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Does Global Fear Predict Fear in BRICS Stock Markets? Evidence from a Bayesian Graphical Structural VAR Model*

Abstract

We examine the predictive power of implied volatility in the commodity and major developed stock markets for the implied volatility in individual BRICS stock markets. We use daily data from 16 March 2011 to 07 October 2016 and employ the newly developed Bayesian Graphical Structural Vector Autoregressive (BGSVAR) model of Ahelegbey et al. (2016). We report evidence that the predictability of individual implied volatilities in BRICS is generally a function of both global and within the group stock market implied volatilities, and that the role of commodity market volatility is marginal, except for South Africa. Important implications for policy-makers and portfolio-managers are discussed.

Keywords: Bayesian graphical structural VAR; volatility predictability; implied volatility index; VIX; BRICS

JEL Codes: C32, G15

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1. Introduction

BRICS stock markets are not only active and vibrant but also useful for portfolio diversification. They attract capital inflows from foreign investors as BRICS economies continue to gain ground in international finance and enjoy higher economic growth than developed economies (Bhuyan et al., 2016) mired in a slow growth environment. At the end of 2015, data from the World Federation of Exchanges show that the total market capitalization of BRICS countries is 12,809 trillion USD, a value that exceeds by 1,200 trillion USD the total combined market capitalization of Europe, Middle-East and Africa. Also BRICS economies are home-based of major sources of demand and supply for strategic commodities, such as gold and crude oil. In fact, China and India are key consumers of crude oil, whereas Russia is one of the largest producers of crude oil and natural gas[1]. Concerning the gold market, China is the world's largest producer, as well as the second largest gold consumer, followed by India[2]. In 2015, the World Gold Council show that both China and India consumed 1,845.80 metric tonnes of gold representing more than 53% of world consumption[3].

Similar to emerging markets, BRICS markets are sensitive to changes in macroeconomic and global market conditions (Mensi et al., 2014). While, the role of domestic factors in driving economic and financial conditions in BRICS countries cannot be ignored, there a lot of evidence that external factors predominately drive many of the economic and financial conditions in BRICS countries. For example, BRICS countries suffered the impact of the global financial crisis (GFC) and, as a result, experienced volatile capital flows and stock market returns. Undoubtedly, robust economic conditions in the US and the reset of developed economies are beneficial for the economies of BRICS which share significant

[1] According to the latest figures from IndexMundi, in 2013, China (India) imported and consumed respectively 5,664 (3,272) and 10,480 (3,660) million barrels of crude oil per day. Interestingly, China has surpassed the US and become the largest oil importer in 2015 with record 6.7 million barrels imported from overseas. Further, the Energy Information Administration (EIA) indicates that India's demand for oil is expected to expand to 10 million barrels per day by 2040. As for Russia, it is the second largest producer and exporter of crude oil after Saudi Arabia.

[2] Altogether, China, Russia, South Africa and Brazil produce around 31% of world gold production.

[3] The World Gold Council also shows that, as of June 2016, China, Russia, and India officially hold 1,929.30, 1,498.7 and 557.8 metric tonnes of gold, respectively.

trade and economic ties with developed economies[4]. Conversely, weak economic conditions in developed economies will lead to a decline in exports from BRICS to developed markets and also to a decline of investments and capital inflows from developed to BRICS economies. Given the rising integration of the BRICS in the global economy and evidence of significant financial flows from developed economies to BRICS economies, shocks from the US and developed economies can be transmitted to BRICS and have an effect on their stock markets (Bansal et al., 2005; Ozoguz, 2009; Mensi et al., 2014). Given that the US uncertainty is negatively related with US equity returns (Jubinski and Lipton, 2012), it is therefore possible that the former has significant (negative) impacts on stock returns in major emerging markets such as BRICS. In fact, Sarwar (2012) examines the link between US uncertainty and stock markets returns in BRIC countries from 1993 to 2007 and find that the US VIX is also an investor fear gauge for the stock markets of Brazil, India, and China. Further recent evidence from Sarwar and Khan (2016) implies that the US uncertainty is a good proxy for the stock markets of emerging markets, including BRICS. Importantly, Mensi et al. (2014) provide evidence of comovement of BRICS stock markets with leading global factors (S&P index, oil, gold), and show that the US VIX has some negative effect on BRICS stock market returns during bearish periods. In addition to trade and economic ties, advanced technology and world economic and financial integration are partially responsible for the volatility linkages between developed and BRICS economies. The fact that some of BRICS countries are home-based of major sources of commodity (crude oil and gold) supplies, also suggests that slower growth in develop economies are more likely to affect those economies and their stock market volatility. For example, lower commodity prices, has adversely affected economic activities in commodity-exporting BRICS. This also implies potential linkages between the implied volatilities of crude oil and gold and the implied volatilities of BRICS countries. We also follow some of the logic from Sarwar (2016) and argue that the VIXs of BRICS countries will respond to a change in VIXs of major developed countries because the market risks reflected in the latter are also part of the risks for the former. According to the discounted cash-flow method, stock prices in BRICS are affected by changes in the discount rate which reflect changes in the risk-free rate, risk premium including the inflation expectations. In fact, discount rates depend on the state of domestic economic factors, systematic risk, and monetary policies; given evidence that BRICS countries are also sensitive to global macroeconomic conditions and US decisions by the

[4] In 2015, the US total trade (imports and exports) with BRICS countries reached 760.86 billion USD (599.31 with China, 66.24 with India, 59.11 with Brazil, 23.44 with Russia, and 12.76 with South Africa).

Federal Reserve, it follows that the stock market (implied) volatility in BRICS will rise as this common risk factor rises in the US and the rest of developed economies.

While the existing literature provides evidence on the price formation in the stock markets of the BRICS as well as on their return and volatility linkages with that of developed economies and strategic commodities such as oil and gold (see Section 2), it lacks empirical evidence on whether the implied volatilities of oil, gold, and developed stock markets can be used to predict the implied volatility of individual BRICS stock marktes. While Mensi et al. (2014) consider the US VIX within a quantile regression approach, the authors only examine the impact of the price returns of strategic commodity markets (oil and gold) and the S&P index on the returns of BRICS stock markets, and thus overlooked volatility linkages. However, market participants are also interested with the volatility linkages across markets, especially with that involving implied volatility that reflect investors' expectation of future stock market volatility for the next month and thus are more interesting than other historical measure of volatility such as realized or GARCH-based volatilities (Maghyereh et al., 2016).

Addressing such a significant gap in the literature is important for the planning and execution of investment strategies investment allocation and portfolio diversification inferences, given that evidence of predictability suggests that market participants have quite similar expectation of future volatility. Especially, hedging Vega to offset the negative effect of increased volatility in any portfolio containing options is an important element of risk management given the emergence of some financial derivatives on several VIXs indices (e.g. futures and options).

In addition to the use of global VIXs in assessing the predictability of individual BRICS implied volatilities, where most of the studies rely on historical measures of volatility, we make the empirical investigation more interesting by employing a newly developed methodology based on the Bayesian Graphical Structural Vector Autoregressive (BGSVAR), recently developed by Ahelegbey et al. (2016). Given the lack of indications from economic theory on an association across implied volatility indices, the BGSVAR methodology of Ahelegbey et al. (2016) is suitable to attain the aim of this study that consists of examining the predictive power of implied volatility in the commodity and major developed stock markets for the implied volatility in individual BRICS stock markets. The BGSVAR approach is superior to the standard SVAR model which is often criticized for imposing implausible restrictions or, at least, restrictions that are as plausible as the underlying economic theory that are stemming from. In addition, SVAR models are useful tools to analyze the dynamics of a model by relying on the impulse response function which measures the degree of responses of endogenous variables to isolated unexpected structural shocks. In contrast, the BGSVAR helps uncovering, within a multivariate time series analysis, the presence and effects of contemporaneous and lagged causality across the examined variables by relying on a graph representation of the conditional independence among the examined variables (Ahelegbey et al., 2016).

The closet study to ours is that of Mensi et al. (2014), who examine the asymmetric dependence structure between the stock market returns of the BRICS countries and influential global factors using the quantile regression approach. They show that BRICS markets exhibit dependence with the global stock and commodity markets (S&P index, oil, and gold) as well as changes in the U.S. stock market uncertainty (CBOE Volatility Index). However, our study differs in several aspects. Instead of using a bivariate time series analysis as in Mensi et al. (2014), we follow the BGSVAR that help to uncover the presence and effects of contemporaneous and lagged causality across the implied volatility indices of BRICS, developed countries, and commodity markets, by modelling them simultaneously. In other words, we are able to account for a broader range of predictors simultaneously using a Bayesian approach. Besides, our model does not suffer from possible misspecification due to the omission of an important volatility index involving global stock and commodity markets. Hence, we are able to examine the predictive ability of implied volatilities in BRICS both in the contemporaneous and lagged senses, based on information coming from not only the own VIXs, but also from VIXs global stock and commodity markets. While we acknowledge the fact that quantile regressions used by Mensi et al., (2014) allows one to capture the impact of these global factors on the BRICS stock markets at its various phases (i.e., bear (lower quantiles), normal (median) and bull (upper quantiles)), we provide a time-varying analysis of our network structure by using rolling window estimation to analyze the evolution of the interrelationship between the various global VIXs and BRICS VIXs. Since quantile estimation of BGSVAR is yet to be theoretically developed, we take the rolling regression route to provide a time-varying analysis of the relationships considered.

The paper proceeds as follows. Section 2 reviews the related literature. Section 3 presents the data. Section 4 explains the empirical models. Section 5 reports and discusses the results. Finally, section 6 concludes.

2. Related studies

Along with globalization and the rising importance of BRICS stock markets for international diversification, numerous studies have recently emerged to clarify price return and volatility discovery in the stock markets of BRICS, and to understand their interaction with other global and commodity markets.

A first strand of research considers the return and volatility linkages between developed and BRICS stock markets, and the benefits of diversification and risk management perspectives. Bhar and Nikolova (2009) use a bivariate EGARCH model with time varying correlations and conclude that BRICS stock markets are useful for international portfolio diversification. Aloui et al. (2011) show that the stock markets of Brazil and Russia are more dependent on the US stock market conditions than China and India. Similar results are reported by Bianconi et al. (2013). Dimitriou et al. (2013) use the multivariate fractionally integrated asymmetric power ARCH dynamic conditional correlation (FIAPARCH-DCC) model and report that the dependence between the US and BRICS stock markets is higher in bullish than in bearish markets, highlighting the diversification benefits. Gilenko and Fedorova (2014) employ a multivariate GARCH model and focus on the volatility transmission between the stock markets of the USA, Germany, Japan and the MSCI Emerging market index and BRIC stock markets. After accounting for the effect of the GFC, the authors provide some evidence for the decoupling hypothesis. Mensi et al. (2014) use a quantile regression approach and find that the BRICS stock markets exhibit dependence with the US stock market and its uncertainty. Samargandi and Kutan (2016) use a VAR-based model to show that credit to the private sector has a positive spillover effect on growth in some of the BRICS countries. Using a Bayesian form of Samargandi and Kutan's (2016) methodology, Tsionas et al. (2016) study the transmission of financial and monetary shocks from BRICs to the US and 17 European countries. The authors show that interest rates and total credit have a significant impact on the transmission of shocks. Mensi et al. (2016) employ the same methodology of Dimitriou et al. (2013) and report dynamic correlations between the US and the BRICS stock markets. Furthermore, the effects of both return and volatility transmission from the US market to the BRICS markets have been the subject of Bhuyan et al. (2016) who show that the US market is the mean and volatility transmitter to the BRICS markets, while, interestingly, the Chinese stock market exerts a significant mean spillover effects on the US market. Jin and An (2016) use the volatility impulse response technique and examine the contagion effects between the US and BRICS stock markets. The authors find that the US and BRICS stock markets are interconnected by their volatilities. They also report evidence of contagion effects from the US to the BRICS stock markets during the GFC although the degree of effects differ from one market to another, according to the level of integration with the global economy. Most of the above-mentioned studies, pertaining to the first strand of research focus on the predictability of BRICS stock market returns, reveal evidence of significant effects from developed economies to BRICS stock markets. Furthermore, reported evidence of the volatility transmission is based on historical volatility modelled through a GARCH based framework. We instead use implied volatility indices which reflects investors' expectation of future stock market volatility indices.

Given the important role played by BRICS countries in driving the world commodity markets, a second strand of research focuses on the link between BRICS stock markets and commodity markets, in particular crude oil and gold commodities. Ono (2011) uses a VAR model to examine the impact of oil prices on the stock markets in BRIC countries. They show that the volatility of stock returns in China and Russia in particular are affected by oil price shocks. Hammoudeh et al. (2014) use a copula function to examine the interdependence of commodity and stock markets in China and highlight risk diversification and downside risk reduction benefits from adding commodities in a stock portfolio. Using a multivariate GARCH model, Kumar (2014) use a multivariate GARCH and shows unidirectional significant return spillover from gold to Indian equities and stress on the hedging effectiveness of adding gold to a portfolio of Indian stocks. Thuraisamy et al. (2013) use a multivariate GARCH model and find that the volatilities of gold and oil prices are related to Asian stock market volatility (including China and India). Mensi et al. (2014) focus, among others, on the dependence structure between BRICS stock markets and strategic commodities (oil and gold). They find evidence of positive effects of gold prices on BRICS stock returns regardless of the condition of the stock markets. However, the impacts of oil prices on BRICS stock market indices is not consistent across the countries and differ between upper and lower quantiles. Beckmann et al. (2015) use a smooth transition regression to assess the hedge and safe haven roles of gold from 1970 to March 2012 on a monthly frequency, and find that gold exhibits a strong safe haven function in India but not in China and Russia. Chkili (2016) uses an asymmetric DCC model for weekly data on gold and BRICS stock markets and provide evidence that gold can act as a safe haven in times of market stress. Using a quite similar methodology, Jain and Biswal (2016) uncover strong relationships between prices of gold, oil, and Indian stocks and suggest the importance of using gold price to restrain stock market volatility.

As shown above, while prior studies show some interactions between the prices of gold, oil and the BRICS stock markets, they mostly rely on return linkages and, to a lesser extent, volatility linkages. The latter have been usually modelled using historical volatility measures, whereas we use implied volatility indices.

A final strand of research has recently used implied volatility indices, mainly the VIX, and examined the linkages between assets and other financial variables. Mensi et al. (2014) find that the US VIX has a negative effect on BRICS stock market returns in bullish periods. Tsai (2014) examines the volatility spillover effect in the stock markets of the US, UK, Germany, Japan, and France. The author uses the US VIX to explain the volatility spillover effect and finds that this specific non-fundamental factor is the main factor behind the increased correlation between markets. Basher and Sadorsky (2016) employ the US VIX within a GARCH-based framework and associates between emerging stock prices, oil, gold, and the VIX. Interestingly, Maghyereh et al. (2016) use implied volatility indices and report that manly crude oil transmits its effect on developed and emerging stock markets. Sarwar (2016) examines, among others, implied volatility linkages between gold and US equities and shows that the US VIX Granger causes the volatilities of gold, but not the other way around. Sarwar and Khan (2016) use GARCH-based model and Granger causality test to examine the effects of US stock market uncertainty, as measured by the VIX, on the stock returns in Latin America and broader emerging equity markets before, during, and after the 2008 financial crisis. The authors find that intensified market uncertainty reduces emerging market returns but raises the variance of returns. Sousa et al. (2016) find weak evidence of return predictability for BRICS countries based on the commodity price growth variable, and the US VIX, but report stronger evidence for the role of global equity returns. In an interesting paper, Chen (2014) uses copula-based bivariate Markov-switching model and examines the linkages among implied volatility indices of Canada, Japan, Germany and the United States. The author highlights the dominant role played by the US stock market and argues that the linkages are more pronounced when the implied volatility indices rise and during crisis periods. Bouri et al. (2017) focus on the implied volatility linkages across gold, oil, and Indian equity markets. They find significant cointegration and nonlinearity in the relation. We instead examine whether implied volatility indices in strategic commodity markets (oil and gold) and major developed stock markets (Canada, France, Germany, Holland, Japan, Sweden, Switzerland, United Kingdom, and USA) have predictive ability with respect to the implied volatilities in individual BRICS stock markets. Such an innovative research question surprisingly remains unexplored. We also add to the related literature by using a newly developed methodology based on the graph representation of the conditional independence among the implied volatility indices (Ahelegbey et al., 2016). In particular, this methodology is suitable to our case as no comprehensive theory appropriately relates between the implied volatility indices under study. There are several advantages of the BGSVAR approach. The first and the most attractive feature is that the BGSVAR enables a data-driven identification of the most dominant VIX in the system where temporal financial shocks may largely diffuse through the international financial market. Second, because the BGSVAR is a class of multivariate analysis that uses graphs consisting of nodes and edges to study the interaction and path dependence between variables (i.e. VIXs), it enables researchers to discover hidden and complex links, interactions, and non-linear dependence structure of multiple variables (see Ahelegbey, 2016, for a more comprehensive review).

3. Data

For the purpose of this study, we rely on daily data for the implied volatility indices of 16 stock and commodity markets. These indices include five *response* variables representing the implied volatility indices of BRICS countries: (BRL), Brazil; (RUA), Russia; (INA), India; (CHA), China; (SOA), South Africa. As for the *predictor* variables, they are 11 implied volatility indices representing nine developed countries: (CAA), Canada; (FRC), France; (GEY), Germany; (HOD), Holland; (NII), Japan; (SWN), Sweden; (SWD), Switzerland; (UK), United Kingdom; (CBE), USA; and two commodity markets: (GOLD), Gold; (OIL), Crude oil. Our full sample period spans from 16 March 2011 to 07 October 2016, where the start and end-points are primarily driven by the availability of the data. The latter is compiled from DataStream. As in the pioneered methodology of the US VIX, implied volatility indices are derived from option prices and reflect the 30-day measure of the expected volatility of the respective asset market. We use the log-transformed data for empirical analysis.

Table 1. Descriptive statistics of implied volatility indices

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Brazil	33.170	72.830	16.670	9.673	0.883	3.429	200.085*
Russia	33.359	97.050	15.420	10.441	1.202	5.178	636.814*
India	18.918	37.700	11.560	4.803	1.175	4.008	395.534*
China	27.588	63.420	16.930	7.109	1.623	6.092	1216.619*
South Africa	19.798	34.070	10.610	3.853	0.638	3.470	112.048*
Canada	16.791	36.710	7.800	4.871	1.226	4.284	463.541*
France	21.766	55.594	11.819	6.438	1.384	5.227	764.194*
Germany	22.086	50.740	12.170	6.664	1.558	5.776	1054.588*
Holland	19.521	47.250	5.770	6.303	1.353	4.744	627.674*
Japan	24.508	69.790	14.000	5.880	1.525	8.238	2224.216*
Sweden	18.215	46.510	9.300	6.320	1.544	5.476	948.768*
Switzerland	16.976	44.470	10.010	5.146	2.009	8.141	2577.027*

UK	17.196	43.610	9.672	5.625	1.731	6.331	1396.798*
US	17.228	48.000	10.320	5.700	2.095	7.922	2529.586*
Gold	18.840	39.950	11.970	4.500	1.427	5.671	925.225*
Crude oil	34.283	78.970	14.500	12.278	0.535	2.860	70.627*

Notes: This table covers the full sample period from 16 March 2011 to 07 October 2016 (1,453 daily observations); * on the Jarque-Bera test statistics indicates the rejection at the 1% significance level of the null hypothesis that the data are normally distributed.

The summary statistics for all of the 16 VIXs under study are shown in Table 1. Among all the examined variables, crude oil volatility has the highest mean and standard deviation. This result is not surprising given the sample period covers large swings in the crude oil volatility, which coincide with the sharp decline in oil price especially in the second half of 2014. However, among the stock market implied volatility indices, Russia has the highest mean and standard deviations, whereas, BRIC countries have the highest mean. These results are in line with the overall view that less matured – emerging – stock markets experience more volatility than – matured – developed markets. Intuitively, gold implied volatility has one of the lowest mean and standard deviation. All the series are positively-skewed, indicating that the implied volatility distribution has an asymmetric tail extending to the right (i.e. towards more positive values), especially in the US and Switzerland. These results imply that extreme increases are more frequent than extreme decreases in the level of VIXs. Except for crude oil, the volatility series are more peaked than the normal distribution, especially in Japan, Switzerland, and the US, suggesting that there are more chances of extreme outcomes compared to a normal distribution. Before conducting the formal analysis, we examined the stationarity of VIX indices in its log form; the results from the ADF test suggested that they are stationary. Further, as the data are volatile, we further confirm its stationarity by applying the recently developed GARCH-based unit root test of Liu and Narayan (2010)[5]. The results, reported in the table A1 and A2 in the Appendix, indicate that all VIX indices in the log form are stationary.

4. Methodology[6]

This paper aims to model the contemporaneous and delayed causality between the five individual VIXs for BRICS, as response variables, and 11 VIXs in the global markets, as predictor variables, over full and rolling sub-samples. To this end, the dependence/causality relationship can be represented by a structural vector autoregressive (SVAR) model as:

[5] The test of Liu and Narayan (2010) has been widely applied to financial and energy markets (see for example, Narayan and Liu, 2015; Narayan, Liu and Westerlund, 2016; Salisu and Adeleke, 2016).
[6] This segment relies on the discussion available in Balcilar et al., (2016).

$$Y_t = B_0 Y_t + \sum_{i=1}^{p} B_i Y_{t-i} + \sum_{i=1}^{p} C_i Z_{t-i} + \varepsilon_t \qquad (1)$$

where $t = 1, \ldots, T$ and p is the maximum lag order. Y_t and Z_t are n_y and n_z vector of response (the five VIXs of BRICS) and predictor variables (11 other VIXs covering developed equity, oil and gold markets), respectively. ε_t is n_y vector of structural residuals which are independently, identically and normally distributed with mean zero and covariance matrix Σ_ε ; B_0 is a $(n_y \times n_y)$ zero diagonal matrix of structural contemporaneous coefficients, with zero diagonals; B_i and C_i with $1 \leq i \leq p$ are $(n_y \times n_y)$ and $(n_y \times n_z)$ matrices of the parameters of interest, respectively. For notational simplicity, the reduced form of model (1) is given by:

$$Y_t = A_1 X_{t-1} + \ . \ . \ . \ A_p X_{t-p} + u_t \qquad (2)$$

where $X_t = (Y_t, Z_t)' = (X_{1t}\ ,\ X_{2t}, . \ . \ . \ ,\ X_{nt})'$ is an $n = n_y + n_z$ dimensional time series; $B_i^* = (B_i, C_i)$, $1 \leq i \leq p$, are $(n_y \times n)$ matrices of unknown coefficients; $A_0 = (I_{n_y} - B_0)$ is a $(n_y \times n_y)$ matrix; $A_i = A_0^{-1} B_i^*$, $1 \leq i \leq p$, are $(n_y \times n)$ reduced-form lag coefficient matrices; and $u_t = A_0^{-1} \varepsilon_t$ is an $(n_y \times 1)$ independently and identically distributed reduced-form vector residual term with zero mean and covariance matrix Σ_u. It is worth noting here that in order to estimate the parameters of the SVAR model it is necessary to obtain a reduced form equation (2) and impose a certain number of restrictions as the parameters cannot be directly estimated due to misidentification of the system of equations[7]. However, the standard SVAR model is often criticized for imposing implausible restrictions or, at least, restrictions that are as plausible as the underlying economic theory that are stemming from (Ahelegbey *et al.*, 2016). This critics is very relevant to our case given the lack of indications from economic theory on an association across implied volatility indices. Accordingly, we follow Ahelegbey et al. (2016) and employ the BGSVAR model, which is a SVAR model based on a

[7] One can wonder that in a SVAR, the ordering of the variables may matter because of the restrictions that are imposed in the SVAR model. We argue that since we are using the so called Bayesian graphical structural VAR (BGSVAR) to unveil the network structural relationships following Ahelegbey et al. (2016), the causal analysis does not require ordering of variables, as this is also the case in classical VAR estimation. However, what is important is to identify the main variables of interest to focus on (which happens to be the VIXs of the BRICS in our case) when determining the network structure. The ordering of variables is important in VAR analysis, when we try to identify structural shocks and conduct impulse response-, variance- and historical decompositions- type of analyses. The aim here is not to identify structural shocks, but contemporaneous and lead-lag causal structure. Moreover, note that identifying structural shocks as well as using impulse response, variance and historical decompositions are so far unavailable in the context of the BSGVAR.

graph representation of the conditional independence among the examined variables, to overcome the above-mentioned critics. In the BGSVAR model, the Dynamic Bayesian Network technique[8] is applied to the standard SVAR model presented in equation (1). The BGSVAR model offers at least two advantages over the standard SVAR model. First, there is no need to obtain the reduced form and restrictions imposed on the contemporaneous variables are unnecessary. Second, the BGSVAR model decomposes the SVAR causality structure into two simple representations: the Contemporaneous Network (CN) and the Lagged Network (LN) causality structures. These structures, given in equation (3), can be evaluated over an out-of-sample.

Let $X_t = (X_t^1, X_t^2, \ldots, X_t^n)$ be the vector of realized values of n variables with X_t^i representing the realization of the i-th variable. Equation (1) can be represented as a graphical model with a one-to-one correspondence between the coefficient matrices of the SVAR model in equation (1) and a directed acyclic graph (DAG):

$$X_{t-s}^{j} \longrightarrow X_t^i \Leftrightarrow B_{s,ij}^{*} \neq 0, \quad 0 \leq s \leq p \tag{3}$$

Following the representation in equation (3), we define the coefficient matrices of the SVAR in equation (1) as:

$$B_s^* = (G_s \circ \Phi_s), \quad 0 \leq s \leq p, \tag{4}$$

Where $(G_s \circ \Phi_s)$ are the graphical model structural coefficient matrices whose non-zero elements describe the value associated with the contemporaneous and temporal dependences, respectively. For $s = 0$, $B_0^* = B_0$ is $n_y \times n_y$ structural coefficients of contemporaneous dependence, G_0 is $n_y \times n_y$ binary connectivity matrix of contemporaneous dependence, and Φ_0 is a $n_y \times n_y$ coefficient matrix. For $1 \leq s \leq p$, $B_s^* = (B_s, G_s)$ is $n_y \times (n_y + n_z)$ binary connectivity matrix and Φ_s is a $n_y \times (n_y + n_z)$ coefficient matrix. The operator "∘" is the element-by-element Hadamard's product (i.e. $B_{s,ij}^* = G_{s,ij}\Phi_{s,ij}$). It is worth to note that G_0 and G_s ($1 \leq s \leq p$) represents the connectivity matrix of contemporaneous dependence and the matrix of the temporal dependence, respectively. Elements in G_s ($1 \leq s \leq p$), are indicators such that $G_{s,ij} = 1 \Leftrightarrow X_{t-s}^{j} \longrightarrow X_t^i$ and 0 otherwise. Elements in Φ_s ($1 \leq s \leq p$) are coefficients in structural regression such that $\phi_{sij} \in \mathbb{R}$ represents the value and magnitude of the effect of

[8] The Dynamic Bayesian Network is a technique which relates variables to each other over adjacent time steps. For more details, interested readers are referred to Dagum et al. (1992).

X_{t-s}^{j} on X_t^i. There is a one-to-one correspondence between regression matrices and the directed acyclic graphs such that[9].

$$B_{s,ij}^{*} = \begin{cases} \phi_{s,ij} & \text{if } B_{s,ij}^{*} = 1 \\ 0 & \text{if } B_{s,ij}^{*} = 0 \end{cases} \quad (5)$$

Considering the SVAR in equation (1), the DAG model can be represented as equation (6) based on the notation as specified in equation (5):

$$Y_t = \underbrace{(G_0 \circ \Phi_0)}_{CN} Y_t + \sum_{i=1}^{p} \underbrace{(G_i \circ \Phi_i)}_{LN} X_{t-i} + \varepsilon_t \quad (6)$$

Where $(G_i \circ \Phi_i)$ are the graphical model structural coefficient matrices whose non-zero elements describe the value associates with the contemporaneous and temporal dependences. The prior distribution for B^* is assumed to be normally distributed, i.e. $B^* \sim \mathcal{N}(\bar{B}^*, \bar{V}_B)$. Estimating equation (6) requires the choice of the optimal lag order, ρ, inference of the causal structure, $G=(G_0 , G_1, \ldots, G_p)$, and the set of parameters, $\{B_0^*, B_1^*, \ldots, B_p^*, \sum_\varepsilon\}$ that are estimated from $\sum_x$. The choice of optimal lag order is based on the sample data and the Bayesian information criteria (BIC). In line with Grzegorczyk et al. (2010), Ahelegbey *et al.* (2016) propose a Bayesian scheme with an efficient Markov Chain Monte Carlo (MCMC) process in order to estimate the LN component. As for the CN, Ahelegbey *et al.* (2016) follow the lines from Giudici and Castelo (2003) and suggest a necessary and sufficient condition to check the acyclicity[10] constraint in a small-size networks.

Let $b_i = (b_{i1}, b_{i2}, \ldots, b_{in})$ be a row vector of B_s, where its entries b_{ij} are the regression coefficients of the effects of X_{t-s}^{j} on X_t^i. It follows that the relationship between B_s and Φ_s has the following form:

$$b_{ij} = \begin{cases} \phi_{ij} & \text{if } g_{ij} = 1 \\ 0 & \text{if } g_{ij} = 0 \end{cases} \quad (7)$$

In line with Ahelegbey *et al.* (2016), we assume that both the marginal prior of g_{ij} and the marginal posterior to be Bernoulli-distributed:

[9] It means there is a one-to-one correspondence between Φ_s and B_s^* conditionally on G_s. See Murphy (2002) for details.

[10] For more details, see Murphy (2002).

$$a_{ij}|data = \begin{cases} 1 & \text{if} \quad P\left(a_{ij} = 1|data\right) > \tau \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where τ is a threshold value set by the user $\tau \in (0, 1)$; and $P\left(a_{ij} = 1|data\right)$ is the confidence score that is the posterior probability of the existence of an edge from X^j to X^i.

Our Bayesian graphical model provides the posterior probabilities for both instantaneous and lagged relationships between the predictors and the five individual VIXs for BRICS, namely multivariate instantaneous (MIN) and multivariate autoregressive (MAR) structures. The optimal lag of MAR as indicated in Equation (6) is selected by BIC. We then estimate the MAR of *Gs* that comprises all the stacked temporal structures stacked. The proposed sampling scheme guarantees irreducibility as the probability of selecting a node is strictly positive for all nodes, and therefore guarantees the ergodicity of the MCMC chain. Ahelegbey et al. (2016) applies both MIN and MAR to estimate a SVAR model with 20 macroeconomics variables.

Moreover, Balcilar et al. (2016) use the same methodology of Ahelegbey et al. (2016) to predict South African excess stock returns based on economic policy uncertainty (EPU) index of South Africa and twenty other countries, over and above many other standard financial and macroeconomic predictors. The authors concluded that only MAR (i.e. temporal or lagged relationships) model can reasonably predict the equity premium of South Africa, with the EPUs playing an important role.

5. Results

The posterior probabilities of full-sample estimates for the 16 predictors of both MIN and MAR structures are reported respectively in Table 2 and Table 3. The lag order (p) of the VAR is set to 1 based on the full sample data using the Bayesian Information Criterion,[11] and 50,000 draws are used. First, we estimate a model of MIN with the following five response variables: BRL, RUA, INA, CHA, and SOA. We then consider the following 11 additional

[11] We also applied other lag-length tests like the AIC, FPE and HQ, and all of them confirmed the use of one lag as the optimal. This is probably an indication of the importance of the first lag of the VIXs in creating spillover transmission within a day rather than taking a longer period of time. Complete details of these results are available upon request from the authors. In addition, it is also important to point out that stock market-based analyses which rely on a predictive regression framework, also tend to use one lag in general (Rapach and Zhou, 2013). Also, using more than one-lag is likely to produce inefficient results in the time-varying analyses based on a rolling-window of 60 observations (as discussed later).

variables as predictor variables: GEY, FRC, UK, HOD, SWN, SWD, NII, CBE, CAA, OIL, and GOLD.

Table 2. Results of the MIN structure

	Brazil$_{,t}$	Russia$_{,t}$	India$_{,t}$	China$_{,t}$	South Africa$_{,t}$
Brazil$_{,t}$	0	*0.3212*	0.0268	*0.4224*	**0.5312**
Russia$_{,t}$	**0.6788**	0	0.2194	0.0883	**0.6744**
India$_{,t}$	0.0719	**0.7615**	0	**0.8799**	*0.3438*
China$_{,t}$	**0.5776**	0.078	0.1201	0	**0.6093**
South Africa$_{,t}$	***0.4688***	*0.3256*	0.0856	*0.3907*	0

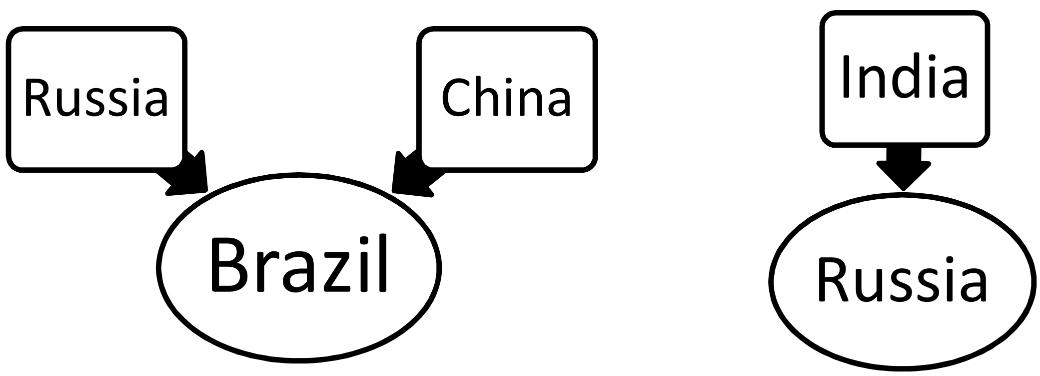
Note: Bold entries represent the selected edges for the MIN structures based on posterior probabilities greater than 0.50; Italic entries indicate posterior probabilities greater than 0.30 but less than 0.50.

In the case of MIN structure (Table 2), the highest posterior probabilities are for BRL is the Russia volatility index (Russia, with a value of 0.6788), followed by China volatility index (China, with a value of 0.5776). The highest posterior probabilities are for Russia is the India volatility index (India, with a value over 0.75), followed by Brazil and South Africa volatility index (Brazil and South Africa, with a value greater than 0.3, but less than 0.40). The highest posterior probabilities are for India is the Russia volatility index (Russia, with a value of 0.2194). The highest posterior probabilities are for China is the India volatility index (India, with a value over 0.85), followed by Brazil volatility index (Brazil, with a value of 0.4224). The highest posterior probabilities are for South Africa is the Russia volatility index (Russia, with a value over 0.65), followed by China volatility index (China, with a value of 0.6093).

The MIN reveals the following causality patterns based on the posterior probabilities of 50% or above:

$(\text{Russia}_t, \text{China}_t) \rightarrow \text{Brazil}_t$; $\text{India}_t \rightarrow \text{Russia}_t$; $\text{India}_t \rightarrow \text{China}_t$; $(\text{Brazil}_t, \text{Russia}_t, \text{China}_t) \rightarrow$ South Africa_t.

Figure 1. MIN structure



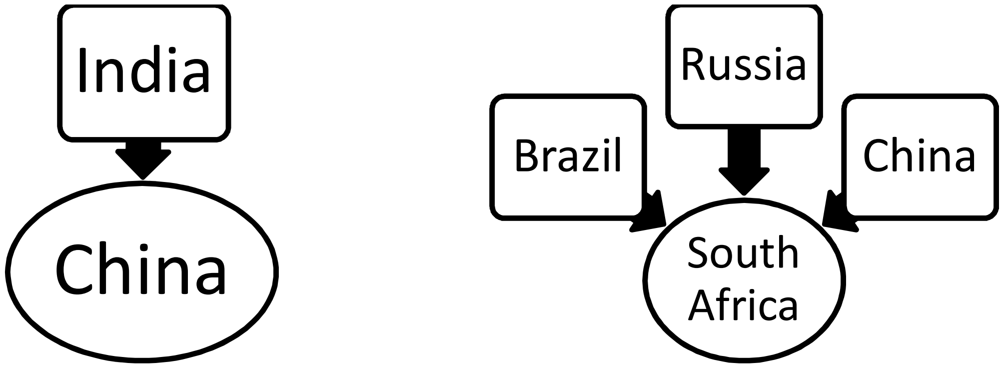


Figure 1 also depicts the MIN structure within BRICS countries. As shown, VIXs of Russia and China each has only one contemporaneous relation with a BRICS country (India), whereas South African VIX has the most contemporaneous relation as it is related to the VIXs of Brazil, Russia, and China. Interestingly, South African VIX has no power to predict the VIX of any BRIC countries.

Now we turn to the MAR structure and the other 11 predictors (see Table 3). Under the MAR structure, current level of Brazil VIX depends on the previous level of VIXs of Brazil, India, France, and Switzerland, while the current level of Russian VIX strongly depends on the previous level of VIXs of Brazil, Russia, Germany, Sweden, and US. The current level of Indian VIX depends on the previous level of VIX associated with India, France and US, while the current level of Chinese VIX strongly depends on the previous level of VIXs from China, and Sweden. The current level of South African VIX depends on the previous level of VIXs of Brazil, US, Oil, and Gold.

Table 3. Results of the MAR structure

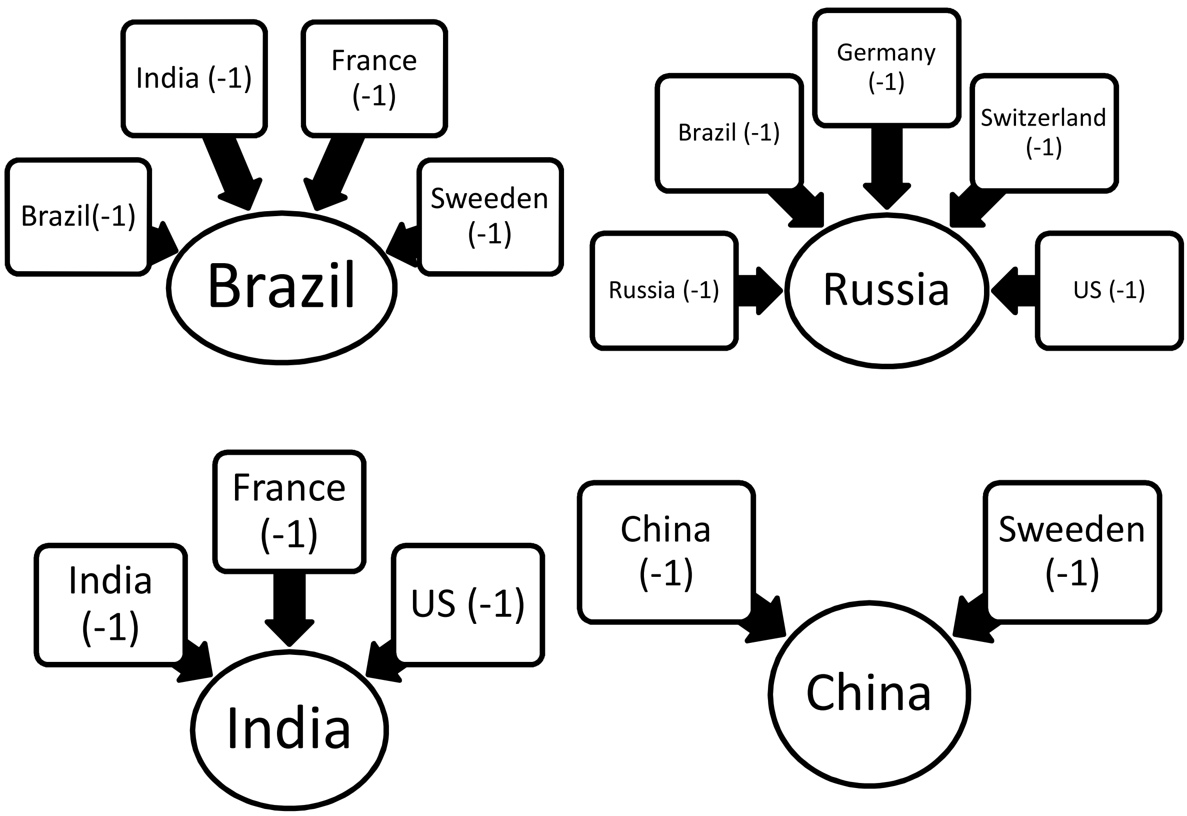
	Brazil,$_t$	Russia,$_t$	India,$_t$	China,$_t$	South Africa,$_t$
Brazil,$_{t-1}$	**1**	**0.9818**	0.0944	0.288	**0.6469**
Russia,$_{t-1}$	0.1759	**1**	0.0925	0.0917	0.1191
India,$_{t-1}$	**0.5225**	0.1091	**1**	0.0959	0.0945
China,$_{t-1}$	0.1701	0.1233	0.2118	**1**	0.108
South Africa,$_{t-1}$	0.1577	0.0902	0.0791	0.1656	**1**
Germany,$_{t-1}$	0.1587	**0.7347**	*0.3802*	0.165	0.1624
France,$_{t-1}$	**0.6281**	0.1052	**0.8538**	0.1548	0.1473
UK,$_{t-1}$	0.121	0.1139	0.1122	0.1327	0.137
Holland,$_{t-1}$	0.2968	0.1538	0.0993	0.227	0.1236
Sweden,$_{t-1}$	0.299	**0.84**	0.1078	**0.604**	0.2872
Switzerland,$_{t-1}$	**0.5971**	0.138	0.1095	*0.4488*	0.1493
Japan,$_{t-1}$	*0.4353*	*0.4896*	0.1204	*0.366*	0.1469
US,$_{t-1}$	0.1075	**0.6813**	**1**	0.1205	**0.8751**

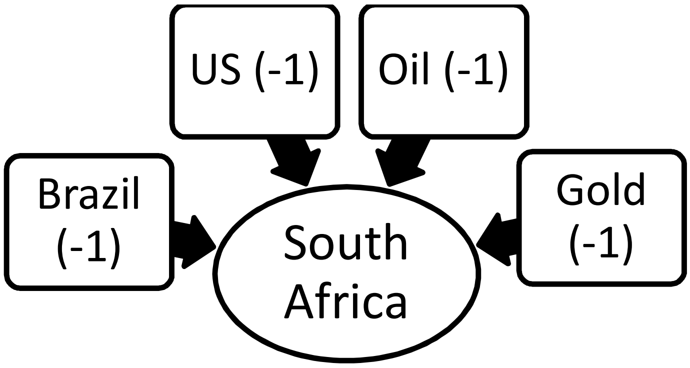
Canada,$_{t-1}$	0.1189	0.0969	0.1946	0.2086	0.1181
Oil,$_{t-1}$	0.2301	0.1119	0.1125	0.0706	**0.5345**
Gold,$_{t-1}$	0.0628	0.0729	*0.3875*	0.1511	**0.5314**

Notes: Bold entries represent the selected edges for the MIN structures based on posterior probabilities greater than 0.50; Italic entries indicate posterior probabilities greater than 0.30 but less than 0.50. Selection of lag length is based on BIC as in Ahelegbey et al. (2016) (see page 364).

Figure 2 illustrates the causality patterns under the MAR structure. Clearly, China implied volatility is the least sensitive among the BRICS countries as it only depends on its lagged value and the lagged value of Sweden implied volatility. In contrast, Russia implied volatility is the most sensitive given its dependence on four lagged VIXs of Brazil, Germany, Switzerland, and US, in addition to its own lagged value. A possible explanation lies in the strong economic and trade ties between Russia and Europe. Surprisingly, the market disturbances in the US are not transmitted to Brazil, a finding that contradicts with the findings of Sarwar and Khan (2016) and the well-established trading relations of US with Brazil. Based on the above findings, we also notice that only the South Africa implied volatility is affected by the implied volatility of the commodity markets (gold and oil). Further, it is only sensitive to US VIX from outside BRICS countries.

Figure 2. MAR structures

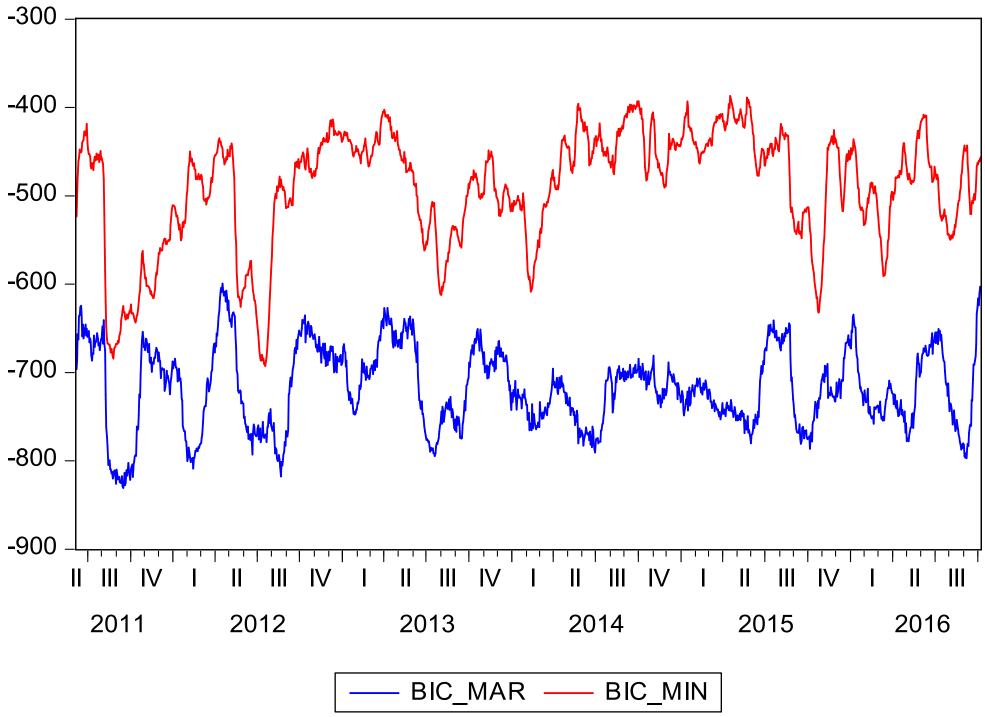




Based on this finding we argue that the Chinese VIX is still relatively segmented (or simply partially integrated) form the VIXs in the commodity and major developed stock markets, suggesting that that local information on risk variables are much more relevant to the Chinese stock market than regional or global information on uncertainty. Our findings also imply that the integration is a dynamic concept (Harvey, 1995). It could be that our sample period that follows the GFC and its relative tranquility has caused some BRICS countries to be insulated from the uncertainty of commodity or developed stock markets.

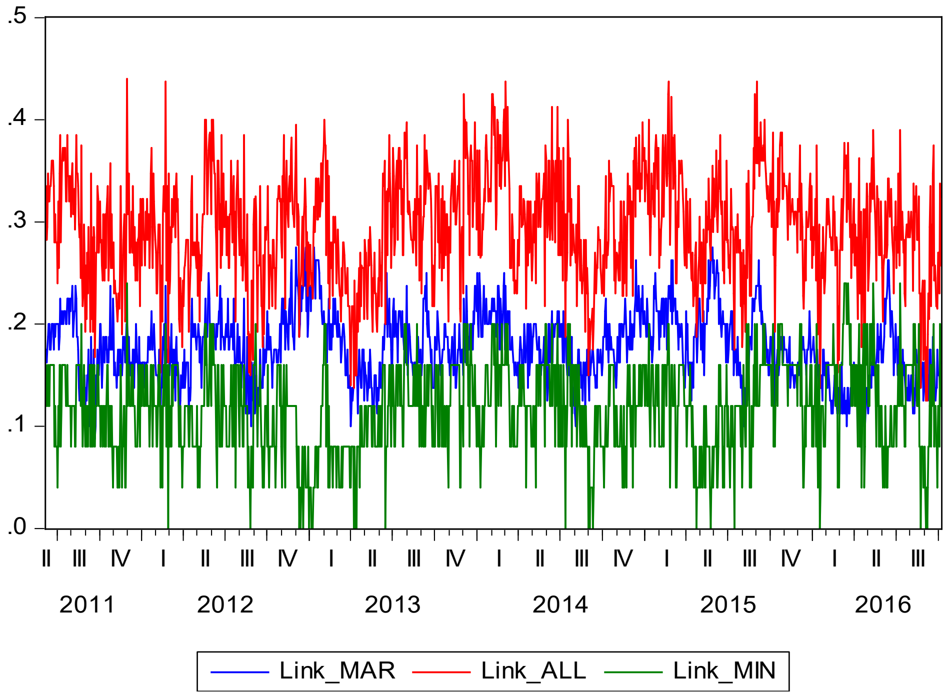
We further estimate the BGSVAR with rolling-window approach to examine the temporal evolution of the BGSVAR .The rolling window estimation uses an initial sample period of 16 March 03 2011-06 June 2011 and a 60-day rolling window estimation over the period of 07 June 2011-07 October 2016, i.e., a total of 1,394 rolling estimations. To be consistent with the full sample, the lag order of the VAR is set to 1, and 40,000 draws are used, with an initial burn-in of 10,000 from 50,000 draws to derive the posterior inclusion probabilities of the predictors. Figure 3 compares the evolution of the BIC scores of MAR and MIN dependence structures over the period of 07 June 2011-07 October 2016. The result shows that the BIC score favors MAR over MIN, giving an indication that MAR provides a better representation of the temporal dependence in the observed time series than the MIN contemporaneous dependence in the observed time series.

Figure 3. The BIC of the contemporaneous and temporal dependence structures



In our study, we focus only on the temporal dependence (i.e. MAR) given that the BIC score favors MAR over MIN. Figure 2 presents the percentage of links from other variables to BRICS obtained for MIN and MAR structures. Using total link, we observe that the period of highest interconnectedness is the year of 2013, while the linkage is decreasing recently from 2015.

Figure 4. Linkage among BRICS VIX and 11 other VIX



Finally, we display the rolling-window posterior probabilities of lagged impact from the 11 VIX indices on the BRICS VIXs (Figures 5-9). For example, Figure 5 shows the lagged posterior probabilities of other VIXs on Brazil's VIX and Figure 6 displays the rolling-window posterior probabilities of lagged impact from the 11 VIX indices on Russia's VIX. In general, we observe that the lagged impact of other VIX indices essentially exceeds the 0.50 threshold probability, and the posterior probabilities of lagged impact from the VIX indices of BRICS countries is much higher than that from the VIXs of developed markets.

Figure 5. The rolling estimates of posterior probabilities of lagged relationship between the Brazil VIX and other VIXs

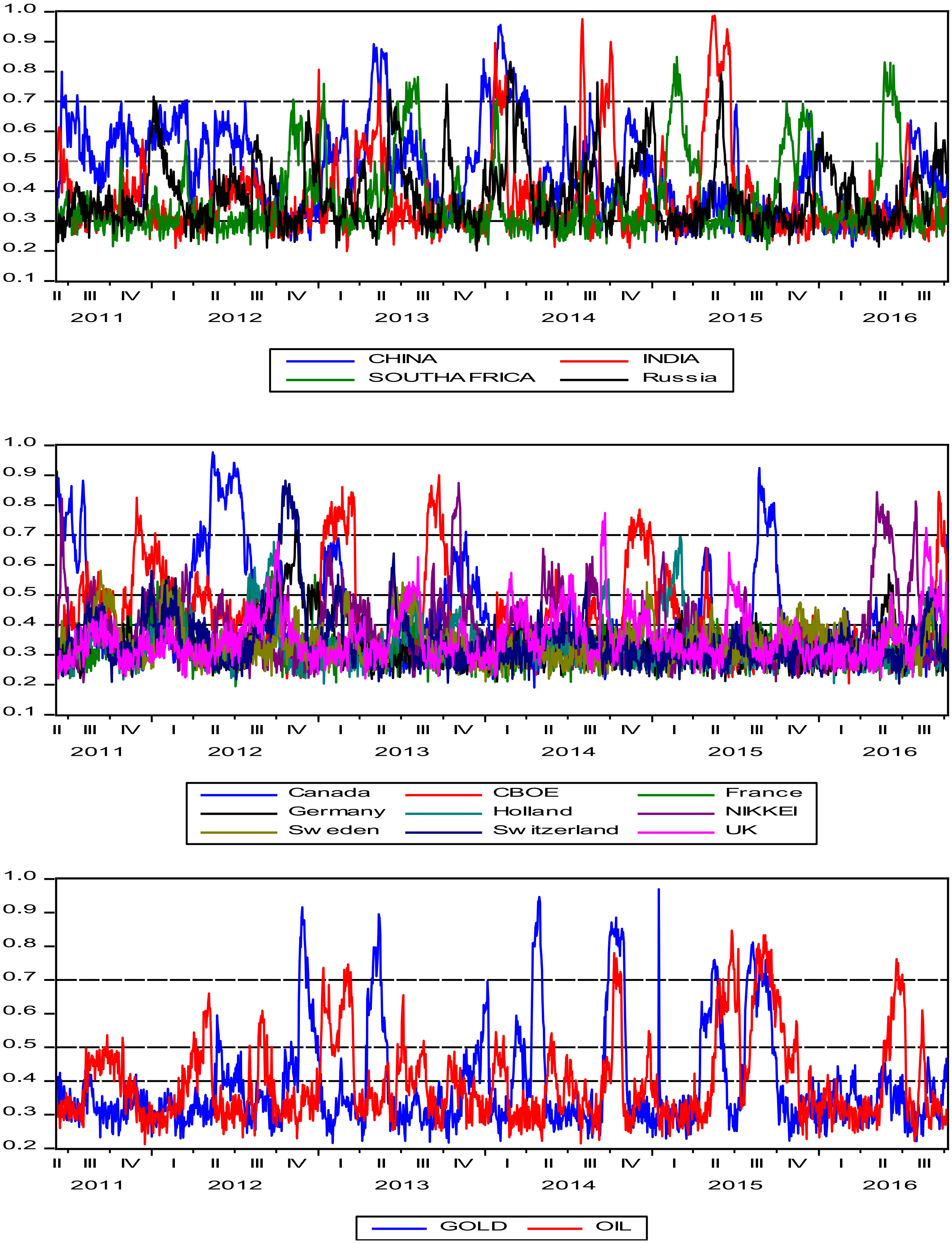


Figure 6. The rolling estimates of posterior probabilities of lagged relationship between the Russia VIX and other VIXs

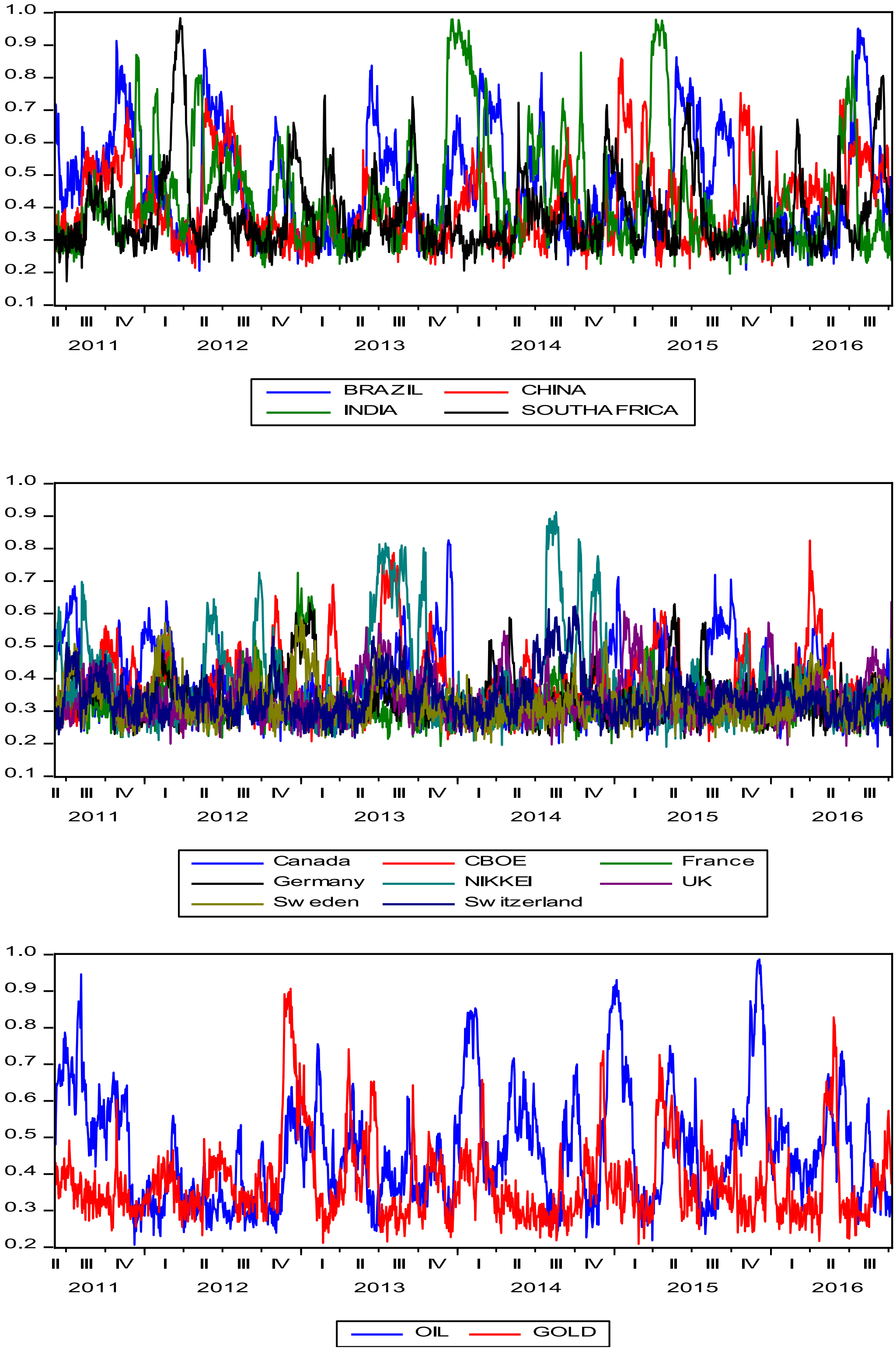


Figure 7. The rolling estimates of posterior probabilities of lagged relationship between the India VIX and other VIXs

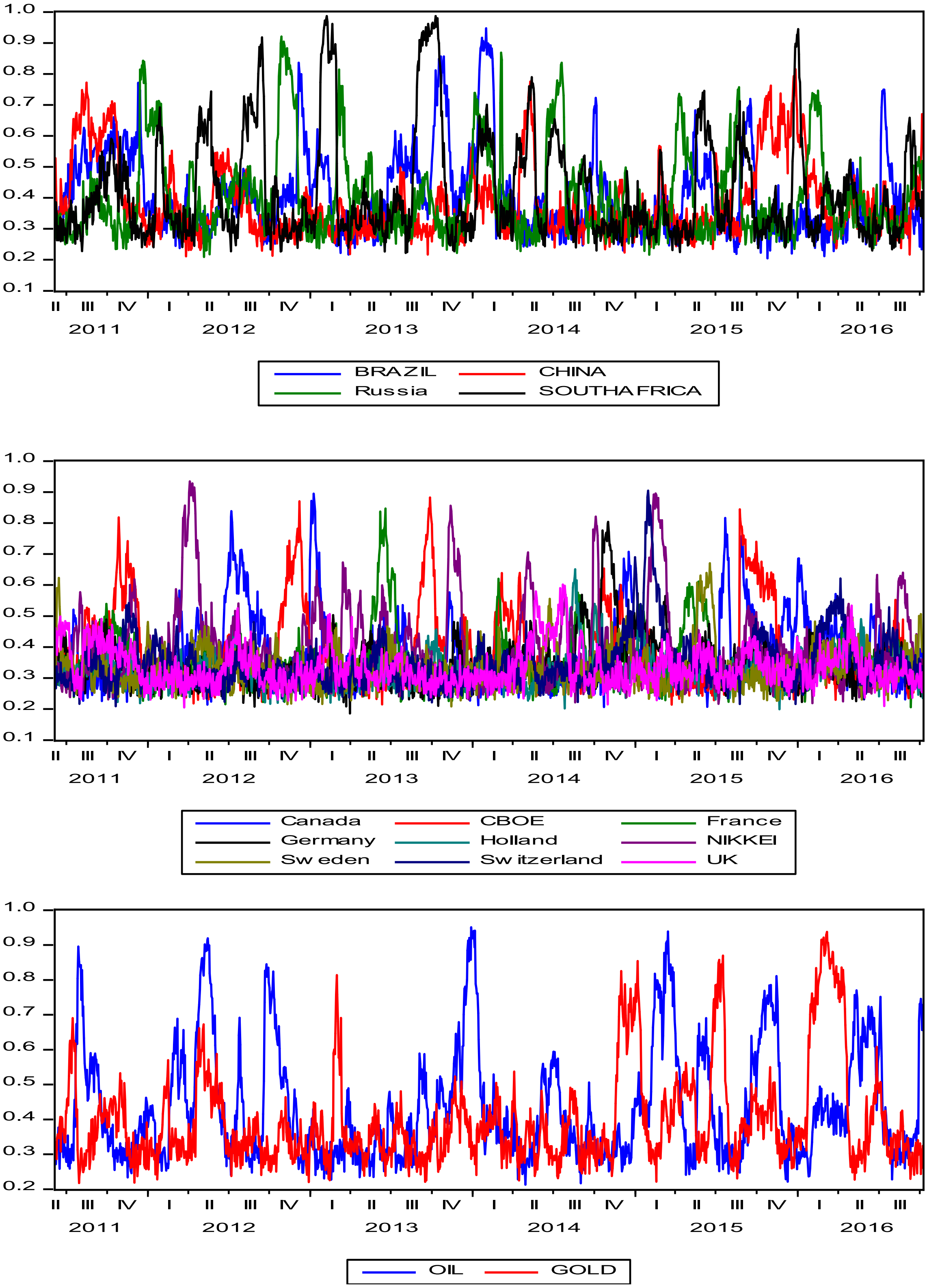
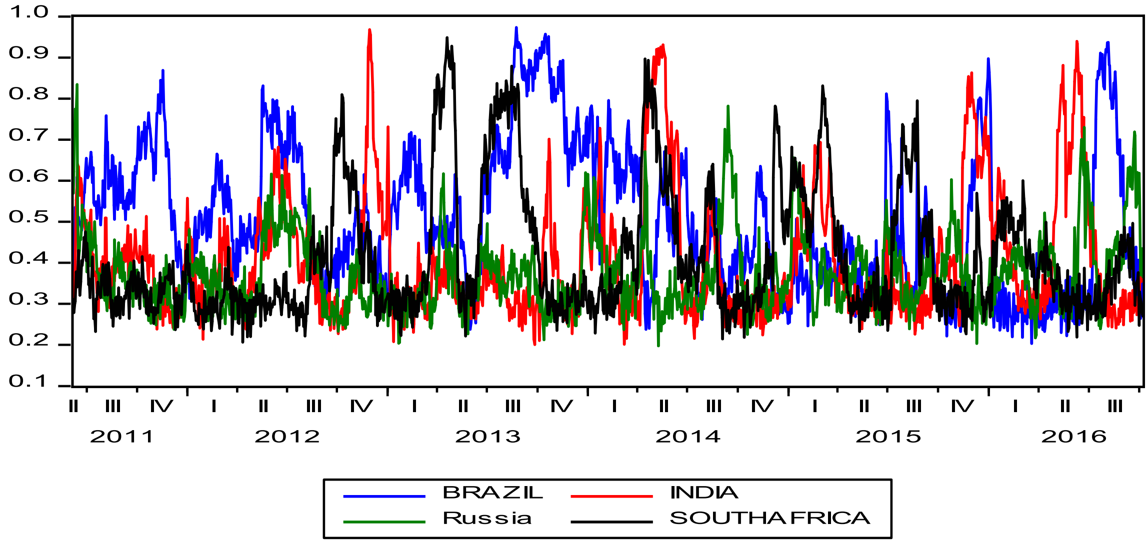
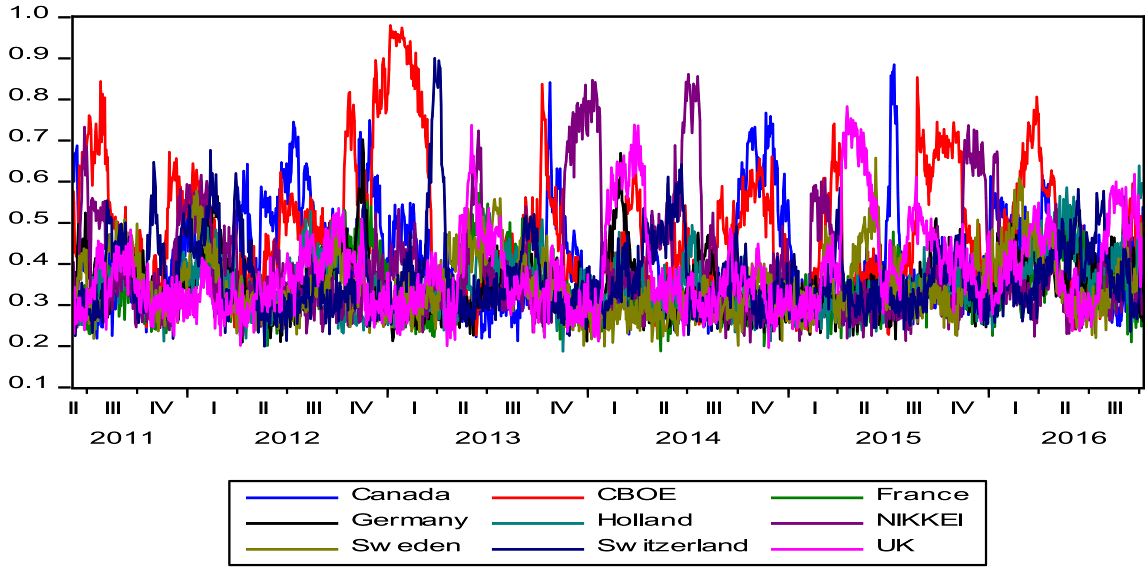


Figure 8. The rolling estimates of posterior probabilities of lagged relationship between the China's VIX and other VIXs





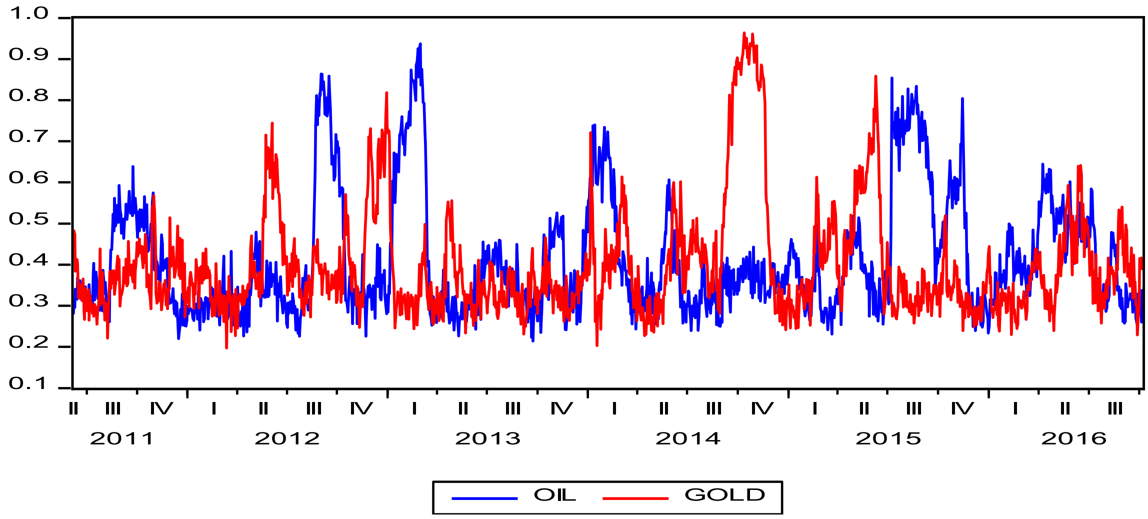
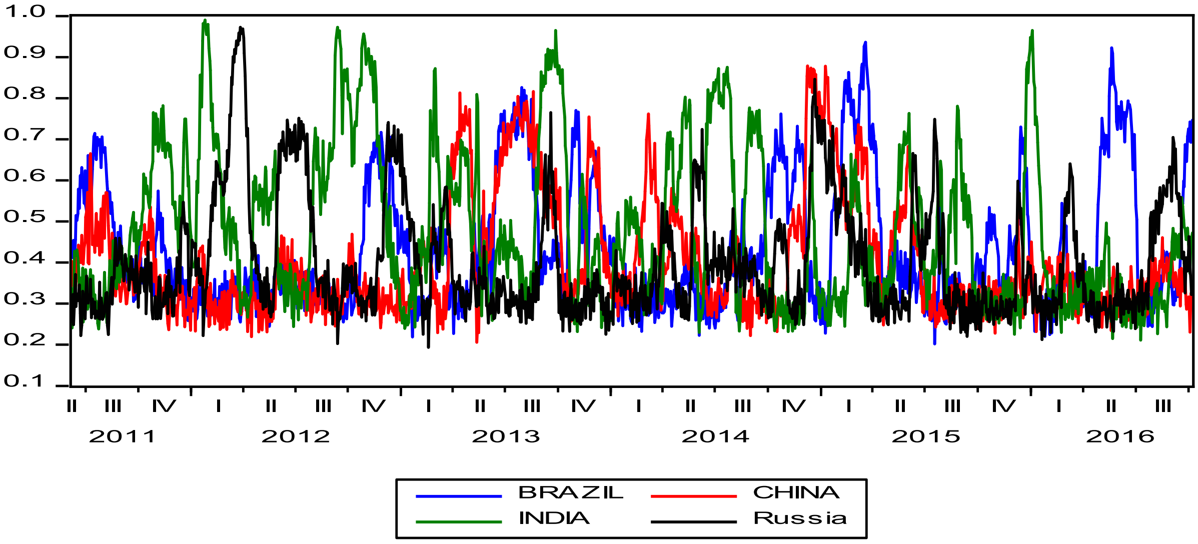
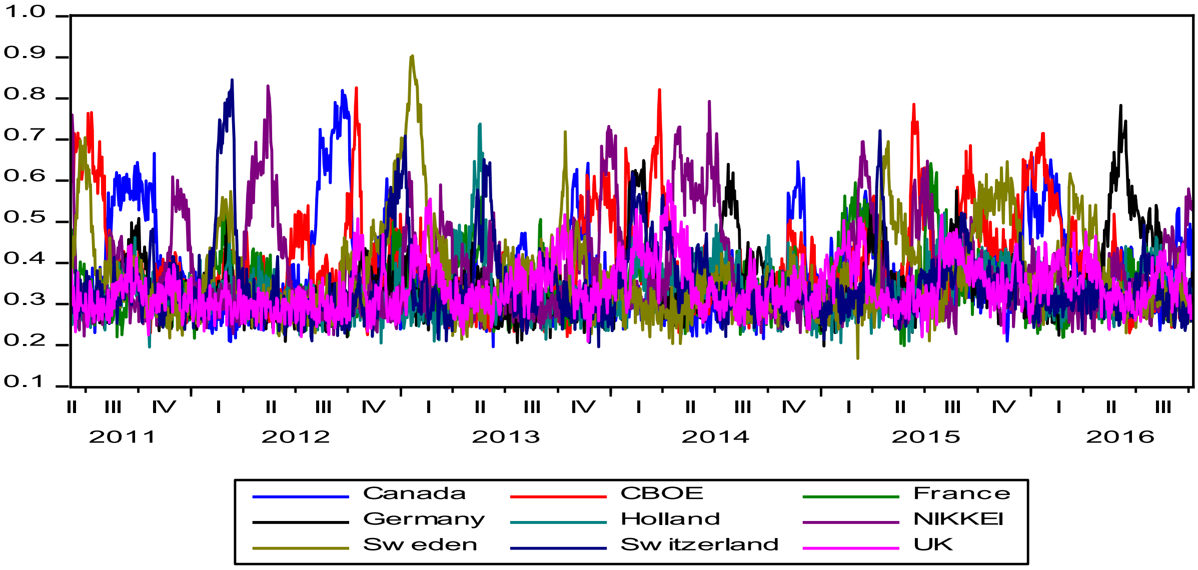


Figure 9. The rolling estimates of posterior probabilities of lagged relationship between the South Africa's VIX and other VIXs





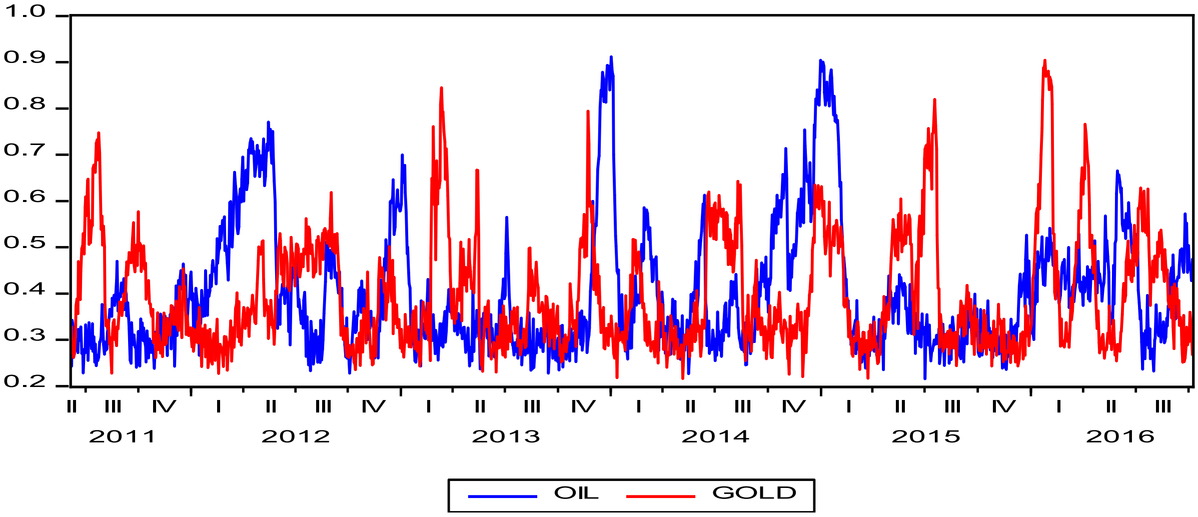


Figure 10 displays the rolling-window posterior probabilities of lagged impact from the oil VIX indices on the BRICS VIXs, while Figure 11 displays the rolling-window posterior probabilities of lagged impact from the oil VIX indices on the BRICS VIXs. It seems the influence of oil VIX on BRICS VIXs is higher than that of the gold VIX in recent years.

Figure 10. The rolling estimates of posterior probabilities of lagged relationship between the Oil's VIX and BRICS VIX

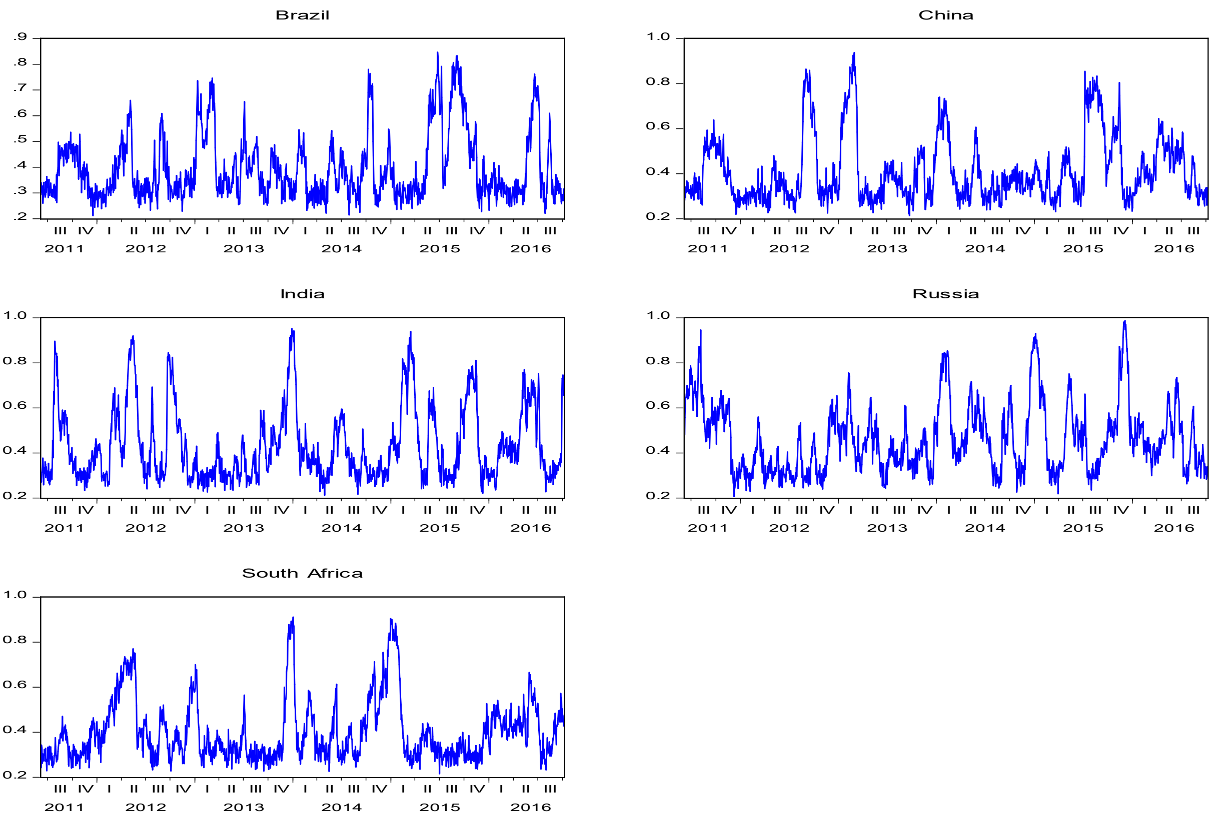
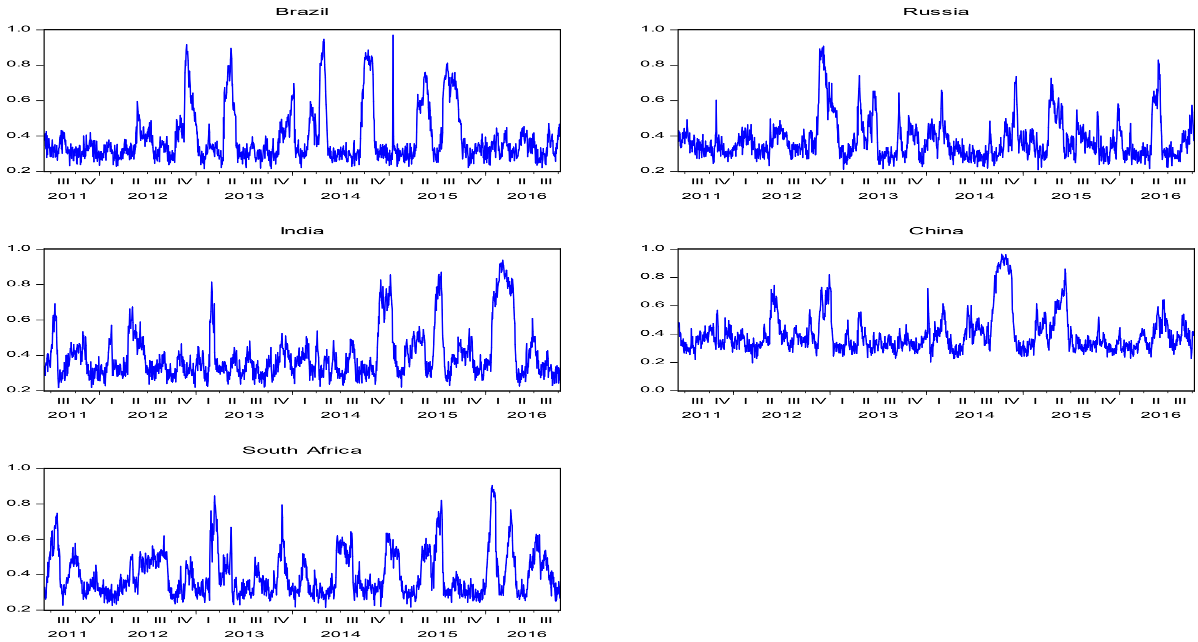


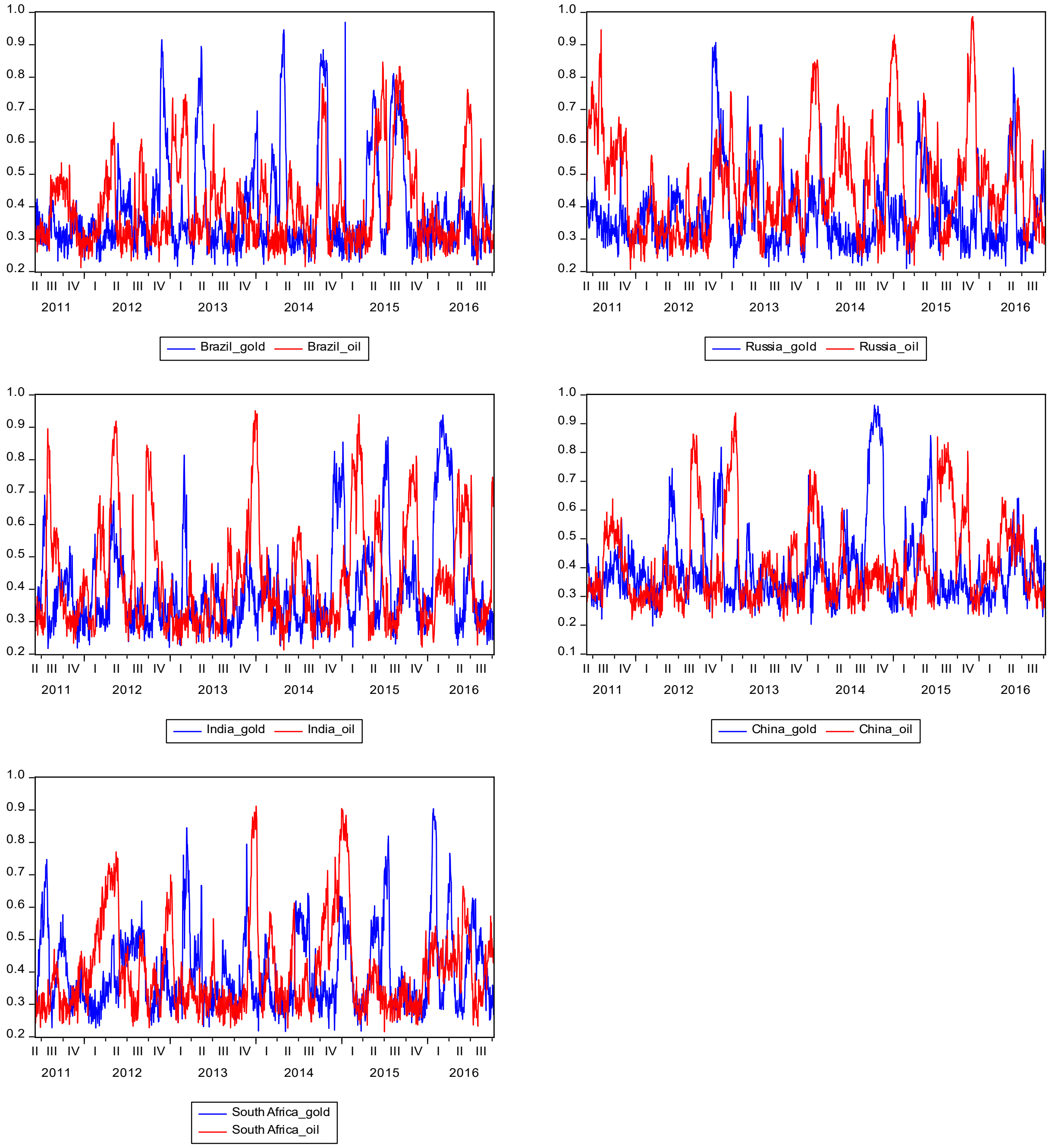
Figure 11. The rolling estimates of posterior probabilities of lagged relationship between the Gold's VIX and BRICS VIX



When also use a measure (i.e. posterior probabilities of oil VIX minus posterior probabilities of gold VIX in a particular day) to examine the relative importance of one commodity over another in predicting BRICS's VIX. As shown in Figure 12, the posterior probabilities of gold VIX is higher for South Africa for most of the time, while the posterior probabilities of oil VIX is higher for Brazil, Russia, China, and India for most of the time across our sample period[12].

Figure 12. Comparison of posterior probabilities for Gold and Oil VIX.

[12] Among 1394 days in our sample, 56% of time was dominated by Oil VIX for Brazil, 66% for Russia, 57% for India, and 52% for China. And 51% of time was dominated by gold VIX for South Africa.



In light of the objective and focus of our study, it is worth noting here that appropriate modeling of volatility is of importance due to several reasons: (i) When volatility is interpreted as uncertainty, it becomes a key input to many investment decisions and portfolio creations; given that, investors and portfolio managers have certain bearable levels of risk, proper modelling (and predicting) of the volatility of asset prices over the investment holding period is of paramount importance in assessing investment risk; (ii) Volatility is the most important variable in the pricing of derivative securities; to price an option, one needs to know the volatility of the underlying asset from now until the option expires; (iii) Financial risk management has taken a dominant role since the first Basle Accord was established in

1996, making proper modeling (and predicting) of volatility a compulsory risk-management exercise for financial institutions around the world.

Unlike GARCH-based, and hence model-contingent measures of volatility, implied volatility indices derived from option prices reflect market's expectation on the future volatility over the remaining life of the options. Accordingly, VIXs are generally considered to be a better measure of market's uncertainty, since implied volatilities not only contain the historical volatility information but also include investors' expectation on future market conditions (Liu et al., 2013). As the volatility index measures investors' expectation on future market changes, the linkage among them could to a large extent reflect uncertainty transmission. In light of this, our paper considers the contemporaneous transmission within the BRICS countries, and also its predictability based on information emanating not only from VIXs within the BRICS group but also from the VIXs of major developed markets and that of gold and oil.

We observe that, in terms of contemporaneous uncertainty spillovers, Russia and China affects Brazil, India affects Russia and China, while Brazil, Russia and China affects South Africa. In other words, the stock market uncertainty in India remains contemporaneously unaffected. The causal patterns (i.e. in the lagged sense), which in turn are in fact preferred over contemporaneous patterns in the statistical sense, tends to suggest that for Brazil, Russia, India and China, there is strong evidence of persistence in the VIXs and hence, the importance of the information content of own VIX in predicting future uncertainty, besides VIXs from both developed and other markets in the emerging group. For South Africa, however, the important predictors are the VIXs associated with Brazil, US, and the two commodities, with no role from its own VIX.

The multivariate predictability analysis pursued in the paper indicates that each of the BRICS countries have their own specific important set of predictors in predicting the future path of uncertainty, and there are not necessarily common predictors, even though the BRICS are clubbed together into a group of similar emerging countries. Investors in these economies, will need to evaluate the role of not only its past uncertainty, but also uncertainty associated with global factors. In other words, while making portfolio decision, barring the case of South Africa, investors would also need to incorporate in addition to the role of its own lagged uncertainty, the uncertainty associated with developed equity markets. In case of South Africa, the uncertainty associated with oil and gold, besides that of US and Brazil, needs to be incorporated into investment decisions instead of South Africa own uncertainty.

As discussed above, appropriate modelling, but more importantly predicting that process of volatility has implications for portfolio selection, the pricing of derivative securities and risk management. Hence, our results can be used by investors to correctly incorporate uncertainty into their investment decisions, as they will now be able to predict the future path of volatility in the BRICS stock markets based on information from uncertainties of its own, uncertainties of other emerging and developed financial markets, and uncertainties of strategic commodities like oil and gold.

Finally, financial market volatility, as witnessed during the recent “Great Recession" of 2008 in the financial markets around the world, is now known to have wide repercussion on the economy as a whole, via its effect on public confidence. Hence, the future path of uncertainty can serve as a measure of the vulnerability of financial markets and the economy in general, that is expected in the future, and help policy makers to design appropriate policies. In our context, policy-makers of the BRIC countries need to worry not only about global uncertainty, but also its own existing levels of uncertainty, to gauge how volatile and risky the future is likely to look. For South African policy-makers, however, what matters is uncertainty in the US, Brazil and the commodity markets of oil and gold.

6. Conclusions

The purpose of this study was to examine whether the implied volatility indices in developed markets (Canada, France, Germany, Holland, Japan, Sweden, Switzerland, UK, US), and commodity markets (Crude oil and gold) contain information to predict the implied volatility indices of individual BRICS countries—an under-researched topic in the vast finance literature. While this study differs from the existing literature in its entire reliance on implied volatility data (Mensi et al., 2014; Sarwar and Khan, 2016), it also presents another contribution through the employment of the recently developed method of Ahelegbey et al. (2016), which enables us to uncover the presence and effects of contemporaneous and lagged causality across the implied volatility indices of BRICS, developed countries, and commodity markets, by modelling them simultaneously. Given the lack of indications from economic theory on a link across implied volatility indices, this novel method of Ahelegbey et al. (2016), called the BGSVAR, avoids posing misleading or implausible restrictions in a standard SVAR model and thus represents an appropriate framework to conduct our empirical study while accounting for a broader range of predictors simultaneously.

The main results provide evidence on the predictability of global implied volatility indices in individual BRICS countries based on the uncertainty in commodity and developed stock markets, although this predictability differs across countries. The results indicate that the US

VIX is relatively the dominant predictor in the VIXs of BRICS, which is not surprising given the huge size of the US stock market and ample evidence on the high predictability of the emerging stock market returns based on the US stock market returns (see, among others, Mensi et al., 2014). However, such an evidence on the dominance of the US VIX was not present in Brazil and China, suggesting that local investors' worry more about other local and regional stock market uncertainties than the US market uncertainty. One possible explanation lies in the weak ability of investors in China and Brazil to gather and process information about the conditions of the global commodity and stock markets. Our detailed finding adds to Sarwar and Khan (2016) who only show that the US VIX is a gauge of fear for emerging economies. We also show that the predicting roles of the VIXs of crude oil and gold is only relevant to the market uncertainty in South Africa. These results highlight some evidence of the emergence of some domestic factors in explaining the implied volatility which is the opposite of what have been found in most of the existing literature who argue that external risk factors are more important than internal factors for BRICS returns and historical volatility. Practically, our findings point toward the need of policy-makers in some BRICS countries to monitor the significant volatility transmitters from the perspective of *expected* (implied) volatility. With the emergence of financial derivatives based on the implied volatility indices, and given that (implied) volatility has central role in pricing derivatives and managing portfolios, investors and portfolio managers can exploit evidence of risk predictability from a forward-looking perspective to improve forecasts of market uncertainty in several BRICS markets.

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Appendix:

Table A1. ADF and PP unit root test results:

	ADF		PP	
Brazil	-3.3481	**	-3.2434	**
Russia	-3.6223	***	-3.7304	***
India	-4.2456	***	-4.0717	***
China	-4.269	***	-4.0686	***
South Africa	-2.7814	*	-3.0117	**
Germany	-4.2231	***	-3.8895	***
France	-4.8308	***	-4.4822	***
UK	-5.256	***	-4.8877	***
Holland	-4.0767	***	-4.4722	***
Sweden	-4.121	***	-4.0178	***
Switzerland	-4.6863	***	-4.3687	***
NIKKEI	-6.4268	***	-6.2089	***
Canada	-4.7251	***	-4.8486	***

Notes: For PP test, the selected truncations for the Bartlett Kernel are based on the suggestion by Newey and West (1994). *, ** and *** denotes the significance levels at 10%, 5% and 1%, respectively.

Table A2: GARCH (1,1)-two break-unit root test results

Brazil	-3.2878	**

Russia	-2.6988	*
India	-4.867	***
China	-4.113	***
South Africa	-4.8067	***
Germany	-5.0185	***
France	-5.4625	***
UK	-5.9082	***
Holland	-3.9197	***
Sweden	-5.1181	***
Switzerland	-4.8428	***
NIKKEI	-5.2802	***
Canada	-5.1752	***

Notes: We extract appropriate critical values from Liu and Narayan (2010) for the 1%, 5%, and 10% levels respectively. We also conducted the simple ADF test and the results indicate that all series are stationary. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively.