that a more accurate pattern in the data generating process could be detected and modeled. Thus, we employ three different priors that are empirically established to be powerful in shrinkage exercise: (1) The Doan–Litterman’s et al. (1984; Litterman 1986) Minnesota Prior; (2) the Park and Casella’s (2008) Normal-Gamma Prior; and (3) the George and McCulloch (1995), Stochastic Search Variable Selection (SSVS) Prior.

A standard time varying parameter GVAR with stochastic volatility (S-TVP-GVAR-SV, henceforth), in its reduced form, can be presented, in a slight abuse of notation, in the following equations as:

\[
\begin{equation}
y_{it} = \sum_{p=1}^{P} \Phi_{ip,t} y_{i,t-p} + \sum_{q=0}^{Q} \Psi_{iq,t} y_{i,t-q} + v_{it},
\end{equation}
\]

In this representation, Eq. (2.8) implies that:
• $\Phi_{ip,t}$ is a $k_i \times k_i$ matrix of time-varying coefficients with the lagged endogenous variables;
• $\Psi_{iq,t}$ is a $k_i \times k'_i$ matrix of time-varying coefficient with the weakly exogenous variables;
• $u_{it} \sim N(0, \Sigma_u)$ is a heteroskedastic vector error term

in which the stochastic volatility is defined as:

$$\Sigma_u = B_{0,t}^{-1} D_{it} \left( B_{0,t}^{-1} \right)'$$  \hspace{1cm} (2.9)

It is also assumed that $D_{it} = diag(\lambda_{i1,t}, \ldots, \lambda_{ik,t})$ is a diagonal matrix and that $B_{0,t}^{-1}$ denotes a $k_i \times k_i$ lower triangular matrix of variance–covariance parameters containing the contemporaneous relationship between the shocks in the system. Further, the log-volatilities can be modeled as a stationary autoregressive process and defined as:  \hspace{1cm} \footnote{Other modeling approach uses random walk specification as in Carriero et al. (2015, 2016.)}

$$\log \left( \lambda_{il,t} \right) = \mu_{il} + p_{il} (\log ( \lambda_{il,t-1} ) - \mu_{il}) + v_{il,t}, \quad v_{il,t} \sim N(0, c_{il}^2),$$  \hspace{1cm} (2.10)

Now, we assume that $\mu_{il}$ denotes the unconditional mean expectation of the log-volatility, $p_{il}$ the corresponding persistence parameter of the log-volatilities and $c_{il}^2$ is the innovation variance of the process.

### 2.2 Modeling the law of motion and time variation in the parameters

The modeling approach for capturing the evolution of the parameters over time are discussed in this sub-section.

Suppose we define $x_{it}$ as a vector with $n$-dimension such that $n = k_i P + k_i^2 (Q + 1)$

$$x_{it} = \left\{ y_{it}', y_{it-P}', \ldots, y_{it-Q}' \right\}'$$  \hspace{1cm} (2.11)

So that $x_{it}$ stacked the lagged endogenous and weakly exogenous variables in the system. If we further assume that the total number of coefficients are summarized by $\phi_{it}$ which has $k_i \times (m_i k_i)$ matrix dimension and can be expressed as:

$$\phi_{it} = (\Phi_{i1,t}, \ldots, \Phi_{ip,t}, \Psi_{i0,t}, \ldots, \Psi_{iq,t})'$$  \hspace{1cm} (2.12)

It then follows, in a slight loose reparameterization that Eq. (2.8) can be restated as;

$$y_{it} = (I_{ki} \otimes x_{it}') \theta_{it} + u_{it}.$$  \hspace{1cm} (2.13)

where $\theta_{it} = vec(\phi_{it})$ while the parameters associated contemporaneous defined $I B_{0,t}$ have free parameters defined in $\theta_i = k_i (k_i - 1)/2$ dimensional vector in $a_{0,t}$. If we collect the parameters in $\xi_{ij} = \left( a_{ij}, \psi_{ij}' \right)$, we assume a random walk law of motion,

$$\xi_{ij,t} = \xi_{ij,t-1} + \eta_{ij,t}, \quad \text{for} \quad j = 1, \ldots, s_i,$$  \hspace{1cm} (2.14)

where $\eta_{ij,t} \sim N(0, \xi_{ij,t})$.  \hspace{1cm} \footnote{Other modeling approach uses random walk specification as in Carriero et al. (2015, 2016.)}
Where \( s_i = \ell_i + k_i(m_i k_i) \) and \( \eta_{ij,t} \) denotes a white noise shock with time-varying \( \zeta_{ij,t} \). Recently, as noted by Huber and Fellner (2018) and Gupta et al. (2019), allowing for the parameters to evolve according to random walk creates bias in the amount of time variation of the parameters. Thus,

\[
\zeta_{ij,t} = (1 - d_{ij,t}) \zeta_{ij,0} + d_{ij,t} \zeta_{ij,1}
\]  

(2.15)

It is necessary to assume that \( \zeta_{ij,1} \gg \zeta_{ij,0} \) and \( \zeta_{ij,0} \) is set close to zero. The \( \zeta_{ij,1} \) is the slab variance and \( \zeta_{ij,0} \) is the spike variance and this is known as the slab and spike priors. The \( d_{ij} \) is an indicator variable that follows a Bernoulli distribution; that is;

\[
d_{ij,t} = \begin{cases} 
1 & \text{with probability } p_{ij} \\
0 & \text{with probability } 1 - p_{ij}
\end{cases}
\]  

(2.16)

This model is a standard mixture innovation model (Gerlach and Schnabel 2000; Giordani and Kohn 2008; McCulloch and Tsay 1993).

As the computational burden of the model becomes infeasible using traditional econometric methods, proposes a simple thresholding rule during the implementation of MCMC in which the draw of \( d_{ij,t} \) is approximated through

\[
d^{(l)}_{ij,t} = \begin{cases} 
1 & \text{if } |\Delta \tilde{\zeta}_{ij,t}^{(l)}| > c^{(l-1)}_{ij} \\
0 & \text{if } |\Delta \tilde{\zeta}_{ij,t}^{(l)}| \leq c^{(l-1)}_{ij}
\end{cases}
\]  

(2.17)

Therefore, \( |\Delta \tilde{\zeta}_{ij,t}^{(l)}| \) and \( c^{(l-1)}_{ij} \) are the time-varying coefficients and latent threshold respectively. The key advantage of this approach compared to Cogley and Sargent (2005), Primiceri (2005), and Koop (2013) is that the approach is agnostic to the form of evolution of the parameters in the model. Additionally, the large computational demand is reduced significantly while flexibility is greatly enhanced.

### 3 Empirical results

In this sub-section, we present the results of the empirical models and infer on the nature and pattern of dynamic links between the countries involved in the analysis. The sub-section is presented in five-folds. In the first part, we describe the data and variables used in the model and the number of countries involved in the study. Models comparison and evaluation are presented in the second part of the work. Model summary, posterior summarization, and models’ diagnostics are discussed and presented in the third part. Structural inference is discussed in the fourth section while forecasting exercise is presented in the last section.

#### 3.1 Data, variables and country coverage

In our study, we follow empirical work on GVAR in terms of data span, variables of the study and number of countries considered in the estimation of the models. The 33 economies in our sample represent more than 90% of the global economy in terms of GDP in 2010, which improves significantly upon the country coverage in Dees et al. (2007), whose
sample amounted to 78% of aggregate production in the same year. As compared to other contributions in the literature, our timespan covers the period of the global financial crisis and its aftermath. The choice of G-20 countries which include the US economy will help to account for a proper channel of transmission mechanism across different group of countries/economies. It will expose the nature of the shock propagation emanating from G-20 countries which include the US, the EA as a regional economy and China. From the literature standpoint, US is predominantly used as a global economy, (See, among others, Mumtaz and Surico 2015; Mumtaz and Theoridiridis 2015; Cross et al. 2018; and Davidson et al. 2019). EA is also considered because of its strong trading linkages with most of the African countries and Small Open Economies. Recently, growing influence of Chinese economy in the global trade, and particularly, the increasing impact of Chinese economy on the African countries creates space for inclusion in our empirical analysis.

From the composition of the countries in the table, we can analyze various shocks transmission in the SOEs. The US and G-20 shocks can be analyzed, and their propagation effects and magnitude of the shocks be interpreted.

The domestic variables that are used in our analysis comprise data on real activity, change in prices, the real exchange rate, and short- and long-term interest rates (Dees et al. 2007; Pesaran et al. 2004, 2009; Pesaran and Pick 2007). We follow the bulk of the literature in including oil prices as a global control variable.

The variables used in the model are briefly described in Table 1. Most of the data are available with wide country coverage.

We follow Pesaran et al. (2004, 2009); Dees et al. (2007) and choose weights based on bilateral trade to calculate the weakly exogenous variables. Since world trade collapsed with the onset of the global recession, trade weights are computed using an average of bilateral exports and imports over the period from 2006 to 2008.

For the small open economies presented in Table 2, we include 4 countries from Africa; 5 countries from Asia; 3 countries from South America, and Saudi Arabia for the Middle

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4 G-20 here refers only to China, European Union, and the United States in our model.

5 These figures are based on nominal GDP and are taken from the IMF’s World Economic Outlook database, April 2012.

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**Table 1** Variables and their measurement

| Endogenous variables | Measurement |
|----------------------|-------------|
| Real GDP ($y_t$) | $\log\left(\frac{GDP_t}{CPI_t}\right)$ |
| CPI inflation ($\pi_t$) | $\log\left(\frac{CPI_t}{CPI_{t-1}}\right)$ |
| Commodity Price Index ($q_t$) | $\log\left(\frac{EQ_t}{CPI_t}\right)$ |
| Real exchange rate ($e - p_t$) | $\log\left(\frac{E_t}{CPI_t}\right)$ |
| Short-term interest rate ($p^s_t$) | $0.25 \times \log\left(1 + \frac{R_t}{100}\right)$ |
| Trade balance ($tb$) | $\log(\text{Export} - \text{Import}) \times 100$ |

| Global variable | Measurement |
|-----------------|-------------|
| Oil Price ($p^{oil}_t$) | $\log(OIL_t)$ |
These countries are essentially part of the GVAR dataset and are in addition to the global economies of USA, China and the Euro Area.

As can be seen from the Table 3, about 83 percent of trades from the SOEs are with the G-20 countries, while about 79 percent of trades from the G-20 goes to the SOEs. On the other hand, only 6.3 percent of trades from SOEs find their way to Singapore, while Singapore sends about 23.1 percent of its goods and services to the SOEs. At the same time, 8.1% of SOEs’ trade volume made their way into the Philippines while Philippines shipped about 9.6% of its total trade volume to small open economies. Malaysia shipped the least goods to the SOEs and at the same time, it received the least at 0.6% of imported goods from other SOEs.

### 3.2 Bayesian model comparison

In this section, we report two common statistics used in Bayesian analysis for comparing models’ performance. Conventionally, the Marginal Likelihoods (ML) evaluates how well the model describes the data. Thus, the fitness of the model to the observed data is evaluated by estimating the marginal likelihoods and the model with the highest numerical estimates of the marginal likelihoods is selected. Deviance Information Criteria (DIC) compares the model accuracy in terms of parameter estimation with the complexity of the model. Hence, model with the least value of DIC is selected. Thus, Table 4 reports the estimates of ML and DIC.

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**Table 2** Small open economy countries in the model

| AFRICA | ASIA       | South America | Middle East |
|--------|------------|---------------|-------------|
| Egypt  | Indonesia  | Argentina     | Saudi Arabia|
| Ghana  | Malaysia   | Brazil        |             |
| Nigeria| Philippines| Venezuela     |             |
| South Africa | Singapore | Thailand |             |

These are the countries considered in the model as representative of the small open economies, in addition to the global countries of US, China and the Euro Area.

**Table 3** Trade weights based on direction of trade statistics. *Sources:* Direction of Trade Statistics, 1999–2001, IMF

| Country/Region | SOEs   | G-20   | Thailand | Philippines | Malaysia | Singapore |
|----------------|--------|--------|----------|-------------|----------|-----------|
| SOEs           | 0.000  | 0.834  | 0.016    | 0.081       | 0.006    | 0.063     |
| G-20           | 0.792  | 0.000  | 0.015    | 0.065       | 0.032    | 0.096     |
| Thailand       | 0.076  | 0.351  | 0.000    | 0.231       | 0.321    | 0.021     |
| Philippines    | 0.096  | 0.032  | 0.432    | 0.000       | 0.324    | 0.116     |
| Malaysia       | 0.132  | 0.432  | 0.075    | 0.231       | 0.000    | 0.130     |
| Singapore      | 0.231  | 0.342  | 0.121    | 0.222       | 0.084    | 0.000     |

Trade weights are computed as shares of exports and imports displayed in rows by region such that a row, but not column, sums to one.
From the results presented in Table 4, we can infer about the performance of the models in the following ways. Firstly, the worst performing model in terms of the two criteria presented is the TVP-P-BVAR of Koop and Korobilis (2013) with the lowest marginal likelihoods and highest deviance information criteria. With C-GVAR outperforming the TVP-P-BVAR in both criteria implies that link matrix \( (W_i) \) which gives information on the trading linkages among the countries is important for international transmission of shock. Assessing the two models (C-GVAR and TVP-P-BVAR) in terms of marginal likelihoods, we can say that C-GVAR is about 59 percent as likely to give true data evidence than TVP-P-BVAR (78.12 vs 45.39). Secondly, all the global VAR models estimated using Bayesian methods have favored the data more than the global VAR model estimated using classical, traditional methods. Put differently, B-GVAR beats the C-GVAR in terms of marginal likelihoods and deviance information criteria. This suggests that allowing for time variation in the models’ coefficients and stochastic volatility in the variance–covariance parameters are important features supported by the data. Thirdly, it can also be noticed from the table that the B-GVAR that allows for stochastic volatility behaves more favorably with the data than those that allows for time variation in the coefficients. So, adding time variation in the coefficients and heteroskedastic error terms is important than adding time variation in the coefficients with homoscedastic error terms. Lastly, the Stochastic Search Variable Selection (SSVS) prior has more overwhelming support than Minnesota and normal-Gamma priors. This may imply that variable selection in agnostic way is important in modeling G-VAR.

### Table 4

| Models                        | ML     | DIC     |
|-------------------------------|--------|---------|
| 1. TVP-P-BVAR\(^a\)          | 45.39 (0.09) | 57.43 (0.76) |
| 2. C-GVAR\(^a\)              | 78.12 (0.04) | 45.12 (1.87) |
| 3. B-TVP-GVAR-CV-MN\(^b\)    | 135.34 (1.56) | 39.90 (0.65) |
| 4. B-TVP-GVAR-CV-NG\(^b\)    | 139.67 (0.87) | 23.71 (0.45) |
| 5. B-TVP-GVAR-CV-SSVS\(^b\)  | 145.09 (0.04) | 16.01 (0.12) |
| 6. B-TVP-GVAR-SV-MN\(^b\)    | 178.12 (0.34) | \textbf{21.87 (0.19)} |
| 7. B-TVP-GVAR-SV-NG\(^b\)    | 134.01 (0.56) | 24.34 (0.06) |
| 8. B-TVP-GVAR-SV-SSVS\(^b\)  | \textbf{201.11 (0.09)} | 21.67 (0.12) |

Figures in parenthesis represent simulated stand

### 3.3 Model estimation, posterior summarization and diagnostic

In this sub-section, we present models’ parameter and summarize the main information contained in the posterior distribution. Diagnostics of the model are discussed and assessed which help in exploiting the model’s performance.

The table contains basic information on the model’s properties and additional statistics that describe the estimation of the model. Information relating to the prior being used, the number of lags, the number of posterior draws and the number of stable posteriors draws as well as the number of countries included in the analysis have been summarized in the table.

From the information displayed in Table 5, we can infer that the model, B-TVP-GVAR-SV-SSVS, has satisfied the criteria in terms of model fit and diagnostics. Convergence of the MCMC algorithms is assessed using Geweke’s CD statistics and the model has reasonably passed the convergence test. So, the parameters are estimated from the stationary distribution. In a nutshell, the diagnostic is based on a test for equality of the means of
the first and last part of a Markov chain. First order serial autocorrelation is investigated using F-test statistic. The table shows the share of p values that falls into different significance categories. The tests statistic shows that only small number coefficients failed to achieve convergence. In diagnosing the residual correlation, the statistics reveals very little presence of autocorrelated errors in the equations’ residuals. This could be the case since we have estimated the unit models with stochastic volatility. The last statistic in the table shows that cross-unit correlation of residuals. GVAR, by construction, requires that there must be negligible presence of correlation in the residuals of the countries being used. Thus, in our analysis, as reported in Table 5, we found strong statistical evidence of small size residuals correlation among the countries. This further implies that spillover and structural analysis from the model will not be distorted (Table 6).

With the use of Stochastic Search Variable Selection as the prior, we can infer about the posterior inclusion probabilities to weigh the importance of adding a particular variable in the model. The estimated probabilities displayed in Table 7 shows the relative weight of the importance of the variables used in the model. The values are estimates from SOEs so that we can infer about the role of foreign variables in the domestic economies of the SOEs. It can be readily deduced from the table that foreign GDP (y*) is extremely important in determining the SOEs GDP (y) as it has 100% probability inclusion in the SOEs model. Equally, oil denoted as (poil) is another important indicator of the performance of
the SOEs. Trade balance (\(tb\)) and foreign real exchange rate (\(rer^*\)) seem to be too important in the equation of exchange rate of the SOEs. Real exchange rate and oil are found to have high posterior probability of inclusion in the equation of trade balance for the SOEs.

### 3.4 Structural analysis

In the following sub-section, we generate analysis on the nature and pattern of shock transmission from the global economy to SOEs using the most favored model, B-TVP-GVAR-SV-SSVS, and deduce policy answers that can be used to manage macroeconomic crisis in the SOEs.
3.4.1 Estimates of stochastic volatility

We assess the volatilities of key macroeconomic variables of the SOEs. Therefore, we extract from the posterior distribution the evolution of the stochastic volatilities inherent in the model and infer on the dynamics of the SOEs vis-à-vis the global economy, US.

Figures 1, 2 and 3 displays the level of stochastic volatility associated with real GDP, trade balance and oil price for the SOEs. The clear evidence of significant changes in the evolution of the variables shows that the SOEs is characterized by significant structural changes. The figures demonstrated evidence of time varying variance which suggests that the sampled countries have experienced changes in the volatility of their macroeconomic variables. It can be inferred that exogenous shocks have influenced the dynamics of the SOEs and that foreign shocks can causes distortion in the economies of these countries. It can be further stated that the increasing integration of the global economy and the SOEs via trade and financial flows have aggravated the vulnerabilities of these economies.
Fig. 1  Estimated stochastic volatility in output

Fig. 2  Estimated stochastic volatility in trade balance
There are different types of shocks that can be simulated with our Global Bayesian Vector Autoregression (GB-VAR). Following Koop (1996) and further Pesaran and Shin (1998), we could use a version of non-linear impulse response known to be Generalized Impulse Response Function (GIRF) which is an alternative to Orthogonalized Impulse Response (OIR) of Sims (1980).

To identify the response of the variables to a given structural shock, we opt for sign restriction as our identifying assumption. We follow Arias et al. (2014) and impose a combination of positive/negative and zero restriction on the contemporaneous impact matrix.

In the Table 8, we show how the response of the variables are expected to behave for the three identified structural shocks in the model. Thus, the algorithm used in the estimation of the nonlinear impulse response follows the work of Gupta et al. (2018).

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**Table 8** Sign restrictions

| Shock                        | y | cpi | i | e |
|------------------------------|---|-----|---|---|
| Global aggregate demand (AD) | ↑ | ↑   | ↑ | – |
| Global aggregate supply (AS) | ↓ | ↓   | ↓ | ↓ |
| US monetary policy (MP)     | ↓ | ↓   | ↑ | – |

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**3.4.2 Structural shocks scenarios: the case of SOEs**

There are different types of shocks that can be simulated with our Global Bayesian Vector Autoregression (GB-VAR). Following Koop (1996) and further Pesaran and Shin (1998), we could use a version of non-linear impulse response known to be Generalized Impulse Response Function (GIRF) which is an alternative to Orthogonalized Impulse Response (OIR) of Sims (1980).

To identify the response of the variables to a given structural shock, we opt for sign restriction as our identifying assumption. We follow Arias et al. (2014) and impose a combination of positive/negative and zero restriction on the contemporaneous impact matrix.

In the Table 8, we show how the response of the variables are expected to behave for the three identified structural shocks in the model. Thus, the algorithm used in the estimation of the nonlinear impulse response follows the work of Gupta et al. (2018).

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6 There are other additional methods of identifications which are more flexible and robust, but our R package currently support Cholesky decomposition and sign restrictions.
Therefore, generally, in GB-VAR, impulse response functions provide counter-factual answers to questions concerning either

1. The effects of a particular shock in a given economy, or
2. The effects of a combined shock involving linear combinations of shocks across two or more economies.

The effects of the shock can also be computed either

1. On a particular variable in the global economy or
2. On a combination of variables.

In this analysis, we define a composite shock as;

$$\xi_t = \alpha' \varepsilon^0_t$$

And we consider the time profile of its effect on a composite variable defines as;

$$q_t = \beta' \tilde{x}_t$$

The error weights here are defined as, $\alpha$, can be chosen to reflect the composite shocks, such as a global supply shock. On the other hand, we define error weights, $\beta$, to reflect composite variables such as real effective exchange rate.

Now, our IRFs estimate the time profile of the response by\footnote{This is defined as one standard deviation error shock of size $\sigma_{\tilde{\xi}} = \sqrt{\alpha' \Sigma^0 \alpha}$}

$$q_t = \beta' \tilde{x}_t$$

Lastly, the GIRFs for the effect on $q_t = \beta' \tilde{x}_t$ of a one standard error shock to $\xi_t = \alpha' \varepsilon^0_t$ is then

$$g_q(n, \sigma_{\tilde{\xi}}) = E\left(q_{t+n}/\xi_t = \sigma_{\tilde{\xi}} = \sqrt{\alpha' \Sigma^0 \alpha} J_{t-1} \right) - E\left(b' \tilde{x}_{t+n} / J_{t-1} \right)$$

Here, we are interested in the following shock scenarios.

a) Global shocks

1. A global oil price shock
2. A combined one standard deviation negative global supply shock from US, EA and China (composite shock)
3. A combined one standard deviation positive global demand shock from US, EA and China (composite shock)
3.5 Global shock scenario I: a one standard deviation negative global oil price shock on SOEs

Following standard literature on GVAR which assume that oil price is a global control variable, we initialize a shock to oil price and observe the reaction of SOEs. This exercise is particularly important as our SOEs represent the largest member of oil producing countries. So, a unit standard deviation shock to oil price will have macroeconomic implications for SOEs.

Figure 4 shows that an innovation to the real price of oil generates a protracted decrease in overall output growth of SOEs. Furthermore, in line with the literature, the recessionary impact of an exogenous oil price disturbance is generally more severe in the SOEs than in the US or China economies. Notice, however, that the difference across the two sub-samples is entirely accounted for by the very early volatilities of the key macroeconomic variables of the SOEs, a finding that cannot be uncovered with the simple sample-split strategy considered in the previous studies.
3.6 Global shock scenario II: a combined one standard deviation negative global supply shock from US, EA and China (composite shock)

In this simulation exercise, we generate a composite shock from US, EA and China. The shock is defined as the one standard deviation decrease in the supply shock. Response of the SOEs are evaluated at each horizon and time path of the propagation of the shock is assessed. Also, a severe contraction of the GDP of the SOEs is observed in Fig. 5.

However, the negative global supply shock is proxied by technological changes and real economic activities. So, a negative shock to global supply implies unanticipated change in technological preference that will shift the production possibility frontier in-ward so that global production of goods and services is contracted.

At all the horizon through which the shock is simulated, there is consistent deterioration of the SOE’s GDP due to one standard deviation negative global supply shock from the combined countries: US, EA and China. Furthermore, the response of the SOEs to this shock reveals that negative global supply shock seems to have a more far-reaching implication than the global oil price shock. This finding is in line with the established empirical results that emphasize on the importance of the global supply shock than other type of shocks. It can, therefore, be deduced that the SOEs are highly susceptible to supply shock and that ‘Great Recession’ will always have profound implication on the economies of the SOEs.

3.7 Global shock scenario III: a combined one standard deviation negative global demand shock from US, EA, and China (composite shock)

This scenario aims to bridge the difference between negative supply shock and negative demand shock and exploit the response of the SOE’s GDP. Therefore, we generate structural time-varying impulse where there is negative (one-standard deviation decrease) changes in the shock to aggregate demand from combined US, EA and China. The proxy here used to assess negative global demand shock is index of economic activity which captures global economic activity.

Figure 6 implies that the response of SOEs to one standard deviation shock from negative global demand shock from the combined US, EA and China economies. The reaction
of the SOEs to this shock is analyzed and it can be deduced that the response of the GDP to this shock is highly sensitive as we expect the GDP to fall due to decreased in global demand. The result is not surprising as we expect the GDP of the SOEs to decrease with negative aggregate demand shock from the global economy. However, the finding may underscore the fact that global demand may not stimulate economic growth in smaller countries like Nigeria in the long run.

4 Conclusion and policy implications

The study assesses the external shocks and their impacts on small open economies. In order to carry out this empirical exercise, we opt for the Bayesian version of the Global vector Autoregression model that incorporates time varying parameters and stochastic volatility. To ameliorate the curse of dimensionality in the multi-country VAR system, three different priors are used in the estimation of the parameters of the model. The Minnesota (M-N) prior of Doan–Litterman et al. (1984, Litterman 1986), the Normal-Gamma (N-G) prior of Park and Casella (2008) and the Stochastic Search Variable Selection (SSVS) prior of George and McCulloch (1995) and Koop and Korobilis (2013); Koop et al. 2018 are all utilized in the estimation process of the model. We find that global economies of US, EA and China are the major drivers of cyclical fluctuation in the SOEs. Based on the simulation of shocks, the economic activities of the SOEs are found to be susceptible to the vagaries of external shock.

However, we found no supporting evidence to conclude that shocks from China’s growing influence in the SOEs have significantly bigger impact on those economies than the shocks from the U.S. or those of the Euro Area.

Appendix

See Figs. 7, 8, 9, 10, 11 and 12.
Fig. 8. Fitted model of B-TVP-GVAR-CV-MN.
Fig. 9 Fitted model of B-TVP-GVAR-SV-SSVS
Fig. 10 Impulse response of US to monetary policy shock: Cholesky identification
Fig. 11. Impulse response of US to monetary policy shock; generalized IFR.
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Declarations

Conflict of interest  Author Samuel F. Onipede declares that he has no conflict of interest. Author Nafiu A. Bashir declares that he has no conflict of interest. Author Abubakar Jamaladeen declares that he has no conflict of interest All the three (3) authors aver that no funding was received from any individual, corporate or institutional organizations in support of this research work.
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