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Integration and Volatility's Persistence in Emerging and Developed Countries: Impulse Responses and Multivariate DCC GARCH

Abdelkafi ZS[1]* and Khoufi W[2]

[1]Faculty of Economics and Management of Sfax, University of Sfax, Sfax, Tunisia
[2]High Institute of Commercial Studies of Sfax, University of Sfax, Sfax, Tunisia

Abstract

The financial sectors have significant direct and indirect effects on the real economy because they are responsible for saving mobilization and credit allocation. So as to maximize their utility and well manage potential risks, stockholders and investors can use various financial products. If the financial sector is healthy, credit should become more available and the cost of finance should be more affordable. Up to this point, little is known about how stock markets, exchange rates and crude oil respond to financial stress shock. This paper uses monthly stock indexes, exchange rates and crude oil prices data from April 2003 until December 2014 to test and model the international markets' integration, short term shock and volatility persistence in both emerging and developed countries. Trivariate DCC GARCH model and impulse responses show several interdependences and integration between international stock markets, exchange rates and crude oil.

Keywords: Impulse response; DCC GARCH (1,1); Short term persistence shock; Integration; Volatility's persistence

Introduction

The international financial markets have become closely integrated since regulations and barriers have been gradually removed over the past years so that people in different parts of the world can invest into the markets of other countries. This provides investors an opportunity to optimize portfolios by higher returns and lower risk. But, this makes the financial markets become more dependent to each other and the system more complex. However, over the last few decades international financial markets have experienced a succession of serious crisis of different causes and origins. For example, the 2007-2009 global financial crisis, which originated in the United States was sparked by the subprime real estate crisis, and then turned into a world financial crisis. Most of these crises are characterized by high volatility and contagion [1]. Moreover, recent studies suggest that crises (subprime crisis and sovereign debt) stoked greater correlations between the world's financial markets, in particular in periods of high and extreme volatility, and thus lowered the diversification benefit potential from investing in traditional stocks.

The highly volatility and widespread contagion have prompted investors to consider alternative investment instruments as a part of diversified portfolios in order to be used as a hedge to diversify away the increasing risk in the stock markets. Since the early 2000s, commodities have emerged as an additional asset class beside traditional ones such as stocks and bonds. Many researchers, using data from before the 2000s, have found a little negative return correlation between commodity and stock returns. Return correlations among commodities in different sectors have also been found to be small. Moreover, several papers have reported decreasing movements of return correlations between commodities and stocks at least before the recent financial crisis. These characteristics of commodity returns implied an opportunity for diversification and, thus, have attracted investors worldwide. Therefore, various instruments based on commodity indices have attracted billions of dollars of investment from institutional investors and wealthy individuals. The increasing presence of index investors precipitated a fundamental process of "financialization" amongst commodities markets, through which commodity prices became more correlated with prices of financial assets and with each other. As a result, time-varying correlations between commodity and traditional assets are becoming an important issue. These relationships imply that these markets share an equilibrium that links prices in the long run.

The modeling of the co-movements of oil with exchange rate and stock indexes both in emerging and developed economies simultaneously has so far received little attention in the financial literature. Yet, it is a subject of considerable importance for the pricing, risk management, and optimization of portfolios composed of different sectors.

Modeling the volatility dynamics between oil and other assets is an important and timely topic to study because recent developments in increased integration between financial markets and the "financialization" of commodity markets are providing investors with new ways to diversify; hedge and risk manage their investment portfolios. To date, most of the research on volatility dynamics and correlations and hedge ratios between oil and other assets has used multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models like BEKK [1] (Baba, Engle, Kraft, and Kroner), DCC (Dynamic Conditional Correlation) [1]. Estimating multivariate GARCH models on large data sets poses challenges. For example, the BEKK model can have a poorly behaved likelihood function which makes estimation difficult, especially for models with more than two variables. The VECH model has a large number of free parameters which makes it impractical for models with more than two variables. The basic problem is that as the number of estimated parameters increases, the likelihood function flattens making optimization very difficult, or in some cases impossible. Restricted correlation models,

***Corresponding author:** Abdelkafi ZS, Faculty of Economics and Management of Sfax, University of Sfax, Sfax, Tunisia, Tel: +251215454; E-mail: abdelkafi_samar@yahoo.com

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like Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC) or Asymmetric DCC (ADCC) are designed to address some of the problems encountered with BEKK and VECH type models and still retain analytical tractability for large data sets. One of the biggest challenges in multivariate GARCH modeling is finding a tradeoff between generality and feasibility, a tradeoff that is often referred to as "The curse of dimensionality".

This paper makes several important contributions to the literature. First, while many existing studies are interested in dynamic correlations between stock markets and exchange rates, this current paper investigates from DCC type models for both emerging and developed economies (stock indexes and exchange rates) with energy sector (crude oil). This provides a more complete understanding of how international financial markets suffer from volatility's persistence.

We emphasize that our investigation uses a more varied and relevant data set to construct for emerging and developed financial markets.

The following sections of the paper set out the relevant literature, empirical methodology, data, empirical results and the conclusions.

Relevant Literature

Energy is an important input into the economics of the world. Large modification in energy commodity price can influence regional and global economic and financial performance. The price of energy commodities is subject to major swings over time, particularly tied to the overall business cycle. When demand for a commodity like oil exceeds production capacity, the price will rise quite sharply as both demand and supply are fairly inelastic in the short run. Since the early 2000s, prices for the majority of energy commodities have more than tripled and have set record highs. Energy market has become increasingly volatile and risky. For this reason, studying the relationships between exchange rates, stock markets and energy prices have become an extremely crucial issue for central governments, businesses and corporations.

Tuhran et al. [2] suggest that "an oil price increase will also have an effect on a country's wealth by a transfer of income from oil importing to oil exporting countries through a shift in the terms of trade thus; inevitably, exchange rates are also expected to change". These facts make it necessary to understand the crude oil price dynamics and its impacts on international stock markets and exchange rates in emerging and developed countries. Financial globalization presents new challenges in understanding the effects of the oil prices on international markets.

We recognize that GARCH models are widely used to model asset price volatility dynamics. In this context, using Multivariate DCC GARCH (1,1), volatility's persistence and dynamic correlations are our focus in this paper. His estimate bivariate GARCH models using weekly data from January 1998 to December 2009 in order to investigate volatility spillovers between oil and stock market sectors in the US and Europe. They find evidence of a spillover effect from oil to stock markets in Europe and a bidirectional spillover effect between oil and US stock market sectors. His estimate bivariate GARCH models over the period 2005 to 2010 to determine return and volatility transmission between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries.

He uses multivariate GARCH (1,1) models to investigate volatility dynamics between the stock prices of clean energy companies, technology companies and oil prices over the period January 1, 2001 to December 31, 2010. The stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices.

During the recent past decade, financial markets have been suffered from global financial crisis (GFC) caused by the bursting of the US mortgage bubble. The literature shows that while the value of US dollar is decreasing, the value of several countries national currency is increasing during crisis period. As a consequence, dramatic movements in one foreign exchange market imply a powerful impact on markets throughout the world. Kodres and Pritsker [3] posit that "the pattern and severity of financial contagion depends on markets' sensitivities to shared macroeconomic risk factors, and on the amount of information asymmetry in each market". Information asymmetries play an important role in increasing the effect of contagion. Lhost [4] highlights that "Because emerging countries have higher levels of asymmetric information than developed markets, it is expected that they are more influenced by contagion than developed ones". He test the existence of contagion phenomenon during the US subprime crisis for six developed and ten emerging stock markets by applying DCC Model. They conclude that contagion is strong between US and the developed and emerging countries during the subprime crisis. Hwang et al. [5] examine the contagion effects of the U.S. subprime crisis on international stock markets using a DCC-GARCH model on 38 country data. Results suggest evidence of financial contagion not only in emerging markets but also in developed ones. The hypothesis of constant variance is too restrictive. Bollerslev [6] introduces a GARCH model, designed to allow for more flexibility in the lag structure. He concludes that the GARCH formulation better matches the data than the classic ARCH framework presented by Bollerslev [6]. Based on Bollerslev [6] findings, other research proposes alternative types of GARCH models. As a result, the literature is very rich in terms of different innovative techniques to model conditional variances. Using the multivariate DCC-GARCH specification from January 1988 to September 2009, Filis [7] finds that the conditional variances of oil and stock prices do not differ for oil-importing and oil-exporting economies. Recently, Choi and Hammoudeh [8] extend the time-varying correlations analysis by considering commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index from January 2, 1990 to May 1, 2006. They show that commodity correlations have increased since 2003, limiting hedging substitutability in portfolios. Modeling the co-movement of stock market returns is a challenging task. Ling and Dhési [9] posit that "the conventional measure of market interdependence, known as the Pearson correlation coefficient, is a symmetric, linear dependence metric, suitable for measuring dependence in multivariate normal distributions". However, correlations may be nonlinear and time-varying as showing by Ling and Dhési [9]. In order to better understand financial markets interdependences, econometric methods are applied such as Vector Autoregressive models (VAR) (Gilmoreand and McManus [10]; Cho and Parhizgari [11] and, Ling and Dhési [9]) and regime switching models, Schwender [12]. We note that the GARCH models gained a lot of popularity. There are several MGARCH models, of which the DCC-GARCH (Dynamic Conditional Correlation GARCH) models have greatly increased in popularity. The both advantages of this specification are the flexibility of univariate GARCH models and the simplicity of parametric correlation in the model; Swaray and Hammad [13]. The literature shows that GARCH models are widely considered for measuring the financial risk. DCC models calculate the correlation between the asset returns as a function of their past volatility and the correlations among them. This specification uses the recent past information for estimating the present correlation between series. DCC model's estimation is achieved in two steps so as to simplify the estimation of the time varying correlation matrix. It was introduced by Engle [1] and its specifications will be discussed in the next section.

Since the development of the ARCH and GARCH models by Engle [1] and Bollerslev [14], a significant literature has focused on using these specifications to model the volatility. In this case, our research focuses on the interdependencies between international stock markets, crude oil and exchange rates. It makes several important contributions to the recent literature on financial interdependence from the existence literature which largely focuses on testing contagion between stock markets.

First, this paper tests the existence of interdependence between different stock markets, exchange rates and crude oil. Second, it aims to answer the question of whether emerging markets are more vulnerable to financial crisis than developed markets during the analyzed period. This research aims to answer these questions: i) Does impulse response allow detecting integration between financial markets? ii) To what extent emerging and developed countries prove volatility's persistence and interdependences? throughout the following sections.

Data

Our data are composed of monthly returns relative to stock market indices, exchange rates and crude oil for seven developed economies (Australia, Canada, France, Japan, New Zealand Switzerland and United Kingdom) and eight emerging countries (Brazil, Chile, China, Mexico, Malaysia, Philippines, Russia and South Africa). The period is chosen between April 2003 and December 2014. This choice is motivated by the inclusion of two important events: the Subprime crisis and that of sovereign debt in Europe.

Model Specification: Multivariate DCC GARCH (1,1)

Bollerslev [14] introduced the model dynamic conditional correlations, the DCC-GARCH, enabling the matrix of conditional correlations vary over time. This model is a generalization of CCC-GARCH model of Bollerslev [14]:

$$r_t=\mu_t+\varepsilon_t \tag{1}$$

$$\varepsilon_t=\sqrt{H}\,\epsilon_t \tag{2}$$

$$H_t=D_t R_t D_t \tag{3}$$

where:

r_t: n x 1 vector yields of n active at time t,

μ_t: n x 1 vector of expected returns of assets at time t,

ε_t: n x 1 vector of errors with E $[\varepsilon_t]=0$ and cov $[\varepsilon_t]=H_t$,

H_t: n × n matrix of ε_t conditional variances at time t,

D_t: n x n diagonal matrix of conditional standard deviation of ε_t at time t,

R_t: n × n matrix of conditional correlations at time t,

ϵ_t: n x 1 vector errors with E $[\epsilon_t]=0$ and E $[\epsilon_t \epsilon_t']=\mathrm{In}$.

This is an estimation model in two stages. The first step is to estimate the conditional variance with univariate GARCH for each series. In the second step, the standardized residuals are used (obtained in the first step) to estimate the parameters of the dynamic correlations' matrix. This specification includes conditions allowing the covariance matrix to be positive definite at all times and the covariance to be stationary.

Analogously to the CCC-GARCH model, the matrix H_t is divided into two matrices, D_t and R_t. D_t matrix parameters derived from univariate GARCH estimated for each series:

$$D_t=\begin{bmatrix}\sqrt{h_{1,t}} & 0 & 0\\ 0\vdots & \sqrt{h_{2,t}}\;0 & 0\\ 0 & 0\cdots & \sqrt{h_{n,t}}\end{bmatrix}$$

$$h_{it}=\alpha_0,i+\sum_{q=1}^{Qi}\alpha_{iq}\,\varepsilon^2{}_{i,\,t-q}+\sum_{p=1}^{Pi}\beta_{ip}\,h_{i,\,t-p} \tag{4}$$

In the previous phase, the univarite GARCH may be of different orders, which enables the analysis of sets with different numbers of delays. The R_t matrix, that of conditional correlations standardized residuals, it is now dynamic.

$$R_t=\begin{bmatrix}1 & \cdots & \rho_{1n,t}\\ \vdots & \ddots & \vdots\\ \rho_{n1,t} & \cdots & 1\end{bmatrix}$$

To ensure that H_t is positive, it is necessary that also the matrix R_t be positive since $H_t=D_t R_t D_t$. The matrix D_t is always positive because $D_t=diag(\sqrt{h_{1,t}},\ldots,\sqrt{h_{n,t}})$ therefore its parameters are always positive. It must also ensure that the R_t elements are ≤ 1 because there are the correlations. To ensure that R_t is positive, this matrix is decomposed into two matrices:

$$R_t=Q_t^{*-1}\,Qt\,Q_t^{*-1} \tag{5}$$

$$Q_t=(1-\alpha_{DCC}-\beta_{DCC})\,\bar{Q}+\alpha_{DCC}\,\varepsilon_{t-1}\,\varepsilon'_{t-1}+\beta_{DCC}\,Q_{t-1} \tag{6}$$

$$Q_t^*=\begin{bmatrix}\sqrt{q_{11,t}} & 0 & 0\\ 0 & \sqrt{q_{33,t}} & 0\\ 0 & 0 & \sqrt{q_{NN,t}}\end{bmatrix}$$

$$Q_t=\begin{bmatrix}q_{11,t} & \cdots & \sqrt{q_{11,t}q_{NN,t}}\\ \vdots & \ddots & \vdots\\ \sqrt{q_{11,t}q_{NN,t}} & \cdots & q_{NN,t}\end{bmatrix}$$

The Q_t matrix must be positive so that is also the R_t. In the previous equation, $Q_t=\mathrm{Cov}\,[\varepsilon_t\varepsilon'_t]=E\,[\varepsilon_t\varepsilon'_t]$, either the unconditional covariance standardized residuals obtained by univariate GARCH. Note that α_{Dcc} and β_{Dcc} are scalar. The following conditions must be met for H_t is positive definite:

$$\alpha_{DCC}\geq 0 \tag{7}$$

$$\beta_{DCC}\geq 0 \tag{8}$$

$$\alpha_{DCC}+\beta_{DCC}<1 \tag{9}$$

The general structure of DCC dynamic correlation (p, q) is as follows:

$$Q_t=(1-\sum_{i=1}^{P}\alpha_{DCC,i}-\sum_{j=1}^{Q}\beta_{DCC,j})\bar{Q}+\sum_{i=1}^{P}\alpha_{DCC,i}\left(\varepsilon_{t-i}\varepsilon'_{t-i}\right)+\sum_{j=1}^{Q}\beta_{DCC,j}Q_{t-j} \tag{10}$$

The advantages of DCC GARCH are direct modeling of the variance and the covariance and its flexibility. However, it also has limitations: the likelihood function becomes complicated when the number of variables is greater than or equal to 3 and the conditional correlation matrix must be positive for all t. The number of variables is limited to 3 in our investigation. This model will examine transfers of volatility between stock indexes, exchange rates and crude oil.

DCC GARCH (1, 1) Model estimation

We assume that ε_t standardized residuals have a Gaussian distribution, the estimation method is maximum likelihood. The likelihood function for $R_t = \sqrt{H_t \varepsilon_t}$ is

$$L(\theta) = \prod_{t=1}^{T} \frac{1}{\sqrt{2\Pi^n |H_t|}} exp\left(-\frac{1}{2} r_t^T H_t r_t\right) \tag{11}$$

The parameters of H_t, θ, are divided into two groups: $(\phi_1, \phi_2, \phi_3, \ldots, \phi_k, \delta) = (\phi, \psi)$.

The elements of ϕ_i correspond to the parameters of the univariate GARCH of the ith series or $\phi_i = (\alpha_o, \alpha_{1,i}, \alpha_{Pi\,i}, \beta_{1i}, \beta_{Qii} \ldots)$ and ψ elements to parameters of the dynamic correlation of structure $(\alpha_{DCC}, \beta_{DCC})$. R_t matrix in the log-likelihood is replaced by an identity matrix h which gives the log quasi-likelihood of the first step.

The log-likelihood is derived as follows:

$$L = -\frac{1}{2} \sum_{t=1}^{T} (n \log(2\Pi) + \log|H_t| + r'_t H^{-1}_t r_t) \tag{12}$$

$$L = -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\Pi) + \log|D_t R_t D_t| + r'_t D^{-1}_t R^{-1}_t D^{-1}_t r_t\right) \tag{13}$$

$$L = -\frac{1}{2} \sum_{t=1}^{T} (n \log(2\Pi) + 2\log|D_t| + \log|R_t| + r'_t D^{-1}_t R^{-1}_t D^{-1}_t r_t \tag{14}$$

According to Engle (2002), the log-likelihood is the sum of a term volatility and correlation term, the settings in D_t are then rated by θ and R_t parameters are noted by ϕ.

$$L(\theta, \phi) = L_v(\theta) + L_c(\theta, \phi) \tag{15}$$

Where the portion of the volatility is:

$$L_v(\theta) = -\frac{1}{2} \sum_{t=1}^{T} (n \log(2\Pi) + 2\log|D_t| + r'_t D^{-1}_t R^{-1}_t D^{-1}_t r_t \tag{16}$$

And part of the correlation is:

$$\theta, \phi \;= -- \sum \left(\log|Rt| + \varepsilon' tR' t\, \varepsilon t - \varepsilon' t\, \varepsilon\right) \tag{17}$$

In the first stage, θ it is estimated by maximizing θ *=arg max θ Lv (θ), and in the second step, ϕ it is estimated by maximizing ϕ *=arg max Lc (θ, ϕ).

First step: We maximize the results found in eqn. (14). R_t is replaced by an identity matrix I_n, giving

$$\begin{aligned} L_v(\theta) &= -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\Pi) + \log|In| + 2\log|Dt| + r'_t D_t^{-1} I_n D_t^{-1} r_t\right) \\ &= -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\Pi) + 2\log|Dt| + r'_t D_t^{-1} D_t^{-1} r_t\right) \\ &= -\frac{1}{2} \sum_{t=1}^{T} \left(n \log(2\Pi)\right) + \sum_{t=1}^{T} \left(\log(h_{it}) + \frac{r_{it}^2}{h_{it}}\right) \\ &= -\frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{n} (n \log(2\Pi) + \log(h_{it}) + \frac{r_{it}^2}{h_{it}} \end{aligned} \tag{18}$$

The first term of eqn. (18) is constant, we will maximize only:

$$L_v(\theta) = -\frac{1}{2} \sum_{t=1}^{T} \sum_{i=1}^{n} (\log(h_{it}) + \frac{r_{it}^2}{h_{it}}) \tag{19}$$

We get as an estimator:

$$\theta^* = \arg\max \theta\, Lv(\theta). \tag{20}$$

Second step: Once the estimate of the first completed step that of the second step is done using the likelihood function:

$$\begin{aligned} L_c(\theta, \phi) &= -\frac{1}{2} \sum_{t=1}^{T} n \log(2\Pi) + 2\log|D_t| + \log|R_t| + r'_t D^{-1}_t R^{-1}_t D^{-1}_t r_t \\ &= -\frac{1}{2} \sum_{t=1}^{T} (n \log(2\Pi) + 2\log|D_t| + \log|R_t| + \epsilon'_t R_t^{-1} \epsilon_t \end{aligned} \tag{21}$$

Since we maximize only the correlations settings, it is only the terms log |Rt| and $\epsilon'_t R_t^{-1} \epsilon_t$ that will be used, we can simplify the likelihood function:

$$L_c(\theta, \phi) = -\frac{1}{2} \sum_{t=1}^{T} \log|R_t| + \epsilon'_t R_t^{-1} \epsilon_t \tag{22}$$

The resulting estimator is expressed as follows:

$$\phi^* = \arg_{\phi} \max L_c(\theta, \phi) \tag{23}$$

Under general conditions, the likelihood estimator will be consistent and asymptotically normal:

$$\sqrt{T}(\theta^{\wedge -} \theta_0) \xrightarrow{d} N(0, V(\theta_0)) \tag{24}$$

Statistical Test

Descriptive statistics

In developed countries, crude oil provides the maximum monthly return followed by Japanese and French stock markets. The developed exchange markets have maximum yields between 2% and 3%. The minimum monthly returns are represented by the Australian Dollar. All markets have a negative skewness coefficient indicating that they experience more negative impacts than positive shocks. The kurtosis demonstrates that all series show leptokurtic distribution. The Jarque-Bera test emphasizes the rejection of the normality assumption for all series. Standard deviation coefficient shows that Australian Dollar and crude oil are the most volatile (Tables 1a and 1b).

Descriptive statistics analysis, in emerging countries, highlights that the maximum monthly return is provided by Russia followed by China. Chile and Russia are the emerging countries whose exchange rates represent the maximum monthly return. Stock markets presenting the minimum returns are Russia and Brazil. For exchange rates, those with the minimum monthly returns are Mexico and Philippines. The kurtosis exceeding the critical value (3) indicates the presence of fat tails at all series: all series show an excess of kurtosis, this finding is consistent with the empirical literature which postulates that financial data is leptokurtic.

Correlation matrices

By examining the correlation matrices for each country, we detect that for emerging economies, the strongest correlation for the pair [stock index -exchange rate] is recorded in Brazil (59.224%), the lowest in Chile (20.942%). The correlation provided by the pair [Stock Index-Crude Oil] emphasizes that Russia (60.218%), followed by South Africa have the highest value, the least important is registered in China (7.345%). The pair of variables [Crude-Oil-Exchange Rate] suggests

	Developed Countries											
	Australia			Canada			France			Japan		
	ASX	**AUD/USD**	**CRUDE OIL**	**SPTSX**	**CAD/USD**	**CRUDE OIL**	**CAC**	**EUR/USD**	**CRUDE OIL**	**NIKKEI**	**JPY/USD**	**CRUDE OIL**
Mean	0.002022	-0.070335	0.001348	0.002565	0.0006	0.0013	0.001731	0.000223	0.0013	0.0024	-0.0001	0.0016
Median	0.006069	-0.060637	0.007375	0.005273	0.0010	0.0073	0.005513	0.000420	0.0073	0.0028	-0.0005	0.0077
Maximum	0.030640	0.032609	0.112988	0.046141	0.0268	0.1129	0.052316	0.027411	0.1129	0.0525	0.0256	0.1129
Minimum	-0.0588	-0.215711	-0.171477	-0.08057	-0.0416	-0.1714	-0.06307	-0.030466	-0.1714	-0.1181	-0.031	-0.1714
Std. Dev.	0.0166	0.062933	0.039791	0.016979	0.0089	0.0397	0.020741	0.010621	0.0397	0.0248	0.0103	0.0397
Skewness	-1.02074	-0.151284	-0.774236	-1.49802	-0.501	-0.7742	-0.67036	-0.109192	-0.7742	-1.0278	-0.0391	-0.7968
Kurtosis	4.134924	1.955682	4.889736	7.914288	5.9536	4.8897	3.805965	3.377191	4.8897	6.1382	3.3044	4.9691
Jarque-Bera	32.27947	6.994377	35.31580	195.9982	57.557	35.315	14.47858	1.123955	35.315	82.685	0.5806	37.701
Probability	0.0000	0.0302	0.0000	0.0000	0.0000	0.0000	0.0007	0.5700	0.0000	0	0.748	0
Sum	0.2871	-9.9875	0.1914	0.3642	0.0869	0.1914	0.245786	0.0317	0.1914	0.3402	-0.0039	0.238
Sum SqDev.	0.0389	0.5584	0.2232	0.040649	0.0113	0.2232	0.060656	0.0159	0.2232	0.0861	0.015	0.2209
Observations	142	142	142	142	142	142	142	142	142	141	141	141
	New-Zealand			Switzerland			United-Kingdom					
	DJNZ	**NZD/USD**	**CRUDE OIL**	**SUI**	**CHF/USD**	**CRUDE OIL**	**FTSE**	**GBP/USD**	**CRUDE OIL**			
Mean	0.00101	0.00086	0.00160	0.002199	0.001206	0.001348	0.001911	-4.93E-05	0.0013			
Median	0.00358	0.00208	0.00737	0.004451	0.001093	0.007375	0.004057	0.000407	0.0073			
Maximum	0.03452	0.03233	0.11298	0.046058	0.031945	0.112988	0.036046	0.039206	0.1129			
Minimum	-0.05588	-0.03931	-0.17147	-0.05223	-0.044472	-0.17147	-0.06061	-0.045133	-0.171477			
Std. Dev.	0.01482	0.01300	0.03960	0.015846	0.011085	0.039791	0.016620	0.011182	0.039791			
Skewness	-0.92055	-0.49081	-0.79257	-0.57228	-0.194004	-0.77423	-0.73483	-0.477867	-0.774236			
Kurtosis	4.688782	3.56908	5.05233	3.955885	4.410505	4.889736	4.244054	5.299941	4.889736			
Jarque-Bera	35.36927	7.29554	38.1069	13.15699	12.66212	35.31580	21.93654	36.70200	35.31580			
Probability	0.000000	0.02604	0.00000	0.001390	0.001780	0.000000	0.000017	0.000000	0.000000			
Sum	0.138294	0.11714	0.21802	0.312254	0.171212	0.191486	0.271361	-0.006998	0.191486			
Sum SqDev.	0.029685	0.02283	0.21175	0.035405	0.017327	0.223247	0.038947	0.017631	0.223247			
Observations	136	136	136	142	142	142	142	142	142			

Table 1a: Descriptive Statistics (Developed countries).

	Emerging Countries											
	Brazil			Chile			China			Malaysia		
	BOVESPA	BRL/USD	CRUDE OIL	IPSA	CLP/USD	CRUDE OIL	SHANGHAI	CNY/USD	CRUDE OIL	KLCI	MYR/USD	CRUDE OIL
Mean	0.004360	0.000692	0.001348	0.004083	0.000540	0.001348	0.002207	0.000880	0.002359	0.003153	0.000192	0.001348
Median	0.005251	0.003194	0.007375	0.002814	0.001072	0.007375	0.003005	0.000642	0.007794	0.004472	0.000409	0.007375
Maximum	0.062767	0.062732	0.112988	0.064782	0.948460	0.112988	0.105328	0.008979	0.112988	0.055169	0.776076	0.112988
Minimum	-0.123761	-0.072783	-0.17148	-0.04373	-0.918314	-0.17148	-0.12281	-0.006689	-0.17148	-0.07172	-0.778219	-0.17148
Std. Dev.	0.028746	0.019291	0.039791	0.019891	0.136502	0.039791	0.036550	0.002139	0.039058	0.016409	0.092740	0.039791
Skewness	-0.612384	-0.673448	-0.77424	0.146046	0.024824	-0.77424	-0.536863	0.376010	-0.7957	-0.5264	-0.040935	-0.77424
Kurtosis	4.702699	5.371653	4.889736	3.132959	39.00378	4.889736	4.444475	5.639254	5.166791	6.179169	70.44148	4.889736
Jarque-Bera	26.02883	44.01330	35.31580	0.609395	7669.626	35.31580	18.89647	43.93197	42.16047	66.35835	26911.13	35.31580
Probability	0.000002	0.000000	0.000000	0.737347	0.000000	0.000000	0.000079	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	0.619180	0.098281	0.191486	0.579722	0.076648	0.191486	0.308926	0.123224	0.330312	0.447686	0.027232	0.191486
Sum Sq Dev.	0.116511	0.052471	0.223247	0.055787	2.627211	0.223247	0.185686	0.000636	0.212046	0.037967	1.212705	0.223247
Obs	142	142	142	142	142	142	140	140	140	142	142	142
	Mexico			Philippines			Russia			South-Africa		
	IPC	MXN/USD	CRUDE OIL	PSEI	PHP/USD	CRUDE OIL	RTSI	RUB/USD	CRUDE OIL	FTSSA	ZAR/USD	CRUDE OIL
Mean	0.005918	-0.001134	0.001348	0.005683	0.000671	0.001603	0.002193	-0.002175	0.001348	0.005582	-0.001447	0.001603
Median	0.007785	0.000239	0.007375	0.010563	0.000995	0.007375	0.008619	0.000490	0.007375	0.006574	9.58E-05	0.007375
Maximum	0.053760	0.920887	0.112988	0.060582	0.923572	0.112988	0.115888	0.925042	0.112988	0.050332	0.042438	0.112988
Minimum	-0.085412	-0.924959	-0.17148	-0.1196	-0.924741	-0.17148	-0.195058	-0.92021	-0.17148	-0.06528	-0.07326	-0.17148
Std. Dev.	0.021532	0.144744	0.039791	0.024494	0.147134	0.039605	0.045029	0.144177	0.039791	0.019612	0.015907	0.039605
Skewness	-0.754545	0.006947	-0.77424	-1.09276	-0.02351	-0.79257	-0.871867	0.111257	-0.77424	-0.46443	-0.678069	-0.79257
Kurtosis	4.667342	35.89300	4.889736	7.102445	34.87812	5.052334	5.241478	35.83094	4.889736	4.046521	5.341291	5.052334
Jarque-Bera	29.92285	6401.537	35.31580	122.4372	5758.562	38.10695	47.71692	6377.694	35.31580	11.09529	41.48427	38.10695
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.003897	0.000000	0.000000
Sum	0.840377	-0.161092	0.191486	0.772841	0.091285	0.218024	0.311444	-0.308859	0.191486	0.759194	-0.196777	0.218024
Sum Sq Dev.	0.065373	2.954084	0.223247	0.080993	2.922534	0.211751	0.285891	2.930987	0.223247	0.051924	0.034159	0.211751
Obs	142	142	142	136	136	136	142	142	142	136	136	136

Table 1b: Descriptive Statistics (Emerging countries).

that the largest correlation is presented by Brazil (35.521%), followed by South Africa (32. 155%), the lowest level in Chile (1.354%) (Table 2).

The developed countries show that the correlation between [Stock Index -Crude Oil] is strong in Canada (56.687%), followed by Australia, UK, Japan and in the last rank New Zealand (11.807%). Canada also ranks first with regard to the correlation between [Stock Index-Exchange Rate] among all countries. A strong negative correlation was detected between the Nikkei 225 and the Japanese Yen (-40%). Referring to correlations between Crude Oil and Exchange Rate, it appears that the UK provides the highest value (45.884%). In Japan, this value is negative (-11.59%).

This points out that the correlation increases during periods of high market volatility. When markets become more volatile, investors demand diversification. Investment strategies based on simple correlation estimation techniques do not work well during turbulent periods. Investors' expectations may change drastically as a result of significant declines in the financial markets. They suppose that changes in correlations between financial markets explain the impact of shocks on the financial markets during periods of high turbulence. We can conclude that the channels through which the links and co-movements between active studied propagate are not limited to differences between investors and their investment horizons. He showed that crude oil was not correlated with stock indices until 2001. When this commodity begins to be used as a financial asset, the link between oil and other assets is reinforced. The most sensitive financial markets are stock markets and foreign exchange to the extent that any new information highlighted goes quickly, affecting both markets. In other words, when assessing a particular currency, the exporting country will lose its international competitiveness which will drop accordingly sales and profits and lower stock prices.

Stationary and unit root tests

Before studying the linkages between different markets, ADF and KPSS tests are applied to examine the properties of the different series. The null hypothesis of the ADF test is that the series has a unit root,

Emerging countries				Developing countries			
Brazil				Australia			
	BOVESPA	BRL/USD	CRUDE OIL		ASX	AUD/USD	CRUDE OIL
BOVESPA	1	0.59224	0.42364	ASX	1	-0.08166	0.38584
BRL/USD	0.59224	1	0.35521	AUD/USD	-0.08166	1	0.0478
CRUDE OIL	0.42364	0.35521	1	CRUDE OIL	0.38584	0.0478	1
Chile				Canada			
	IPSA	CLP/USD	CRUDE OIL		SPTSX	CAD/USD	CRUDE OIL
IPSA	1	-0.20942	0.25869	SPTSX	1	0.34086	0.56687
CLP/USD	-0.20942	1	0.01354	CAD/USD	0.34086	1	0.44653
CRUDE OIL	0.25869	0.01354	1	CRUDE OIL	0.56687	0.44653	1
China				France			
	SHANGHAI	CNY/USD	CRUDE OIL		CAC	EUR/USD	CRUDE OIL
SHANGHAI	1	-0.02529	-0.07345	CAC	1	0.22507	0.31045
CNY/USD	-0.02529	1	0.13117	EUR/USD	0.22507	1	0.32592
CRUDE OIL	-0.07345	0.13117	1	CRUDE OIL	0.31045	0.32592	1
Malaysia				Japan			
	KLCI	MYR/USD	CRUDE OIL		NIKKEI	JPY/USD	CRUDEOIL
KLCI	1	-0.05855	0.35911	NIKKEI	1	-0.40612	0.34294
MYR/USD	-0.05855	1	0.07879	JPY/USD	-0.40612	1	-0.11593
CRUDE OIL	0.35911	0.07879	1	CRUDEOIL	0.34294	-0.11593	1
Mexico				New-Zealand			
	IPC	MXN/USD	CRUDE OIL		DJNZ	NZD/USD	CRUDE OIL
IPC	1	-0.08497	0.302743	DJNZ	1	0.28086	0.11807
MXN/USD	-0.08497	1	0.15796	NZD/USD	0.28086	1	0.31348
CRUDE OIL	0.30274	0.15796	1	CRUDE OIL	0.11807	0.31348	1
Philippines				Switzerland			
	PSEI	PHP/USD	CRUDE OIL		SMI	CHF/USD	CRUDE OIL
PSEI	1	0.00123	0.32273	SUI	1	-0.10732	0.17824
PHP/USD	0.00123	1	0.13146	CHF/USD	-0.10732	1	0.18139
CRUDE OIL	0.32273	0.13146	1	CRUDE OIL	0.17824	0.18139	1
Russia				United-Kingdom			
	RTSI	RUB/USD	CRUDE OIL		FTSE	GBP/USD	CRUDE OIL
RTSI	1	0.0816	0.60218	FTSE	1	0.26061	0.35816
RUB/USD	0.0816	1	0.16572	GBP/USD	0.26061	1	0.45884
CRUDE OIL	0.60218	0.16572	1	CRUDE OIL	0.35816	0.45884	1
South Africa							
	FTSSA	ZAR/USD	CRUDE OIL				
FTSSA	1	0.25305	0.46902				
ZAR/USD	0.25305	1	0.32155				
CRUDE OIL	0.46902	0.32155	1				

Table 2: Correlation Matrices.

while stationary is the null hypothesis in the KPSS test. We make a KPSS test as confirmation of the results of the ADF. But if the results of both tests are contradictory, then the KPSS is preferable (Table 3).

Lag length selection

Before performing the vector autoregression analysis, Schwarz's Bayesian Information Criterion (SBIC), the Akaike's Information

BRL/USD	CRUDE OIL	BOVESPA	BRL/USD	CRUDE OIL		ASX	AUD/USD	CRUDE OIL	ASX
-12.04372	-9.176819	-9.947420	-12.28834	-9.440125	ADF	-10.04791	-2.344378	-9.176819	-10.05000
0.452880	0.226275	0.032387	0.028440	0.042957	KPSS	0.161291	1.105548	0.226275	0.105585
CLP/USD	**CRUDE OIL**	**IPSA**	**CLP/USD**	**CRUDE OIL**	**Canada**	**SPTSX**	**CAD/USD**	**CRUDE OIL**	**SPTSX**
-11.44187	-9.176819	-10.57229	-11.43688	-9.440125	ADF	-9.382410	-8.169653	-9.176819	-9.422546
0.389202	0.226275	0.043526	0.364626	0.042957	KPSS	0.164110	0.362642	0.226275	0.076828
CNY/USD	**CRUDE OIL**	**SHANGHAI**	**CNY/USD**	**CRUDE OIL**	**France**	**CAC**	**EUR/USD**	**CRUDE OIL**	**CAC**
-8.348339	-9.410863	-6.218562	-8.342802	-9.575016	ADF	-10.36741	-8.653553	-9.176819	-10.32541
0.219982	0.152052	0.064467	0.203884	0.029489	KPSS	0.185872	0.247991	0.226275	0.144824
MYR/USD	**CRUDE OIL**	**KLCI**	**MYR/USD**	**CRUDE OIL**	**Japan**	**NIKKEI**	**JPY/USD**	**CRUDE OIL**	**NIKKEI**
-11.46338	-9.176819	-10.48809	-11.42985	-9.440125	ADF	-9.777106	-9.107105	-9.103575	-9.741921
0.500000	0.226275	0.044110	0.5	0.042957	KPSS	0.158755	0.385534	0.202563	0.158869
MXN/USD	**CRUDE OIL**	**IPC**	**MXN/USD**	**CRUDE OIL**	**New-Zealand**	**DJNZ**	**NZD/USD**	**CRUDE OIL**	**DJNZ**
-9.821742	-9.176819	-10.69284	-9.793172	-9.440125	ADF	-10.42849	-7.915530	-8.491656	-10.42678
0.500000	0.226275	0.062199	0.5	0.042957	KPSS	0.232414	0.060046	0.260418	0.184185
PHP/USD	**CRUDE OIL**	**PSEI**	**PHP/USD**	**CRUDE OIL**	**United-Kingdom**	**FTSE**	**GBP/USD**	**CRUDE OIL**	**FTSE**
-9.996257	-8.491656	-11.37446	-10.03446	-8.724203	ADF	-11.83172	-10.29648	-9.176819	-11.80313
0.500000	0.260418	0.061315	0.5	0.044831	KPSS	0.129519	0.109202	0.226275	0.093443
RUB/USD	**CRUDE OIL**	**RTSI**	**RUB/USD**	**CRUDE OIL**	**Switzerland**	**SMI 25**	**CHF/USD**	**CRUDE OIL**	**SMI 25**
-9.052151	-9.176819	-8.885822	-9.385980	-9.440125	ADF	-8.980768	-10.28086	-9.176819	-8.974406
0.404205	0.226275	0.041444	0.314669	0.042957	KPSS	0.190958	0.053635	0.226275	0.142308
ZAR/USD	**CRUDE OIL**	**FTSSA**	**ZAR/USD**	**CRUDE OIL**					
-8.785553	-8.491656	-12.20967	-8.844799	-8.724203					
0.180774	0.260418	0.099807	0.053097	0.044831					

Table 3: Stationary and Unit Root Tests.

Emerging countries		VAR (1)	VAR (2)	VAR 3)	VAR (4)	VAR (5)	VAR (6)	Developed countries	VAR (1)	VAR (2)	VAR 3)	VAR (4)	VAR (5)	VAR (6)
Brazil	Log Likelihood	936.2018	943.4470	950.1492	953.3405	963.2876	967.8722	**Australia**	1040.687	1050.402	1060.755	1064.345	1069.116	1073.337
	AIC	**-13.79406**	-13.76787	-13.73357	-13.64687	-13.66101	-13.59511		-15.35354	-15.36422	**-15.38440**	-15.30366	-15.24054	-15.1692
	SBIC	**-13.53455**	-13.31373	-13.0848	-12.80347	-12.62298	-12.36244		**-15.09403**	-14.91008	-14.73563	-14.46026	-14.20251	-13.93654
Chile	Log Likelihood	695.4817	705.7867	713.9441	725.4340	733.9083	738.9954	**Canada**	1120.487	1127.057	1133.359	1137.784	1147.272	1153.599
	AIC	-10.20122	-10.2207	-10.20812	**-10.24528**	-10.23744	-10.17904		**-16.54458**	-16.50831	-16.46804	-16.39976	-16.40705	-16.36715
	SBIC	**-9.941712**	-9.766558	-9.559351	-9.401882	-9.199404	-8.946372		**-16.28507**	-16.05417	-15.81927	-15.55636	-15.36902	-15.13449
China	Log Likelihood	1127.869	1138.669	1142.686	1152.803	1157.136	1172.031	**France**	1032.563	1044.247	1047.167	1053.244	1060.500	1065.489
	AIC	-16.90711	**-16.93437**	-16.85887	-16.87581	-16.80509	-16.89441		-15.23228	**-15.27234**	-15.1816	-15.13797	-15.11195	-15.05207
	SBIC	**-16.64504**	-16.47575	-16.20369	-16.02407	-15.7568	-15.64956		**-14.97277**	-14.8182	-14.53283	-14.29457	-14.07391	-13.81941
Malaysia	Log Likelihood	772.3807	786.6040	792.2146	799.8924	811.4965	821.4411	**Japan**	998.7731	1006.060	1011.051	1014.636	1019.580	1029.441
	AIC	-11.34897	**-11.42693**	-11.37634	-11.3566	-11.39547	-11.40957		**-14.83869**	-14.81293	-14.75264	-14.67122	-14.61022	-14.62317
	SBIC	**-11.08946**	-10.97279	-10.72757	-10.5132	-10.35744	-10.17691		**-14.57791**	-14.35656	-14.10068	-13.82367	-13.56709	-13.38445
Mexico	Log Likelihood	671.2953	683.6114	695.1736	708.5698	721.1771	728.6161	**New-Zealand**	746.8787	747.6061	752.1125	753.6102	755.2843	756.1222
	AIC	-9.840228	-9.889723	-9.927964	-9.99358	**-10.04742**	-10.02412		**-11.57623**	-11.5251	-11.53301	-11.49391	-11.45757	-11.40816
	SBIC	**-9.580720**	-9.435584	-9.279194	-9.150179	-9.009388	-8.791458		**-11.44254**	-11.30228	-11.22107	-11.09284	-10.96737	-10.82884
Philippines	Log Likelihood	621.0703	634.5765	640.5277	652.6568	664.0489	675.0904	**Switzerland**	1048.463	1059.660	1066.029	1069.113	1073.127	1080.255
	AIC	-9.516724	-9.587133	-9.539495	-9.588387	-9.625764	**-9.65766**		-15.4696	**-15.50239**	-15.46313	-15.37482	-15.3004	-15.27247
	SBIC	**-9.249346**	-9.119222	-8.871051	-8.719409	-8.556253	-8.387618		**-15.21009**	-15.04825	-14.81435	-14.53142	-14.26237	-14.0398
Russia	Log Likelihood	606.1361	618.2140	628.6473	636.8570	647.8585	657.7490	**United-Kingdom**	1058.179	1063.783	1068.785	1074.201	1077.316	1083.037
	AIC	-8.867703	-8.913642	-8.935034	-8.92324	-8.953112	**-8.96640**		**-15.61461**	-15.56393	-15.50425	-15.45077	-15.36293	-15.31398
	SBIC	**-8.608195**	-8.459503	-8.286264	-8.079838	-7.91508	-7.733741		**-15.35510**	-15.10979	-14.85548	-14.60737	-14.3249	-14.08132
South Africa	Log Likelihood	942.1294	949.8957	955.5799	961.3040	966.1964	972.1832							
	AIC	**-14.53327**	-14.514	-14.46219	-14.411	-14.34682	-14.29974							
	SBIC	**-14.26589**	-14.04608	-13.79374	-13.54202	-13.27731	-13.02969							

Table 4: Lag length selection.

Criterion (AIC) and the Log Likelihood tests are performed to determine the appropriate length of lags to be included in the model (Table 4).

Results and Discussions

Impulse responses

The impulse response function illustrates the impact of innovation on the present and future values of other variables and helps to determine its magnitude and its depreciation.

We investigate the short-term causal relationships among the stock markets, exchange rates and crude oil belonging to eight emerging markets and seven developed economies through impulse response analyses in the two sub-periods. Huyghebaert and Lihong [15] posited that "A shock to the i^{-th} variable not only directly affects the i^{-th} variable but is also transmitted to all of the other endogenous variables through the dynamic (lag) structure of the VAR.

Our results reflect the severity of the last US recession (2007-2009) leading to a combination of similar expansionary fiscal and monetary policies both by the government and the US central bank. According to the theoretical model, current stock prices reflect the expected cash flows (earnings) discounted by the appropriate interest rate. The very low interest rates increase the discounted cash flow. The prices of commodities are rising, and foreign stocks still have more than US equities (Figures 1-15).

In developed countries, results show that the innovations of the ASX stock index's realized volatility have spread to the exchange rate and crude oil. This result confirms the existence of ASX index's volatility transmission effect to the Australian dollar and crude oil on the one hand and the significant influence of the index in other markets on the other hand. Moreover, it appears that the ASX index is influential since a rise in volatility increases uncertainty in the Australian dollar and crude oil. Shock to the crude oil leads to a negligible response from ASX stock index. Crude oil responds positively with a significant amplitude during five periods (shock on S&P/TSX). This important reaction from the Canadian dollar and crude oil reflects the degree of integration of these markets with the S&P/TSX stock index. S&P/TSX and the Canadian dollar are proving insensitive to shocks on crude oil whose reaction to its own impact is negligible (shock amortized after fourth month). In France, innovations of the CAC index's realized volatility are spread to the Euro and crude oil. The Japanese stock market does not seem to have much influence that innovations can disrupt the movements of the other markets' realized volatility. Thus, the analysis of the impulse response functions allowed seeing an important element characterizing the Japanese market, identified by the earlier literature on its evolution. Indeed, when the Nikkei 225 stock index undergoes a positive shock that is to say an increase in its realized volatility or other

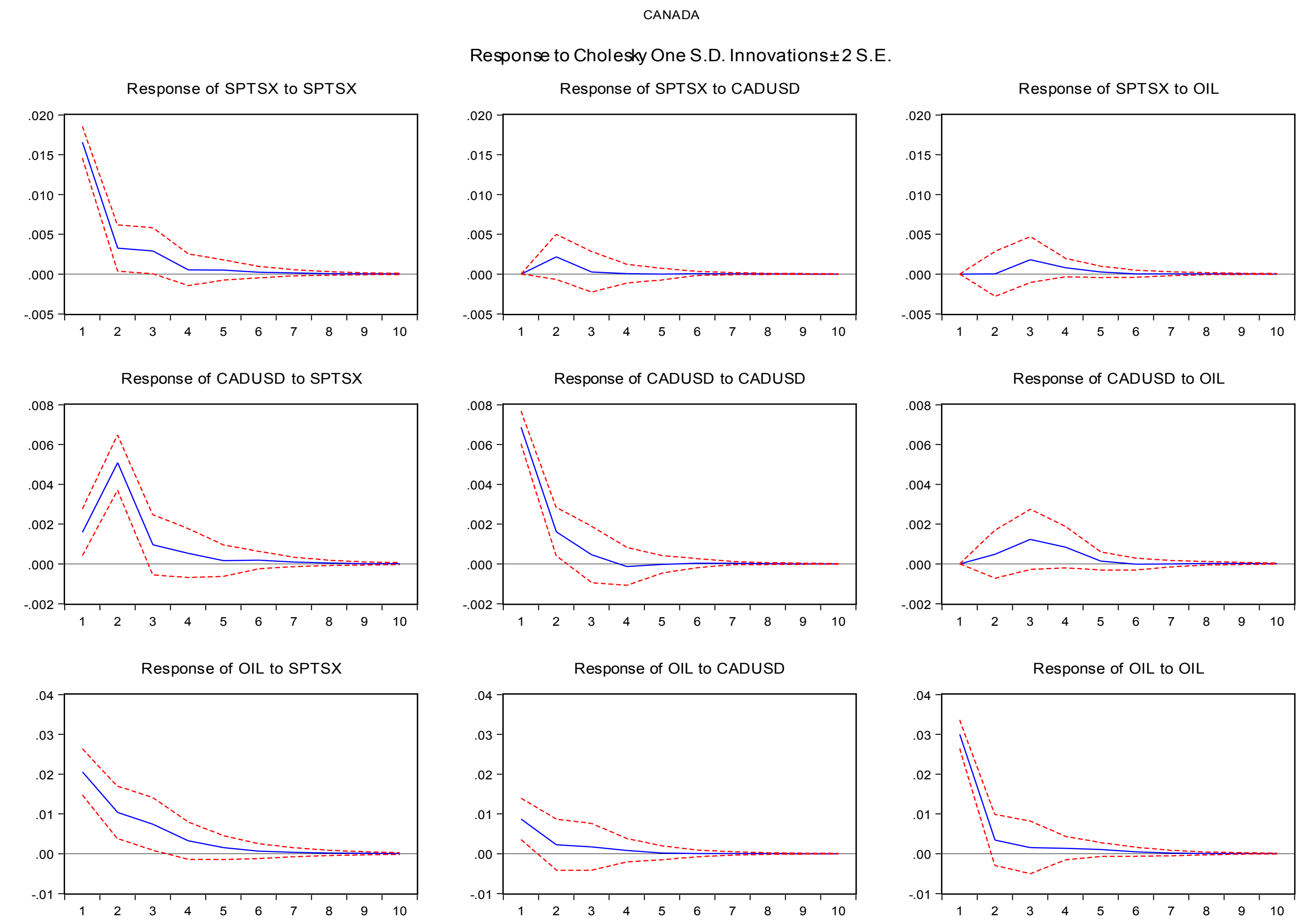

Figure 1: Impulse Responses of Canada.

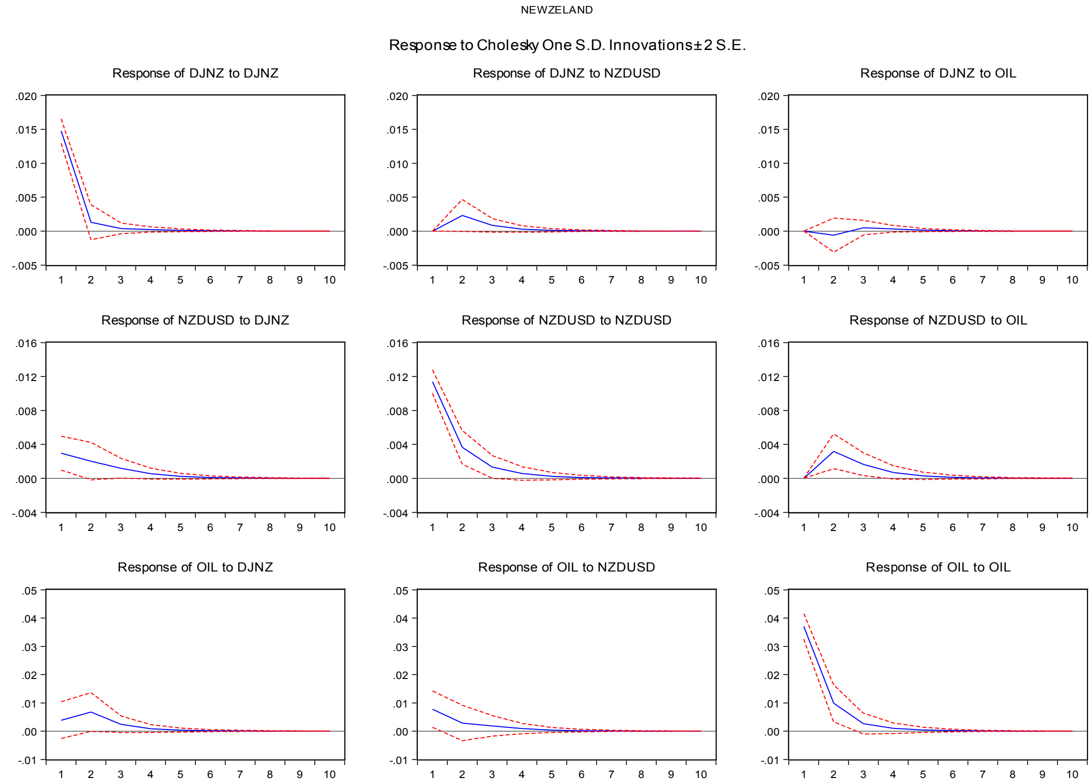

Figure 2: Impulse Responses of New Zealand.

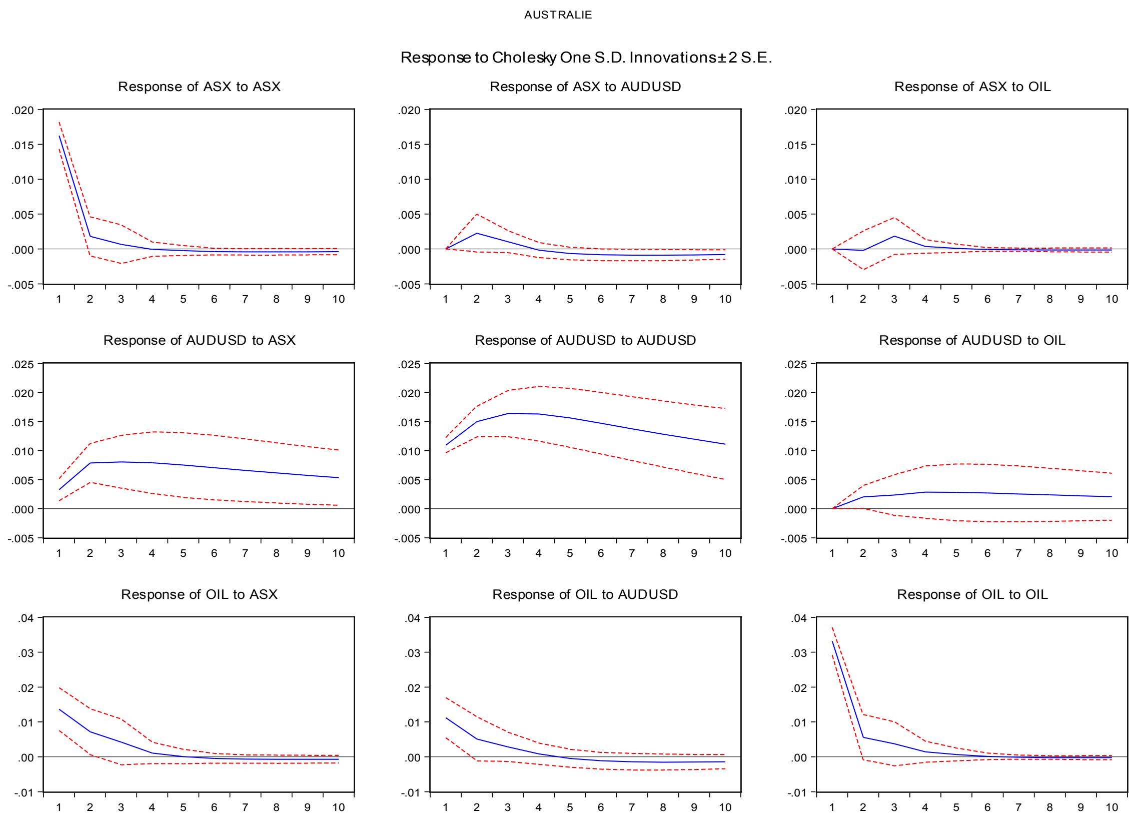

Figure 3: Impulse Responses of Australia.

Citation: Abdelkafi ZS, Khoufi W (2017) Integration and Volatility's Persistence in Emerging and Developed Countries: Impulse Responses and Multivariate DCC GARCH. Arabian J Bus Manag Review 7: 297. doi: 10.4172/2223-5833.1000297

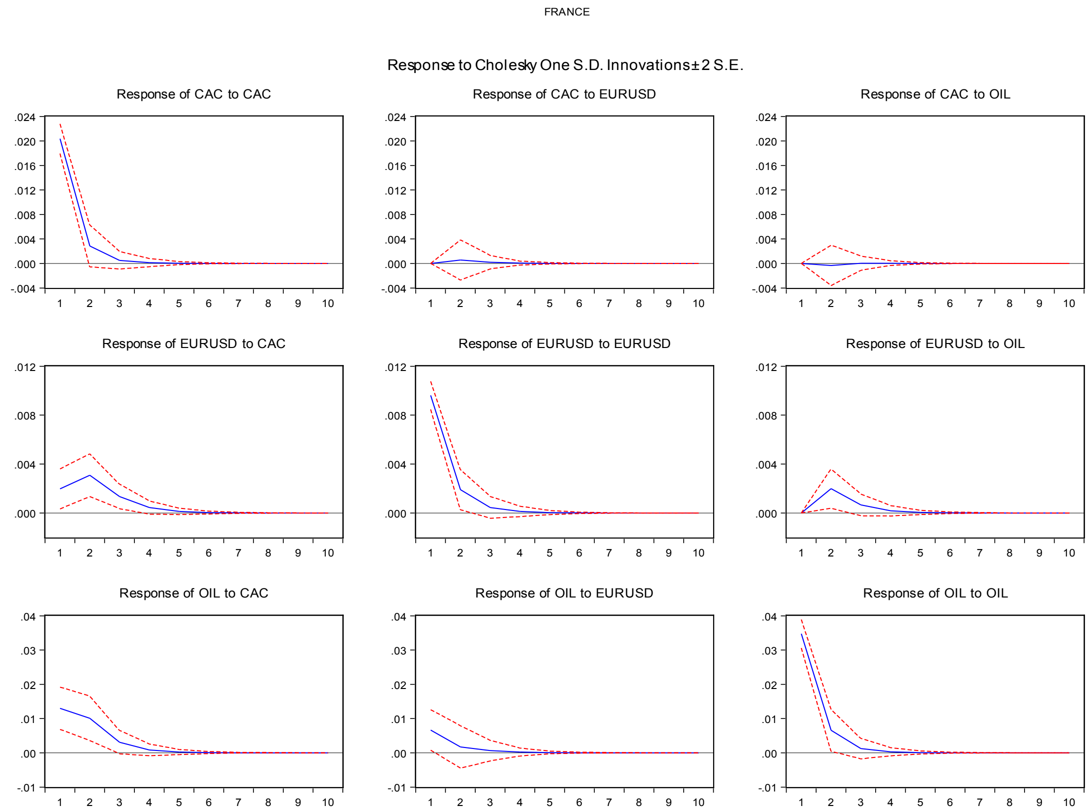

Figure 4: Impulse Responses of France.

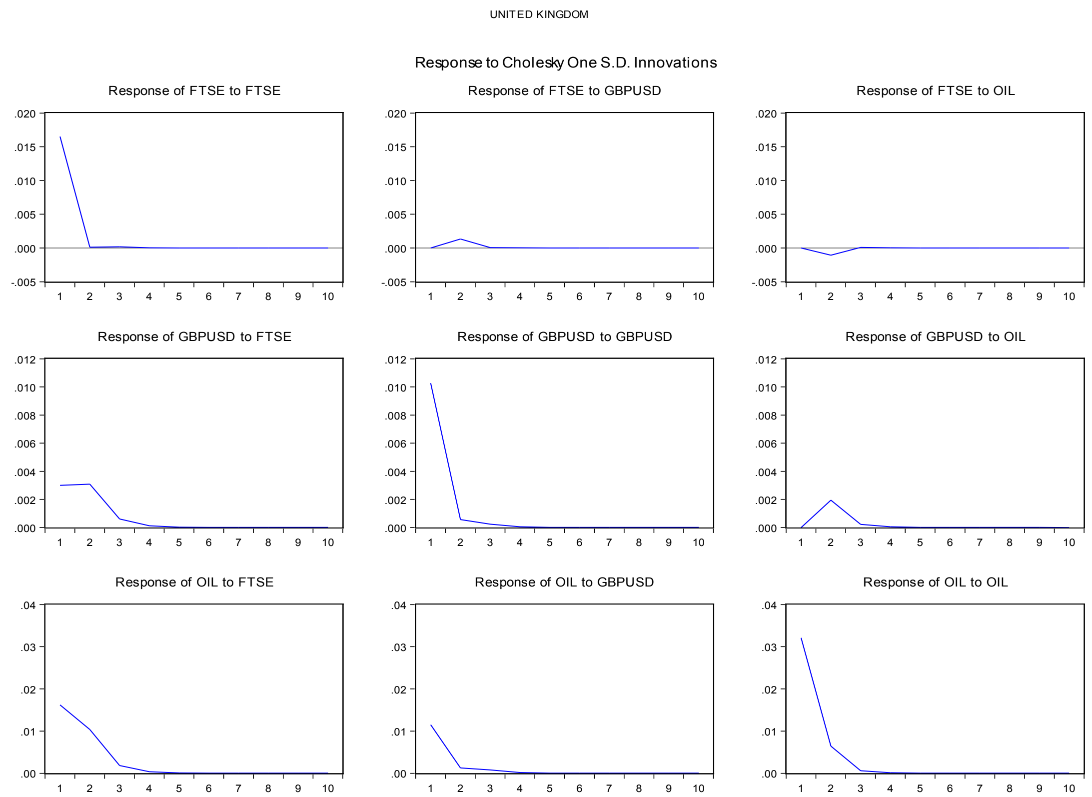

Figure 5: Impulse Responses of United Kingdom.

Citation: Abdelkafi ZS, Khoufi W (2017) Integration and Volatility's Persistence in Emerging and Developed Countries: Impulse Responses and Multivariate DCC GARCH. Arabian J Bus Manag Review 7: 297. doi: 10.4172/2223-5833.1000297

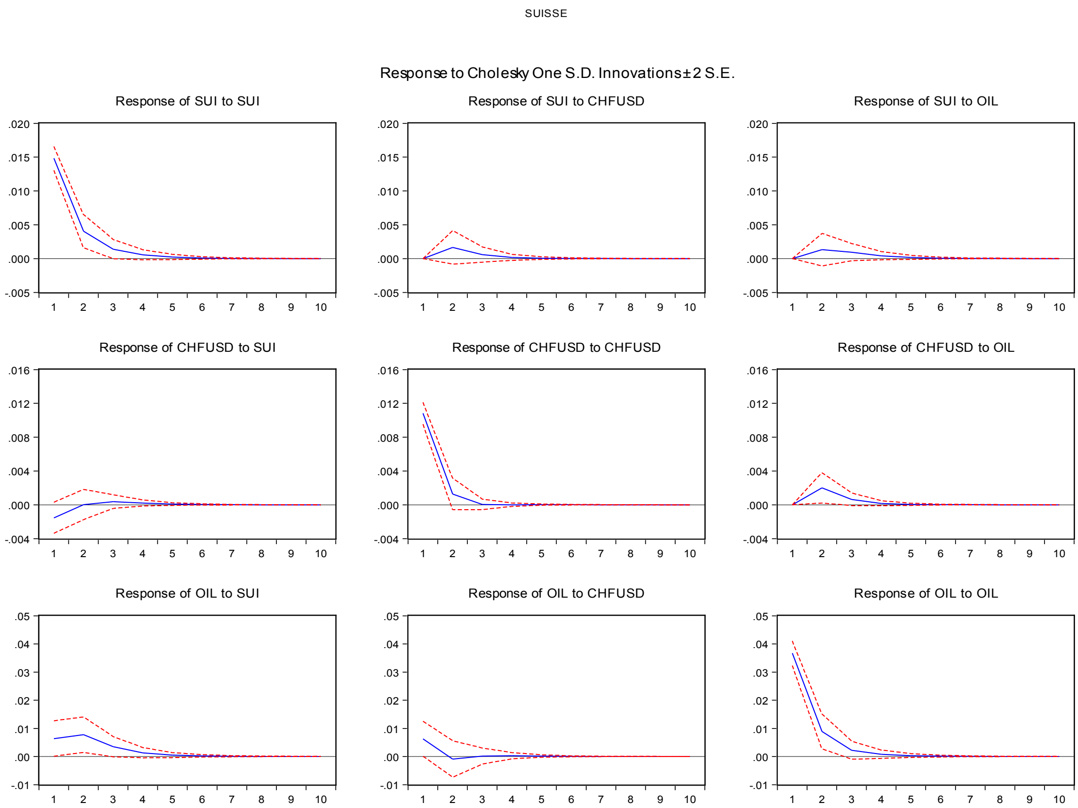

Figure 6: Impulse Responses of Suisse

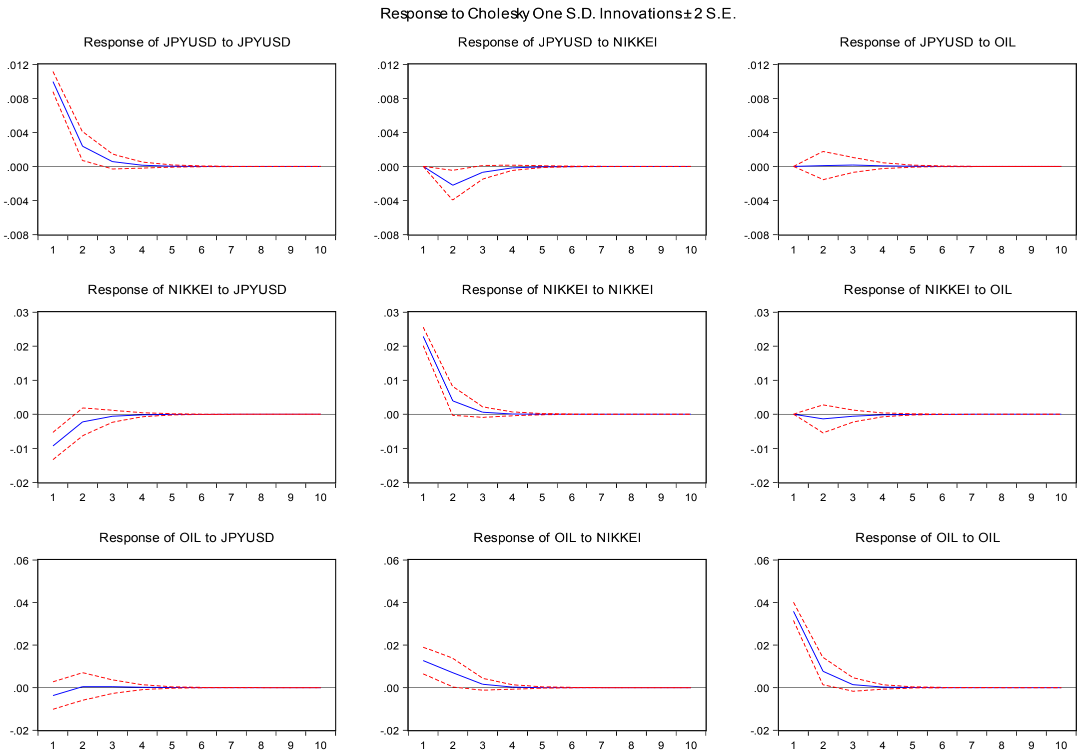

Figure 7: Impulse Responses of Figures 1-6.

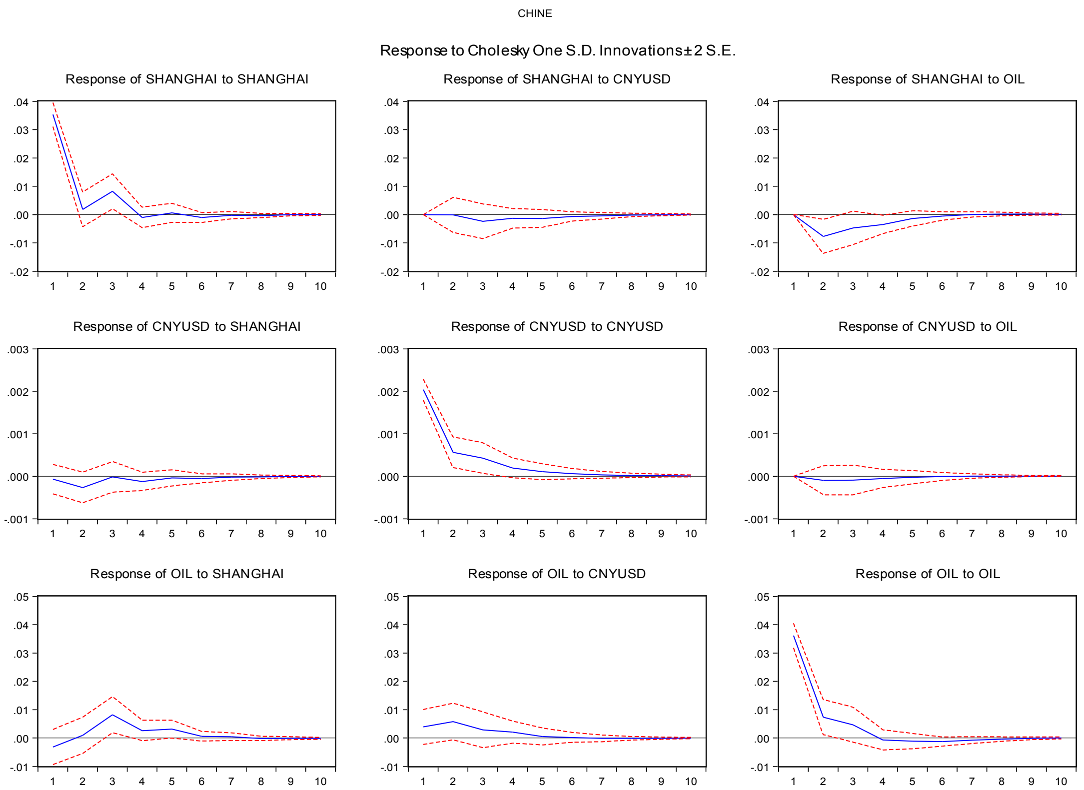

Figure 8: Immune Response of China.

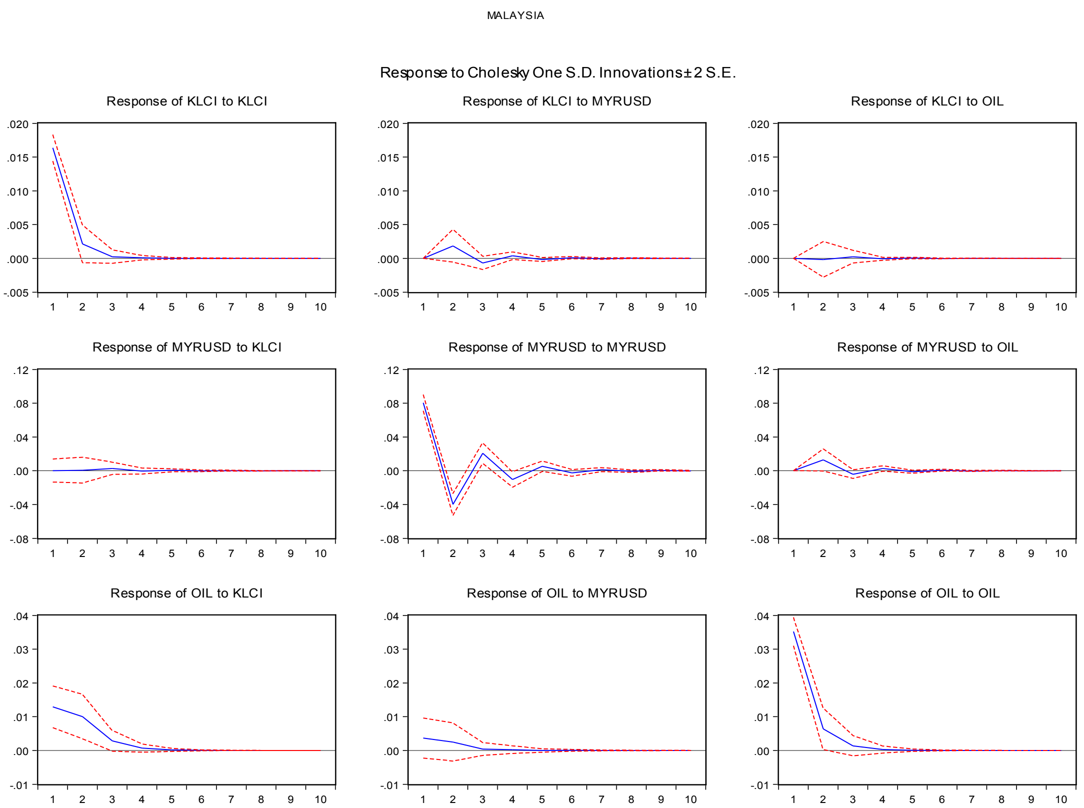

Figure 9: Immune Response of Malaysia.

Citation: Abdelkafi ZS, Khoufi W (2017) Integration and Volatility's Persistence in Emerging and Developed Countries: Impulse Responses and Multivariate DCC GARCH. Arabian J Bus Manag Review 7: 297. doi: 10.4172/2223-5833.1000297

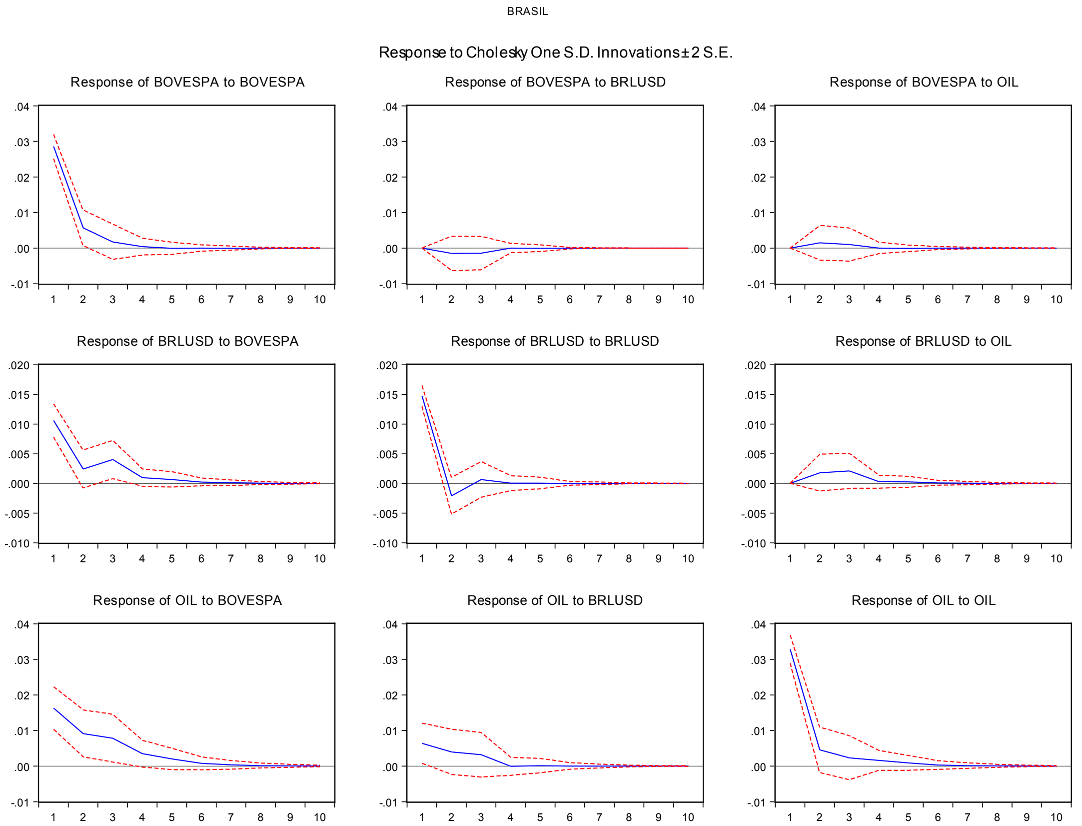

Figure 10: Immune Response of Brazil.

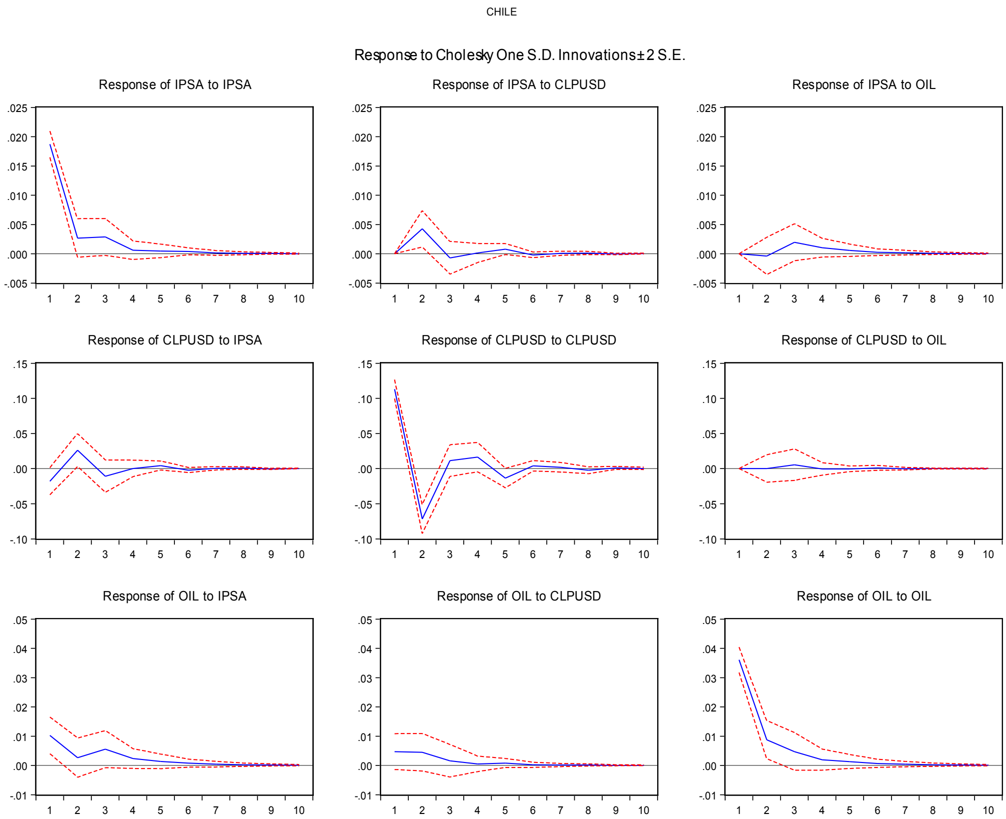

Figure 11: Immune Response of Chile.

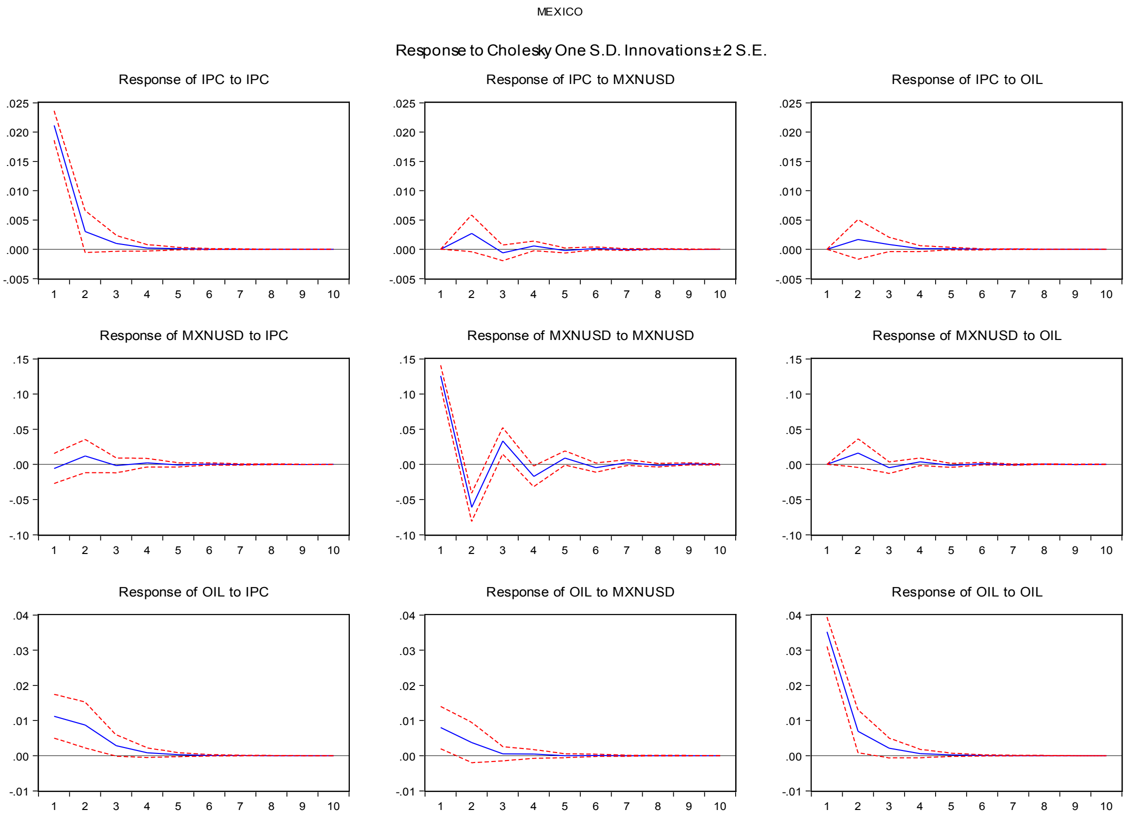

Figure 12: Immune Response of Mexico.

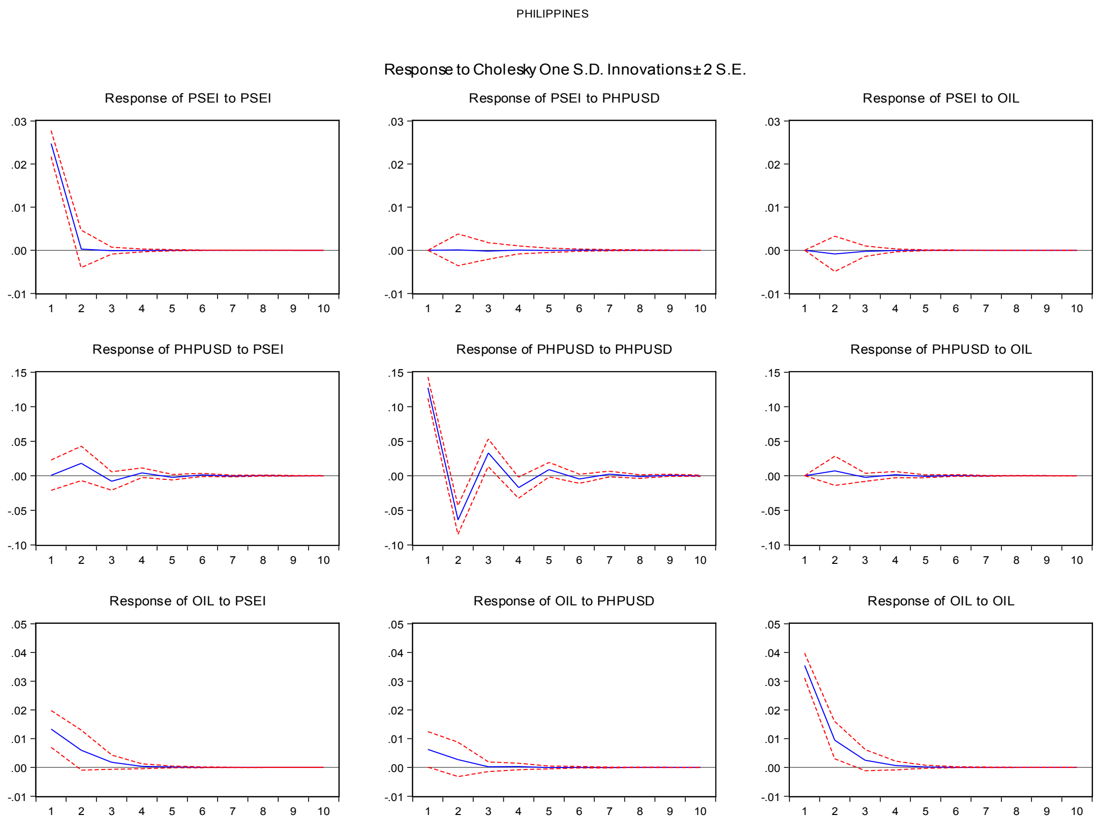

Figure 13: Immune Response of Philippines.

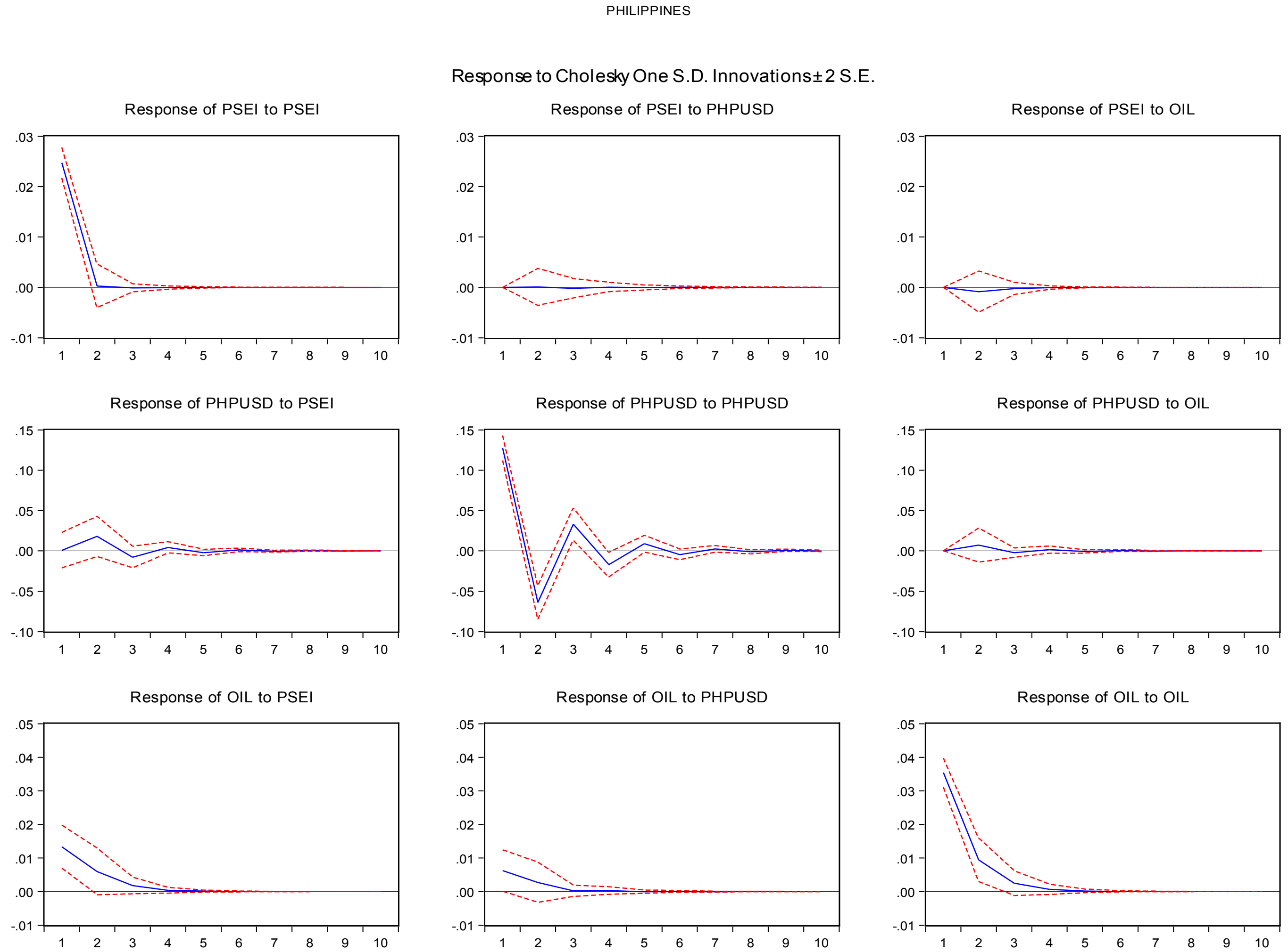

Figure 14: Immune Response of Russia.

markets do not react or react briefly. So we end up this feature with the impulse response functions of the Japanese market compared to other markets from the perspective of the evolution of their volatilities. Only the New Zealand currency responds positively to its own shock. Following a shock on crude oil, the stock market remains insensitive and the exchange market reacts positively with smaller magnitude. The Swiss currency responds positively to its own shock; the reaction of the other two markets remains limited. For the UK, the three markets respond positively to shock exerted on the FTSE 100. The British stock market is influential since rising volatility increases uncertainty in other markets.

By examining the impulse responses' functions corresponding to the emerging countries, it appears that the innovations of the realized volatility of BOVESPA have spread to the Brazilian Real and crude oil. It reflects the degree of integration of this stock index with the other two markets. The Brazilian currency and crude oil respond to them own shocks but other markets appear insensitive. The IPSA stock index responds positively to its own shock, the effect fades the fifth month. Crude oil and the Chilean Peso also respond positively but with limited magnitude: an increase in volatility of the IPSA index increases uncertainty in the other two markets. The crude oil's response to its own shock, in Mexico, is important in comparison with that recorded at the stock and exchange markets. Following a shock on the South African stock market, all markets react positively but with different amplitudes. A shock on the South African Rand brings a significantly positive response in this market: stock market and crude oil react poorly. As part of Philippines, a shock on the PSEI results in positive and increasing amplitude: the other two markets react positively but in a smaller way. The Russian stock index reacts positively to its own shock during five periods but the Russian Ruble's reaction remains small. The crude oil's response is positively significant and the shock's effect is damped after five months. This strong reaction (from crude oil) reflects the degree of integration of the two markets and the significant influence of the RTSI index on crude oil.

Trivariate DCC GARCH

For emerging countries, DCC model show that in South Africa, the three markets do not persist in the short term shock. Only the South African stock market have a high volatility persistence, β_{11}=0.84 (significant at the 1% level), β_{22}=-0.33 and β_{33}=0.63 are not significant. BOVESPA and the Brazilian Real have highly significant volatility persistence. A persistence to short-term shock of the Brazilian stock market is detected. IPSA and the Chilean Peso persist in the short term shock. Also, this currency seems to have a highly significant persistence

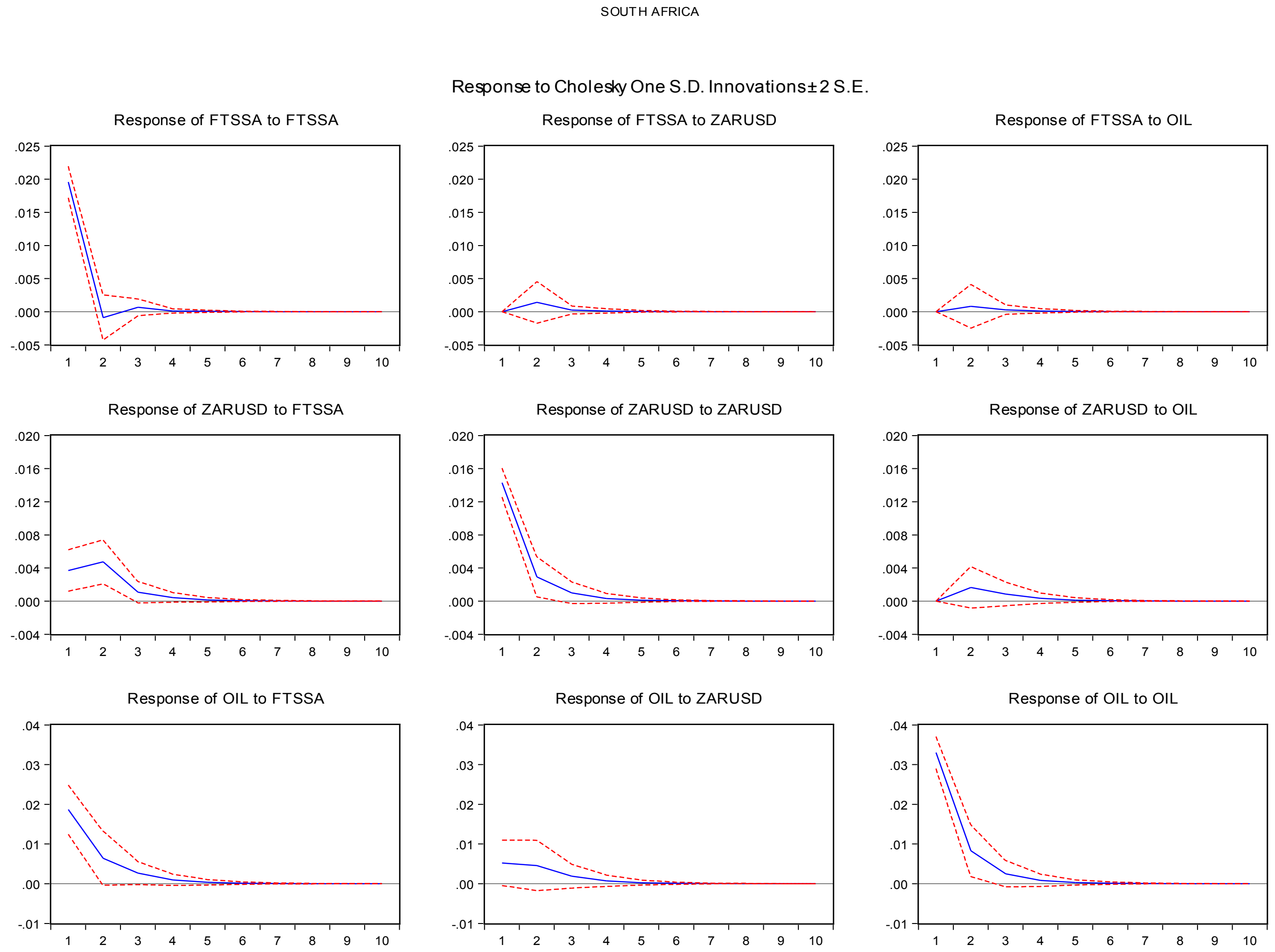

Figure 15: Impulse responses (Emerging countries).

of volatility at the 10% level. In China, the Yuan and crude oil persist in the short term impact: they are sensitive to them own shocks. β_{11}, β_{22} and β_{33} provide information on the volatility's persistence in the three markets. The KLCI index and crude oil are able to persist to the short term shock and the crude oil has the highest level of volatility's persistence. The Mexican Peso and crude oil persist in the short term shock. In Mexico, the three markets prove the volatility's persistence. The Philippine Peso persists in the short term shock and all markets demonstrate a continued volatility. For Russia, all coefficients are significant demonstrating that the three markets persist in the short term shock. The Russian Ruble appears to have the highest level of volatility's persistence (Table 5).

In developed economies, it appears that ASX stock index has highly significant volatility's persistence. α_{DCC} and β_{DCC} (both significant at the 1% level) are equal to 0.019 and 0.98, respectively. These results are consistent with the empirical literature supporting that the α_{DCC} coefficient is almost zero and β_{DCC} approaches unity; Hammoudeh et al. [16]. The Australian currency and crude oil show persistence in the short term shock. They are sensitive to their own impacts. In Canada, only the S&P/TSX has a high level of volatility persistence. No persistence in short-term impact from the S&P/TSX, Canadian dollar and crude oil is recorded. The CAC 40 demonstrates the persistence of volatility. We report a lack of persistence in the short-term impact for both the CAC 40 and Euro. The crude oil, in France, persists in the short term shock: it is sensitive to its own shock. Nikkei and Yen have high levels of volatility persistence. The Japanese currency and crude oil persist in the short term shock. For New Zealand, all markets prove a high level of volatility's persistence. The New Zealand stock index and crude oil persist in the short term shock. In the UK, it appears that the three markets do not persist in the short term shock. In contrast, there is persistence of volatility in the corresponding markets. In Switzerland, only the crude oil persists to short-term shock. β_{11}, β_{22} and β_{33} are significant proving the continued volatility on the three markets. We underline that the statistical significance of the terms α and β provide evidence of volatility clustering.

Conclusion

Globalization as well as the deregulation of financial markets, all means that price volatility will remain a central feature of oil decades to come. Originally developed in finance, GARCH models have become indispensable in short-term volatility modeling of financial market prices, largely because they are very efficient at accommodating irregular periods of price volatility and tranquility that are characteristic of financial markets. Estimating GARCH models on large data sets is

South Africa			Brazil			Chili			China		
Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif
1. FTSSA{1}	0.0318207	0.71403923	1. BOVESPA{1}	0.17013416	0.11543648	1. IPSA{1}	0.145861219	0.27060161	1. SHANGHAI{1}	0.088179325	0.40780613
2. ZAR/USD{1}	0.0991598	0.35393959	2. BRL/USD{1}	-0.0377044	0.80872861	2. CLP/USD{1}	0.02385082	0.43170671	2. CNY/USD{1}	-0.16340516	0.92489757
3. OIL{1}	0.0058397	0.89991034	3. OIL{1}	-0.01707536	0.80720926	3. OIL{1}	0.020859199	0.75150605	3. OIL{1}	-0.13237434	0.08558781
4. Constant	0.2681374	0.07211364	4. Constant	0.37546981	0.15851718	4. Constant	0.000470131	0.88559541	4. Constant	0.134680132	0.72498174
5. FTSSA{1}	0.051954	0.47476985	5. BOVESPA{1}	0.05235037	0.55669985	5. IPSA{1}	0.467484806	0.86143122	5. SHANGHAI{1}	-0.006246457	0.05481216
6. ZAR/USD{1}	0.0873485	0.42758874	6. BRL/USD{1}	-0.10511585	0.38707595	6. CLP/USD{1}	-0.26776404	0.44153812	6. CNY/USD{1}	0.555071793	0.00000018
7. OIL{1}	0.0445765	0.38267066	7. OIL{1}	0.04105585	0.50168844	7. OIL{1}	-0.05000616	0.97194413	7. OIL{1}	-0.001638167	0.64383693
8. Constant	-0.1331269	0.40900964	8. Constant	0.11067546	0.49339271	8. Constant	0.015697716	0.84975836	8. Constant	0.036596522	0.02794139
9. FTSSA{1}	0.064336	0.7011932	9. BOVESPA{1}	0.11102162	0.44409514	9. IPSA{1}	0.103800704	0.58864102	9. SHANGHAI{1}	0.032192734	0.70183
10. ZAR/USD{1}	0.083616	0.69292174	10. BRL/USD{1}	0.09722597	0.58274758	10. CLP/USD{1}	0.033197068	0.9018973	10. CNY/USD{1}	2.361881397	0.11647408
11. OIL{1}	0.0982122	0.38612771	11. OIL{1}	0.02291785	0.82895505	11. OIL{1}	0.128153305	0.29995612	11. OIL{1}	0.036315032	0.75208557
12. Constant	0.0943436	0.80562558	12. Constant	0.43319061	0.19389736	12. Constant	0.001102102	0.80082093	12. Constant	0.365399166	0.2896888
13. C(1)	0.2700392	0.47556806	13. C(1)	14.62535065	0	13. C(1)	0.00042886	0.3470657	13. C(1)	0.820107817	0.24937176
14. C(2)	2.5678235	0.10191808	14. C(2)	7.40679154	0	14. C(2)	0.027770741	0.15136465	14. C(2)	0.002152903	0.13382878
15. C(3)	4.4667127	0.70348307	15. C(3)	5.73652425	0.32686434	15. C(3)	0.001765661	0.16567926	15. C(3)	2.476267552	0.18336831
16. A(1)	0.0475906	0.25618386	16. A(1)	-0.05656677	0	16. A(1)	0.606012870	0.05196181	16. A(1)	0.183783016	0.12756446
17. A(2)	0.1068033	0.5089314	17. A(2)	0.01937335	0.27463757	17. A(2)	0.814477841	0.00112814	17. A(2)	0.724642636	0.00159835
18. A(3)	0.0212908	0.70971881	18. A(3)	0.1341881	0.27475248	18. A(3)	0.062958722	0.62314974	18. A(3)	0.266270842	0.07707399
19. B(1)	0.84090257	0.00000289	19. B(1)	-0.79686833	0.00046391	19. B(1)	-0.234600049	0.84478533	19. B(1)	0.767517744	0.00000001
20. B(2)	-0.3313119	0.61612502	20. B(2)	0.98314939	0	20. B(2)	0.738459246	0.09776856	20. B(2)	0.520310284	0
21. B(3)	0.630317	0.49454593	21. B(3)	0.42537049	0.39571228	21. B(3)	-0.240246759	0.74908328	21. B(3)	0.593702433	0.00000681
22. DCC(1)	0.06327032	0.03239649	22. DCC(1)	0.06253774	0.04301929	22. DCC(1)	0.035989147	0.03217624	22. DCC(1)	0.014279944	0.09713796
23. DCC(2)	0.91080342	0	23. DCC(2)	0.89023041	0	23. DCC(2)	0.930000000	0	23. DCC(2)	0.832123802	0.00210165
Malaysia			Mexico			Philippines			Russia		
Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif
1. KLCI{1}	0.0087403	0.94385376	1. IPC{1}	0.11260507	0.29291968	1. PSEI{1}	-0.015377	0.89537036	1. RTSI{1}	0.03916189	0.72318757
2. MYR/USD{1}	-0.0035949	0.9915046	2. MXN/USD{1}	-0.07758482	0.0000006	2. PHP/USD{1}	0.0082661	0.87824218	2. RUB/USD{1}	-0.55246973	0.01355823
3. OIL{1}	-0.0140897	0.80236842	3. OIL{1}	-0.01054676	0.82636871	3. OIL{1}	-0.1053951	0.21828396	3. OIL{1}	0.14814136	0.22993892
4. Constant	0.0583958	0.77465856	4. Constant	0.45537903	0.01544928	4. Constant	0.8784177	0.00018775	4. Constant	0.54055225	0.16468654
5. KLCI{1}	0.1730827	0.94323318	5. IPC{1}	0.26776586	0.00180297	5. PSEI{1}	0.1635326	0.00950612	5. RTSI{1}	0.0624923	0.00592521
6. MYR/USD{1}	-0.1217512	0.97870629	6. MXN/USD{1}	-0.04016343	0.00000031	6. PHP/USD{1}	-0.9488866	0	6. RUB/USD{1}	0.25732379	0.01674113
7. OIL{1}	0.5640573	0.50429999	7. OIL{1}	0.22344264	0.02030417	7. OIL{1}	-0.0306731	0.38993338	7. OIL{1}	0.05278114	0.00439761
8. Constant	0.5963732	0.89282446	8. Constant	0.48792904	0.18544069	8. Constant	-0.0978548	0.56465214	8. Constant	-0.02151123	0.76102043
9. KLCI{1}	0.0646614	0.77432666	9. IPC{1}	0.13089664	0.47026189	9. PSEI{1}	-0.0208697	0.89375297	9. RTSI{1}	0.10137352	0.1809442
10. MYR/USD{1}	-0.0359014	0.9070695	10. MXN/USD{1}	-0.01135645	0.69526771	10. PHP/USD{1}	-0.0178066	0.83676515	10. RUB/USD{1}	-0.29503328	0.44009692
11. OIL{1}	0.0287158	0.82362679	11. OIL{1}	0.02723733	0.79946218	11. OIL{1}	0.0765339	0.50127668	11. OIL{1}	-0.03604337	0.76605897
12. Constant	0.0998685	0.81415819	12. Constant	0.62890108	0.08977095	12. Constant	0.4669436	0.20239357	12. Constant	0.82884181	0.00648768
13. C(1)	0.7938909	0.55205432	13. C(1)	0.59981814	0.33419612	13. C(1)	0.8042429	0.27157926	13. C(1)	13.5897959	0.00000089
14. C(2)	0.1156673	0.49488093	14. C(2)	70.50912593	0	14. C(2)	0.8828022	0	14. C(2)	0.06878494	0.12904108
15. C(3)	0.9087585	0.27657497	15. C(3)	3.16771166	0.14356015	15. C(3)	0.5179632	0.09521576	15. C(3)	11.76055825	0.00000707
16. A(1)	0.2571602	0.06879045	16. A(1)	0.17609956	0.33086486	16. A(1)	0.1867726	0.14475492	16. A(1)	0.41338418	0.02750041
17. A(2)	0.0405188	0.95956084	17. A(2)	0.80334115	0	17. A(2)	0.3600676	0.04208539	17. A(2)	0.15350824	0.05752827
18. A(3)	0.2578423	0.05131426	18. A(3)	0.21548242	0.03224484	18. A(3)	0.230769	0.13132316	18. A(3)	0.45949579	0.00072648
19. B(1)	0.0257099	0.98765419	19. B(1)	0.67904374	0.01420698	19. B(1)	0.6985094	0.00075859	19. B(1)	(-0.15273104)	0.01928048
20. B(2)	0.023211	0.98684171	20. B(2)	(-98.003989)	0	20. B(2)	(-0.9801491)	0	20. B(2)	0.72860712	0
21. B(3)	0.3559985	0.05256318	21. B(3)	0.57575065	0.00088495	21. B(3)	0.5601043	0.00043075	21. B(3)	(-0.22018695)	0.06906002
22. DCC(1)	0.0258423	0.04655162	22. DCC(1)	0.02208179	0.00136266	22. DCC(1)	0.0198527	0.08281995	22. DCC(1)	0.01212974	0.03067851
23. DCC(2)	0.9523500	0	23. DCC(2)	0.81417119	0	23. DCC(2)	0.9531120	0	23. DCC(2)	0.82608523	0

Table 5a: Estimated coefficients of Trivariate DCC GARCH (1, 1) (Emerging markets).

challenging because of "The curse of dimensionality" (which refers to the tradeoff between generality and feasibility). For some multivariate GARCH specifications, like BEKK, the number of free parameters grows rapidly as the number of variables increases making estimation infeasible for large data sets. Multivariate GARCH models like DCC GARCH offer analytically tractable ways to estimate Multivariate GARCH models on large data sets. DCC type multivariate GARCH models are becoming very popular. DCC captures 1) persistence in volatility and 2) correlation time-varying correlation, but does not capture spill-over effects in volatility nor is DCC closed under linear transformation. This paper presented an empirical application of a range of Multivariate DCC GARCH models and impulse response functions to monthly crude oil, exchange rates and stock markets from January 2003 to December 2014. Trivariate DCC GARCH estimated coefficients show, for emerging countries, short term and long term persistence shock in most markets. For developed economies, it appears also that most markets prove volatility's persistence. Impulse response functions emphasize that the innovations of the ASX stock index's realized volatility have spread to the exchange rate and crude oil. This result confirms the existence of ASX index's volatility transmission effect to the Australian dollar and crude oil in the one hand and the significant influence of the index in other markets in the

South Africa			Brazil			Chili			China		
Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif
1. ASX{1}	0.00698043	0.93743796	1. S&P/TSX{1}	0.02487972	0.8216943	1. CAC{1}	0.025946082	0.82188071	1. NIKKEI{1}	0.165933603	0.16264113
2. AUD/USD{1}	-0.03800905	0.08907674	2. CAD/USD{1}	-0.109356969	0.32535046	2. EUR/USD{1}	0.053291434	0.7953321	2. JPY/USD{1}	-0.054518925	0.81823881
3. OIL{1}	0.16228245	0.00000103	3. OIL{1}	0.005500988	0.9190925	3. OIL{1}	-0.057870661	0.36154644	3. OIL{1}	-0.096401721	0.14806245
4. Constant	-0.07525767	0.70168334	4. Constant	0.001488328	0.36065772	4. Constant	0.324237185	0.10557948	4. Constant	0.003187578	0.12426751
5. ASX{1}	0.14622689	0.0367881	5. S&P/TSX{1}	-0.041159258	0.49337789	5. CAC{1}	0.076520258	0.07592063	5. NIKKEI{1}	-0.09265782	0.0423256
6. AUD/USD{1}	0.97354033	0	6. CAD/USD{1}	0.151732836	0.21337687	6. EUR/USD{1}	0.092605082	0.2457856	6. JPY/USD{1}	0.153983223	0.1627041
7. OIL{1}	0.00317514	0.90409976	7. OIL{1}	-0.008084627	0.75432388	7. OIL{1}	0.073936363	0.00152445	7. OIL{1}	0.010751551	0.72486311
8. Constant	-0.06151411	0.75130466	8. Constant	0.000509417	0.56775727	8. Constant	0.000942201	0.99171082	8. Constant	-0.000045745	0.96466648
9. ASX{1}	-0.25113205	0.3027173	9. S&P/TSX{1}	0.133576852	0.51019578	9. CAC{1}	0.224764908	0.06513037	9. NIKKEI{1}	-0.010313873	0.95217345
10. AUD/ USD{1}	-0.11602194	0.01873198	10. CAD/USD{1}	-0.237047287	0.56775444	10. EUR/USD{1}	-0.344801154	0.32679479	10. JPY//USD{1}	0.15028568	0.7030313
11. OIL{1}	0.06112705	0.61140839	11. OIL{1}	-0.016595268	0.90187171	11. OIL{1}	-0.004507918	0.9725515	11. OIL{1}	0.010978943	0.9316048
12. Constant	-0.15049867	0.75788547	12. Constant	0.003106159	0.4481235	12. Constant	0.709703355	0.05515279	12. Constant	0.006864857	0.04797507
13. C(1)	4.09704662	0.00006414	13. C(1)	0.00003337	0.44186758	13. C(1)	0.376196459	0.31391841	13. C(1)	0.000059653	0.30822337
14. C(2)	1.45314394	0.0000001	14. C(2)	0.000022538	0.46739126	14. C(2)	1.274694069	0.07972132	14. C(2)	0.000005924	0.09758755
15. C(3)	11.01343048	0.00559578	15. C(3)	0.000769383	0.36208257	15. C(3)	7.557775725	0.14598524	15. C(3)	0.001109466	0.02719682
16. A(1)	0.05626314	0.45623595	16. A(1)	0.050132477	0.29511689	16. A(1)	0.123305628	0.26237878	16. A(1)	0.086987184	0.14815371
17. A(2)	0.14764289	0.09084042	17. A(2)	0.134415422	0.5075526	17. A(2)	-0.069412968	0.27014046	17. A(2)	(-0.110628154)	0.02354371
18. A(3)	0.45458137	0.03758552	18. A(3)	0.106948321	0.15921111	18. A(3)	0.367625273	0.00779332	18. A(3)	0.309725863	0.05044055
19. B(1)	(-0.85348512)	0.01098348	19. B(1)	0.802383843	0.00034831	19. B(1)	0.784384821	0.00001792	19. B(1)	0.806981361	0
20. B(2)	-0.18294582	0.15182373	20. B(2)	0.551305791	0.3293037	20. B(2)	-0.297929599	0.70162674	20. B(2)	0.999273313	0
21. B(3)	-0.13963634	0.52037116	21. B(3)	0.342935116	0.58101252	21. B(3)	0.15668713	0.66782042	21. B(3)	-0.076564461	0.82072217
22. DCC(1)	0.01957784	0	22. DCC(1)	0.024208297	0.03848425	22. DCC(1)	0.060482475	0.09285125	22. DCC(1)	0.039363032	0.06797204
23. DCC(2)	0.95042216	0	23. DCC(2)	0.913120000	0	23. DCC(2)	0.95005559	0	23. DCC(2)	0.939264059	0
New Zealand			United-Kingdom			Switzerland					
Variable	Coeff	Signif	Variable	Coeff	Signif	Variable	Coeff	Signif			
1. DJNZ{1}	0.089498191	0.25683325	1. FTSE100{1}	-0.198879074	0.08028351	1. SMI{1}	0.2774589	0.00253805			
2. NZD/USD{1}	0.262881082	0.01225484	2. GBP/USD{1}	0.057957445	0.67639169	2. CHF/USD{1}	0.072595169	0.57848606			
3. OIL{1}	-0.037367432	0.24546968	3. OIL{1}	0.136862312	0.00054632	3. OIL{1}	0.007930551	0.82541764			
4. Constant	0.115370779	0.41281257	4. Constant	0.211545712	0.19589353	4. Constant	0.169698842	0.23206262			
5. DJNZ{1}	0.077730793	0.29693654	5. FTSE100{1}	0.016926734	0.81882329	5. SMI{1}	0.015887952	0.78510716			
6. NZD/USD{1}	0.196875484	0.03494437	6. GBP/USD{1}	0.041224597	0.76638509	6. CHF/USD{1}	-0.00259826	0.98416915			
7. OIL{1}	0.052690715	0.060132	7. OIL{1}	0.101203553	0.00047093	7. OIL{1}	0.067157234	0.00455774			
8. Constant	0.046027905	0.68830567	8. Constant	0.011591361	0.92262972	8. Constant	0.115860399	0.22563927			
9. DJNZ{1}	0.11379359	0.63026367	9. FTSE100{1}	0.099861503	0.70347843	9. SMI{1}	0.28938055	0.1379255			
10. NZD/ USD{1}	-0.110017545	0.70330794	10. GBP/USD{1}	-0.215555154	0.53903042	10. CHF/USD{1}	-0.649127215	0.05815879			
11. OIL{1}	0.059433431	0.60403483	11. OIL{1}	-0.029521272	0.7778197	11. OIL{1}	0.024480601	0.83591717			
12. Constant	0.491605095	0.18512804	12. Constant	0.59872545	0.06967272	12. Constant	0.558555081	0.12073177			
13. C(1)	3.787156471	0	13. C(1)	0.106682177	0.30299322	13. C(1)	3.822756461	0.00000001			
14. C(2)	0.243191527	0.58202064	14. C(2)	2.260964025	0	14. C(2)	0.243335387	0.41395721			
15. C(3)	4.196945384	0.12561777	15. C(3)	2.129428136	0.38186463	15. C(3)	2.212764386	0.12874235			
16. A(1)	0.086438517	0.00046678	16. A(1)	0.075430533	0.17373828	16. A(1)	0.079354739	0.26502233			
17. A(2)	0.051680061	0.55750062	17. A(2)	0.013221447	0.50247818	17. A(2)	0.153980147	0.15809259			
18. A(3)	0.241406601	0.02183995	18. A(3)	0.046185201	0.38653925	18. A(3)	0.191058236	0.01583022			
19. B(1)	(0.999776500)	0	19. B(1)	0.873319601	0	19. B(1)	(-0.869196795)	0.00000012			
20. B(2)	0.760800682	0.0526367	20. B(2)	0.999244782	0	20. B(2)	0.627912654	0.0589188			
21. B(3)	0.491583032	0.00959282	21. B(3)	0.755235060	0.00226697	21. B(3)	0.654615427	0.00000954			
22. DCC(1)	0.016013116	0.02681141	22. DCC(1)	0.019086186	0.08698273	22. DCC(1)	0.048858935	0.04419157			
23. DCC(2)	0.913280000	0	23. DCC(2)	0.932568400	0	23. DCC(2)	0.947922625	0.00000009			

Table 5b: Estimated coefficients of Trivariate DCC GARCH (1, 1) (Developed countries).

other hand. Moreover, it appears that the ASX index is influential since a rise in volatility increases uncertainty in the Australian dollar and crude oil. Besides, impulse response highlights that innovations of the CAC stock index' s realized volatility are spread to the Euro and crude oil. The Japanese stock market does not seem to have much influence that innovations can disrupt the movements of the other markets' realized volatility. Thus, the analysis of the impulse response functions allowed seeing an important element characterizing the Japanese market, identified by the earlier literature on its evolution. Indeed, when the Nikkei 225 stock index undergoes a positive shock that is to say an increase in its realized volatility or other markets do not react or react briefly by a decline in realized volatility. So we end up this feature with the impulse response functions of the Japanese market compared to other markets from the perspective of the evolution of their volatilities. For emerging countries, the innovations of the BOVESPA index's realized volatility have spread to the Brazilian Real and crude oil. It reflects the degree of integration of this index with the other two markets. The strong reaction, from crude oil in Russia, reflects the degree of integration of the two markets and the significant influence of the RTSI index on crude oil. Our investigation revealed the interdependences and integration between financial markets both in emerging countries than in developed economies.

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