ESTIMATING VOLATILITY SPILLOVERS, DYNAMIC CAUSAL LINKAGES AND INTERNATIONAL CONTAGION PATTERNS BETWEEN DEVELOPED STOCK MARKETS : AN EMPIRICAL CASE STUDY FOR USA, CANADA, FRANCE AND UK

CRISTI SPULBAR, Ph.D
PROFESSOR, HABILITATED DOCTOR
UNIVERSITY OF CRAIOVA, FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION, ROMANIA
e-mail: cristispulbar7@gmail.com

JATIN TRIVEDI, Ph.D
ASSOCIATE PROFESSOR
AMITY UNIVERSITY MUMBAI, FACULTY OF FINANCE, INDIA
e-mail: contact.tjatin@gmail.com

RAMONA BIRAU, Ph.D, Ph.Dc
LECTURER
FACULTY OF EDUCATION SCIENCE, LAW AND PUBLIC ADMINISTRATION AT THE CONSTANTIN BRÂNCUȘI UNIVERSITY OF TARGU JIU, ROMANIA
e-mail: ramona.f.birau@gmail.com

TENEA COSMIN ANDREI
Ph.D STUDENT
UNIVERSITY OF CRAIOVA, FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION, ROMANIA
e-mail: andrei.tenea@ymail.com

ABDULLAH EJAZ, Ph.D
INSTRUCTOR AND COORDINATOR OF BUSINESS ADMINISTRATION
ABM COLLEGE CALGARY, CANADA
e-mail: ejazabdullah03@gmail.com

Abstract

This research paper examines in a comparative manner the long-term behavior of certain developed economies, such as USA, Canada, France and UK. The applied financial econometrics approach includes relevant research methods such as descriptive statistics, Unit Root Test, Hodrick-Prescott (HP) filter, Augmented Dickey-Fuller stationary test, BDS test, Granger causality test/Vector AutoRegression (VAR) model and GARCH (1, 1) model. The empirical results provide additional evidence on volatility spillovers, dynamic causal linkages and international contagion patterns between developed stock markets considering international portofolio diversification benefits. The sample financial data series are based on daily returns of selected stock markets major indices, ie during the period from January 2000 until June 2018.

Keywords: *volatility; international portofolio diversification; causal transmission patterns; developed stock markets; global financial crisis;*

Clasificare JEL : *G02, G14*

1. Introduction

This empirical research study includes both a theoretical part and a section of original research. The behavior of capital market is characterized by certain stylized facts such as : volatility clustering, non-stationarity of price levels, chaos, time variation, leverage effect, heteroskedastic log returns, high risk, deviations from normal distribution, unpredictability, fat-tailed distribution, high profit opportunities, atypical movements. Liquidity is a mandatory condition for a stock market to be effective, considering that its capacity and ability to manage financial flows are significantly higher during periods when the market is more liquid. In the case of capital markets, the degree of informational efficiency involves the following categories: weak-form efficiency, semi-strong form efficiency and strong form efficiency. However, the global financial crisis that erupted in mid-2007 in U.S.A. triggered severe consequences on most stock markets all over the world. An extreme financial event is relatively rare and highly unpredictable, so it's quite difficult to predict it with high accuracy since doesn't follow a historical pattern. Stock market crashes followed by sharp financial crisis occurred rather frequently in the last century, sometimes reaching global dimensions, such as : the Great Depression between the years 1929-1933, Latin American financial debt crisis of the 1980s, Black Monday (Black Monday) in 1987, the Asian financial crisis of 1997 – 1998, Russian financial crisis or Ruble crisis in 1998, DOTCOM bubble during 2000 and 2002 and the Subprime crisis that erupted in August 2007 in U.S.A.

Lin (2018) has conducted an empirical study on modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models, ie GARCH (1, 1), TARCH (1, 1), and EGARCH (1,1) and concluded that EGARCH (1, 1) broadly outperforms the other models used in econometric analysis. In addition, Mathur, Chotia and Rao (2016) investigated the effects generated by the global financial crisis on the Indian Stock Market (BSE) based on GARCH models for the period 2001–2012 and the results of the empirical study suggest high volatility for the period 2007–2009. Hassan (2017) has performed an empirical analysis of developed stock markets indices, ie Dow Jones Industrial Average (DJIA), Financial Times Stock Exchange (FTSE 100), and German Stock Index (DAX) using GARCH model.

Ahmed and Suliman (2011) have conducted an empirical research study based on GARCH models to estimate volatility in the daily returns of Khartoum Stock Exchange (KSE) in Sudan for the period January 2006 to November 2010 and empirical results suggested that asymmetric models provide better fit than the symmetric models due to the existance of leverage effect. Lim and Sek (2013) have conducted an empirical research study on volatility modeling of stock market in Malaysia from January 1990 to December 2010 based on GARCH family models. Moreover, Miralles-Marcelo, Miralles-Quirós and del Mar Miralles-Quirós (2013) investigated performance of medium and small firms in Spanish stock market based on a mix of multivariate GARCH models and risk minimizing portfolios.

Sariannidis, Giannarakis, Litinas and Konteos (2010) have provided a detailed framework on macroeconomic effects on U.S. stock market based on Dow Jones Sustainability and Dow Jones Wilshire 5000 indexes using a GARCH model. As a complementary approach, Srinivasan (2011) conducted an empirical study on modeling and forecasting the stock market volatility of S&P 500 index using GARCH family models and concluded that symmetric GARCH model it fits much better in forecasting the conditional variance of emerging stock market return series compared to the asymmetric GARCH model. Abimanyu, Y., et. all (2008) have investigated the international linkages of the Indonesian capital market using cointegration tests to examine the long-run equilibrium relationship between the stock markets of Indonesia, China, France, Germany, Hong Kong, Japan, Korea, Malaysia, Netherlands, Philippine, Singapore, Thailand, Taiwan, UK and USA, and the empirical results highlighted that exist cointegration between selected stock market major indices, except between Indonesia and Philippine. Balios and Xanthakis (2003) investigated international interdependence and dinamic linkages between developed stock markets, namely U.K, Germany, France, Italy, Spain, U.S. and Japan. They concluded that U.S. stock market is the leading stock market in the world and U.K stock market is the leading stock market in Europe. Singh (2010) investigated Chinese and Indian stock market linkages with several developed stock markets, such as U.S., U.K., Japan and Hong Kong and the empirical results revealed that both Chinese and Indian market are correlated with all the selected developed markets based on the analysis of Granger causality. Furthermore, Pretorious (2002) suggested that it is very important for international investors to understand the forces behind the interdependence of emerging stock markets in order to be informed about the potential occurrence of systemic risks and their global implications.

The remainder of the research paper is organized as follows: Section 1 presents a literature review and other relevant aspects on the research topic, Section 2 presents the applied econometric methodology used, Section 3 presents the financial data series and empirical findings, Section 4 presents extended corresponding empirical analysis, and finally, Section 5 concludes this research paper and also provides future directions for research.

2. Econometric Methodology

This paper includes a comparative empirical reserch between stock markets in certain developed economies, such as USA, Canada, France and UK. The empirical analysis is focused on 4 selected developed stock market indices, i.e DJIA index (USA), FTSE 100 (UK), TSX Composite index (Canada) and CAC 40 (France). Financial data series are represented by daily closing prices for each selected index from January 2000 to June 2018 with the exception of legal holidays or other events when stock markets haven't performed any financial transactions.

The continuously-compounded daily returns are calculated using the log-difference of stock markets selected indices as follows :

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \ln(p_t) - \ln(p_{t-1})$$

where p is the daily closing price.

The applied financial econometrics approach includes various research tools such as descriptive statistics, Unit Root Test, Hodrick-Prescott (HP) filter, Augmented Dickey-Fuller stationary test, BDS test, Granger causality test/Vector AutoRegression (VAR) model and GARCH (1, 1) model.

The basic statistical characteristics of DJIA index (USA), FTSE 100 (UK), TSX Composite index (Canada) and CAC 40 (France) stock indices are represented by the following : Jarque-Bera test's statistic which allows to eliminate the normality of distribution hypothesis, parameter of asymmetry of distribution or Skewness and Kurtosis parameter which measures the peakedness or flatness of the distribution, ie leptokurtic distribution. The fundamental characteristics of selected stock market indices are represented by certain international quantitative aspects, such as : Jarque-Bera test's statistic which allows to eliminate the normality of distribution hypothesis, parameter of asymmetry distribution or Skewness and Kurtosis parameter which measures the peakedness or flatness of the distribution (leptokurtic distribution). In addition, the Jarque-Bera test is based on the following mathematical expressions :

$$JB = n\left[\frac{s^2}{6} + \frac{(k-3)^2}{24}\right] = \frac{n}{6}\cdot\left(s^2 + \frac{(k-3)^2}{4}\right), \text{ considering :}$$

$$s = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{\frac{3}{2}}} \quad k = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^2}$$

Financial time series are characterized by the existence of volatility clustering, chaotic behavior, pronounced instability and uncertainty, especially in the context of a global financial crisis. Moreover, financial time series exhibit linear dependence in volatility, and this issue generates the existence of heteroskedasticity. Nevertheless, financial time series data exhibit linear dependence in volatility, which implies the existence of heteroskedasticity which can arise as a consequence of various circumstances and there are several econometric methods, such as graphical method and diagnostic tests for detecting heteroscedasticity, respectively : Breusch-Pagan LM test, White's test, Glesjer LM test, Harvey-Godfrey LM test, Park LM test and Goldfeld-Quand test.

Augmented Dickey-Fuller (ADF) test is used in order to determine the non-stationarity or the integration order of a financial time series. A series noted y_t is integrated of order one, ie $y_t \sim I(1)$ and contains a unit root if y_t is non-stationary, but on the other hand Δy_t is stationary, ie $\Delta y_t = y_t - y_{t-1}$. Moreover, extrapolating the previous expression, a series y_t is integrated of order d, ie $y_t \sim I(d)$ if y_t is non-stationary, but $\Delta^d y_t$ is stationary. Practically, ADF diagnostic test investigates the potential presence of unit roots divided into the following categories : unit root with a constant and a trend, unit root with a constant, but without a time trend, and finally unit root without constant and temporal trend. Theoretically, ADF test is focused on the following regression model :

$$\Delta y_t = c + \beta \cdot t + \delta \cdot y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + \varepsilon_t$$

where p represents the number of lags for which it was investigated whether fulfilling the condition that residuals are white noise, c is a constant, t is the indicator for time trend and Δ is the symbol for differencing. In addition, it is important to emphasize the essence of a stochastic trend that can not be predicted due to the time dependence of residual's variance. Strictly related to the ADF test, if the coefficients to be estimated β and δ have the null value then the analyzed financial time series is characterized by a stochastic trend. The null hypothesis, ie the time series has a unit root is rejected if t-statistics is lower than the critical value.

The Augmented Dickey-Fuller test was applied for the selected period in order to determine the stationarity of the analyzed financial time series. The null hypothesis is that the analyzed time series contains a unit root and it is implicitly non-stationary. Empirical analysis based on the log-returns of the selected indices reflects the fact that t_{test}_ADF<t_{critic} (1%, 5%, 10%) so the null hypothesis H0 is rejected and the analyzed time series is stationary. In addition, the empirical analysis revealed that Prob (0%) < test levels (1%, 5%, 10%) so the null hypothesis H_0 is rejected and the analyzed time series are stationary.

The BDS test was used in order to determine whether the residuals are independent and identically distributed. BDS test is a two-tailed test and is based on the following hypothesis :

H_0: sample observations are independently and identically distributed (I.I.D.)

H_1: sample observations are not I.I.D., aspect involving that the time series is non-linearly dependent if first differences of the natural logarithm have been calculated.

The BDS methodology involves a time series $x_t$for t=1, 2, 3…T based on its m-history $x_t^m = (x_t, x_{t-1}, ..., x_{t-m+1})$ where m is the called embedding dimension. Implicitly, the *correlation integral* (a measure of time patterns frequency) is estimated as follows :

$$C_{m,\varepsilon} = \frac{2}{T_m(T_m - 1)} \sum_{m \le s} \sum_{< t \le T} I(x_t^m, x_s^m, \varepsilon)$$

and $C_m(\varepsilon) = \lim_{n \to \infty} C_{m,n}(\varepsilon)$

where T_m = T-m+1 and $I\left(x_t^m, x_s^m, \varepsilon\right)$represents a binary function which has the following values for i=0, 1, 2…m-1:

$$I\left(x_t^m, x_s^m, \varepsilon\right) = \begin{cases} 1 & if \quad \left|x_{t-i} - x_{s-i}\right| < \varepsilon \\ 0 & otherwise \end{cases}$$

Brock, Dechert, Scheinkman, LeBaron (1996) suggested that the BDS statistics is calculated based on the following formula :

$$V_{m,\varepsilon} = \sqrt{T}\,\frac{C_{m,\varepsilon} - C_{1,\varepsilon}^m}{S_{m,\varepsilon}}$$

where $S_{m,\varepsilon}$is defined as the standard deviation of $\sqrt{T\left(C_{m,\varepsilon} - C_{1,\varepsilon}^m\right)}$. In addition, the BDS statistics converges in distribution to N(0,1) thus the null hypothesis of independent and identically distributed is rejected based on a result such as $\left|V_{m,\varepsilon}\right| > 1{,}96$ in terms of a 5 % significance level.

The null hypothesis was rejected in all sample cases based on selected stock indices. The following outputs highlight the value of the standardised BDS statistics and the corresponding two-sided probabilities. The BDS test was used in order to determine whether the residuals are independent and identically distributed. The BDS statistics converges in distribution to N(0,1) thus the null hypothesis of independent and identically distributed is rejected based on a result such as in terms of a 5% significance level.

The econometric methodology also implies applying Hodrick-Prescott (HP) filter which is a specialized filter for trend and business cycle estimation. Hodrick-Prescott filter has a wide applicability in economics. The basic idea suggests that in the center of the sample financial time series the filter is symmetric and towards the end of the series is becoming increasingly asymmetric. Moreover, Hodrick-Prescott filter involves the decomposition of the sample financial time series into a trend component and a residual component, which may or may not include a cyclical component.

Granger (1969) argued that if some other time series Yt contains informations regarding the past periods which are useful in the prediction of Xt so this informations are included in no other series used in the predictor, then this implies that Yt caused Xt. In addition, Granger argued that if $X_t$and $Y_t$are two different stationary time series variables with zero means, then the canonical causal model has the following form :

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t$$

where ε_t and η_t play the role of two uncorrelated white-noise series, namely $E\left[\varepsilon_t \varepsilon_s\right] = 0 = E\left[\eta_t \eta_s\right]$ for $s \neq t$ and on the other hand $E\left[\varepsilon_t \varepsilon_s\right] = 0$ for $\forall t, s$. Practically, the basic concept of causality requires that in the case when Y_t is causing $X_t$some $b_j$is different from zero and vice versa, ie in the case when X_t is causing Y_t some $c_j$is different from zero. A different situation implies that causality is valid simultaneously in both directions or simply a so-called "feedback relationship between X_t and Y_t". The F-distribution test is used to test the Granger causality hypotheses based on the following formula :

$$F = \frac{\left(RSS_R - RSS_{UR}\right)/m}{RSS_{UR}/\left(n-k\right)}$$

where RSS_R is the residual sum of squares, RSS_{UR} is the unrestricted residual sum of squares, m is the number of lagged $X_t$variables, K is the number of parameters in the restricted regression. The null hypothesis Ho implies that lagged X_t terms do not belong in the regression. The null hypothesis is rejected if the F-value exceeds the critical F value at the selected level of significance (5%) or if the P-value is lower than the α level of significance.

This empirical research article also applies Vector AutoRegression (VAR) model. The basic definition of VAR model suggests a set of linear dynamic equations where each variable is specified as a function of an equal number of lags of itself and all other variables in the system. It can test if selected endogenous variables should not be treated as exogenous. The VAR in first differences can be expressed as :

$$\Delta X_t = \lambda_1 + \sum_{i=1}^{k} a_{1i}\Delta X_{t-i} + \sum_{j=1}^{k} b_{1j}\Delta Y_{t-j} + \mu_{1t}$$

$$\Delta Y_t = \lambda_2 + \sum_{i=1}^{p} a_{2i}\Delta X_{t-i} + \sum_{j=1}^{p} b_{2j}\Delta Y_{t-j} + \mu_{2t}$$

Econometric models such as ARCH (Autoregressive Conditional Heteroskedastic) and GARCH (Generalized Autoregressive Conditional Heteroskedastic) models have become significant econometric tools for applying financial time series heteroskedastic models. Practically, we employ GARCH by Bollerslev (1986) as symmetric GARCH application and EGARCH by Nelson (1992) and GJR by Glosten, Jagannathan and Runkle (1993) as asymmetric GARCH models to measure the volatiity, stylized facts in financial series returns, existance of leverage effect and impact of good and bad news on financial markets.

GARCH (1, 1) model represents conditional variance that represented as leinear function of its own lags. The conditional variance of all variables to be dependent upon previous lags. In the process, the first lag of squared residuals will form mean equation and presents idea about volatility from previous time period. Thus GARCH (1, 1) represents Mean equation and Variance equation.

The mean equation is the following : $rt = \mu + \varepsilon t$

The variance equation is the following : $\sigma_t^2 = \omega + \alpha\varepsilon_{1t-t}^2 + \beta\sigma_{1\,t-1}^2$

Mean equation represents retuns of asset in time (t) that reprsents sum of average return (above denoted by μ and residual returns that denoted by εt. Variance equation assumptions indicates that constant value higher than 0, followed by value of α and β.

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$$

We implement GARCH (1,1) model conditional variance equation $Var(u_t|h_{t-1}) = E(u_t^2|h_{t-1}) = h_t$ and thus it can simply take the following form, ie : $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$. Basically, the final formulation includes the expression $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$ based on both ARCH term and GARCH term, where, $\alpha_1 u_{t-1}^2$ represents ARCH component and $\beta_1 h_{t-1}$ GARCH component.

Model specifications is based on the following econometric framework. In case of a detected presence of unconditional variance, the situation requires to employ the financial modeling process that basically involves calculating the following mathematical expression : $\alpha_1 + \beta_1 < 1$ and for converting it into generates positive result, it is required the clear validation of the condition :$\alpha_0 > 0$.Positive results will indicate good news for market. For the constant, conditional mean we applied the formula : $E(y_t|O_{t-1})$ where $E = c + \phi y_{t-1} + o$ and y_{t-1} is included in $|O_{t-1}$. The previous framework will facilitate the understanding of final empirical results using $h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$. Practically, GARCH (1, 1) model is a combination of ARCH (1) and GARCH (1) terms represented by the the mathematical term $\alpha_1 + \beta_1$ which shows positively results for capital markets econometrical estimations. However, GARCH models are conditionally heteroskedastic but have a constant unconditional variance. Possibly the most important aspect of the

ARCH/GARCH model is the recognition that volatility can be estimated based on historical data and that an inappropriate model can be detected directly using conventional econometric techniques.

3. Empirical results

This research paper aims to provide a comparative study on selected developed financial markets i.e. DJIA index (USA), FTSE 100 (UK), TSX Composite index (Canada) and CAC 40 (France) considering daily financial time series from January 2000 to June 2018. Data have been converted to log returns and further tested for stationarity test using Augmented Dickey Fuller test.

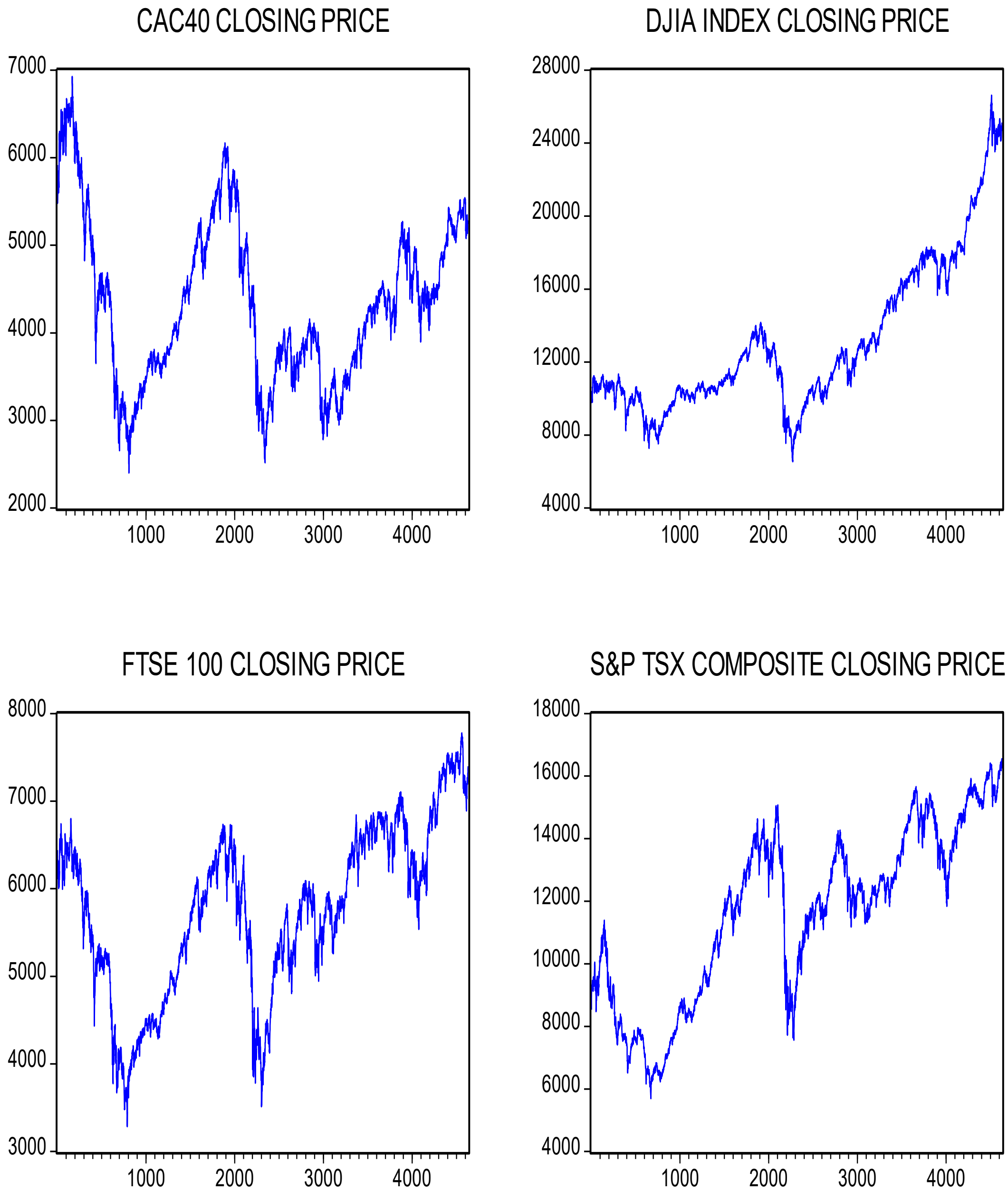


Figure no.1 : The trend of selected stock market indices - individual graphics -
Source: Own computations based on selected financial data series

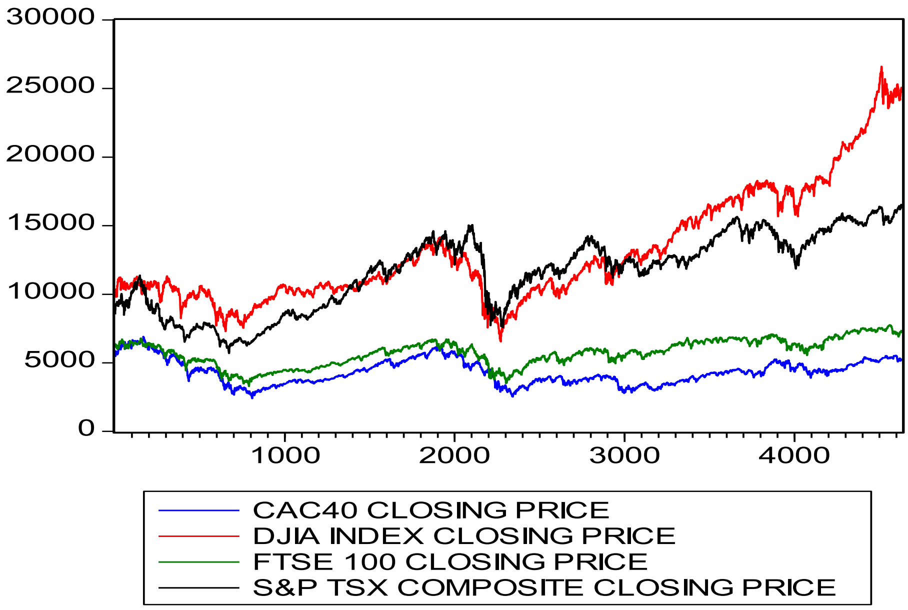


Figure no. 2 : The trend of selected stock market indices - joint graphic -
Source: Own computations based on selected financial data series

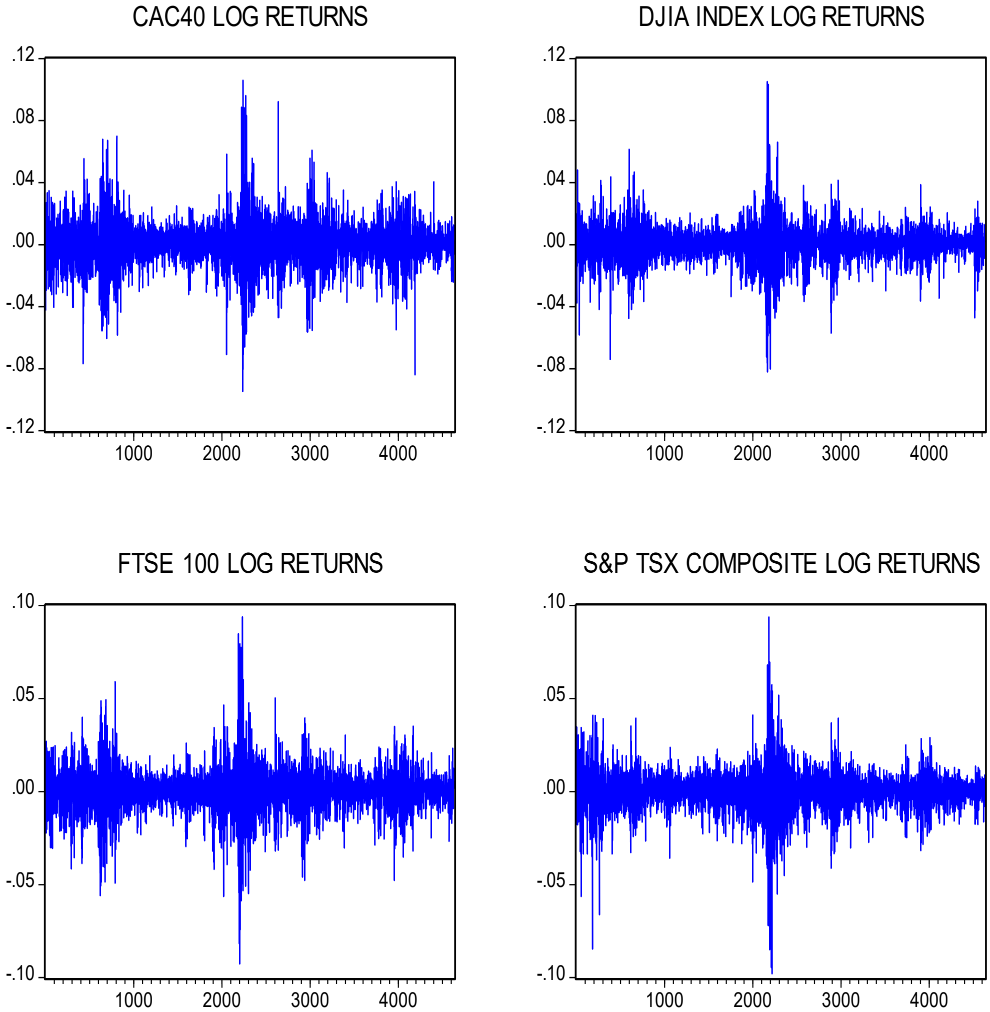


Figure no.3 Log returns series of selected stock indices - individual graphics -
Source: Own computations based on selected financial data series

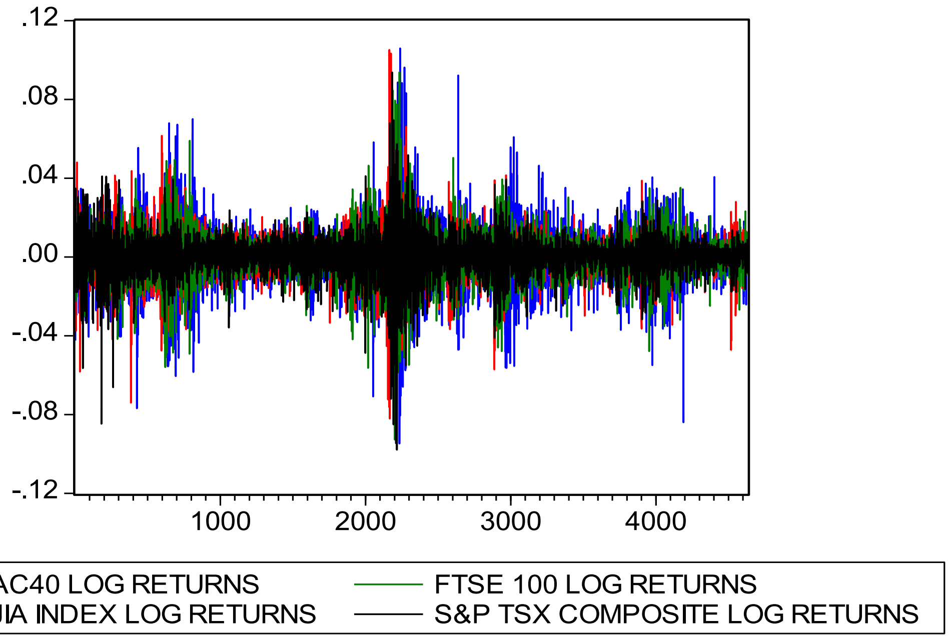


Figure 4 : The log-returns of selected stock indices – joint graph
Source: Own computations based on selected financial data series

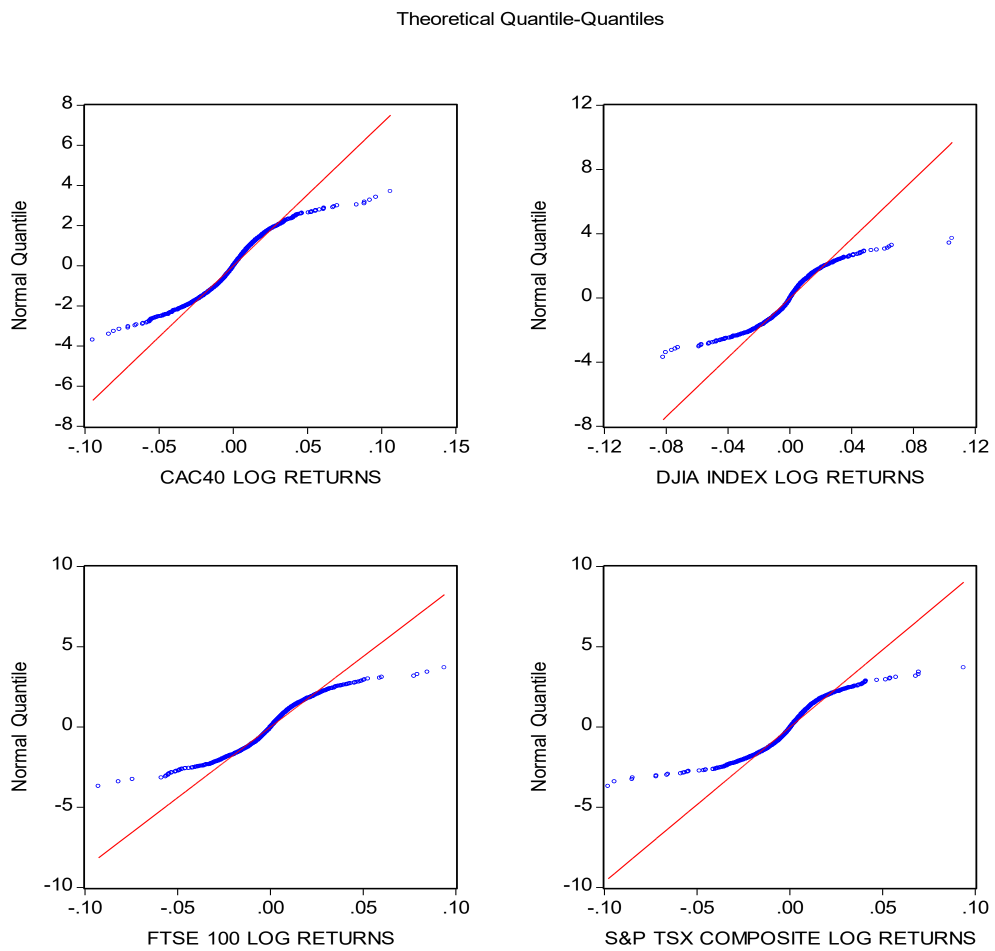


Figure no.5 : Theoretical Quantile – Quantiles
Source: Own computations based on selected financial data series

Table no.1 Descriptive Statistics

Variable	Mean	Median	Minimum	Maximum
USA - DIJA	0.000170303	0.000435576	-0.0820051	0.105083
Canada - S&P TSX	0.000147672	0.000650883	-0.0978786	0.0937023
UK – FTSE100	3.64226e-005	0.000329823	-0.0926557	0.0938434
France - CAC40	-2.24868e-005	0.000298719	-0.0947154	0.105946
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
USA - DIJA	0.0113741	66.7876	-0.111698	8.39606
Canada - S&P TSX	0.0109583	74.2072	-0.654185	9.79679
UK - FTSE100	0.0117578	322.816	-0.142394	6.41107
France - CAC40	0.0144427	642.276	-0.0362980	5.07496
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	
USA - DIJA	-0.0176664	0.0166678	0.00999385	
Canada - S&P TSX	-0.0171920	0.0150487	0.0102156	
UK - FTSE100	-0.0188097	0.0179170	0.0111945	
France - CAC40	-0.0231291	0.0213662	0.0141020	

Source: Author's computation using selected stock market indices

Stock market movement patterns of selected countries indicate interesting outcomes while using filter of summary of statistic. It suggests that all selected four countries have moved a complete cycle from upside down. Mean returns merely zero for all markets, degree of changes from minimum index level point to maximum index level point is almost same. However, Dow Jones Industrial Average (DJIA) index of USA and CAC40 index of France have moved bit further to having higher positive index growth compared to S&P TSX and FTSE100. Degree of standard deviation (SD) indicates highest in CAC40 index (France) compared to the rest of selected stock markets. Nevertheless, while considering lowest skewed returns. Whereas, S&P TSX of Canada delivered highest skewed returns with highest degree of kurtosis making strongest leptokurtosis effect compared to other sample markets. In general, volatility in any financial market reacts on the basis of buying behavior and selling approach of traders and investors.

Table no.2 : Augmented Dickey-Fuller Test

Null Hypothesis: CAC40_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-33.93901	0.0000
Test critical values:	1% level	-3.431584	
	5% level	-2.861970	
	10% level	-2.567042	

Null Hypothesis: DJIA_INDEX_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		46937	0.0001
Test critical values:	1% level	-3.431581	
	5% level	-2.861969	
	10% level	-2.567041	

Null Hypothesis: FTSE_100_LOG_RETURNS has a unit root

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-35.40294	0.0000
Test critical values:	1% level	-3.431581	
	5% level	-2.861969	
	10% level	567041	

Null Hypothesis: S_P_TSX_COMPOSITE_LOG_RE has a unit root

		t-Statistic	ob.*
Augmented Dickey-Fuller test statistic		-50.62014	0.0001
Test critical values:	1% level	-3.431581	
	5% level	-2.861969	
	10% level	-2.567041	

Source: Author's computation using selected stock market indices

Table no. 3 : BDS Test

BDS Test for CAC40_LOG_RETURNS

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.017074	0.001356	12.59204	0.0000
3	0.040413	0.002150	18.79339	0.0000
4	0.060317	0.002556	23.60133	0.0000
5	0.072949	0.002659	27.43841	0.0000
6	0.079703	0.002559	31.14417	0.0000

BDS Test for DJIA_INDEX_LOG_RETURNS

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.021657	0.001438	15.06227	0.0000
3	0.048184	0.002281	21.12538	0.0000
4	0.070522	0.002712	26.00617	0.0000
5	0.085607	0.002822	30.33380	0.0000
6	0.093860	0.002718	34.53601	0.0000

BDS Test for FTSE_100_LOG_RETURNS

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.024609	0.001410	17.45456	0.0000
3	0.051845	0.002243	23.11309	0.0000
4	0.073954	0.002674	27.65169	0.0000
5	0.088301	0.002791	31.63427	0.0000
6	0.096004	0.002696	35.61480	0.0000

BDS Test for S_P_TSX_COMPOSITE_LOG_RE

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.023542	0.001413	16.65778	0.0000
3	0.051407	0.002243	22.91613	0.0000
4	0.072962	0.002668	27.34193	0.0000
5	0.087495	0.002779	31.48838	0.0000
6	0.094870	0.002677	35.43613	0.0000

Source: Author's computation using selected stock market indices

Table no.4 : VAR Granger Causality/Block Exogeneity Wald Tests

VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: CAC40_LOG_RETURNS

Excluded	Chi-sq	df	Prob.
DJIA	6.805424	2	0.0333
FTSE 100	6.808006	2	0.0332
S&P TSX	3.161193	2	0.2059
All	16.54308	6	0.0111

Dependent variable: DJIA_INDEX_LOG_RETURNS

Excluded	Chi-sq	df	Prob.
CAC40_	1.906264	2	0.3855
FTSE 100	0.191593	2	0.9086
S&P TSX	7.848346	2	0.0198
All	9.923389	6	0.1279

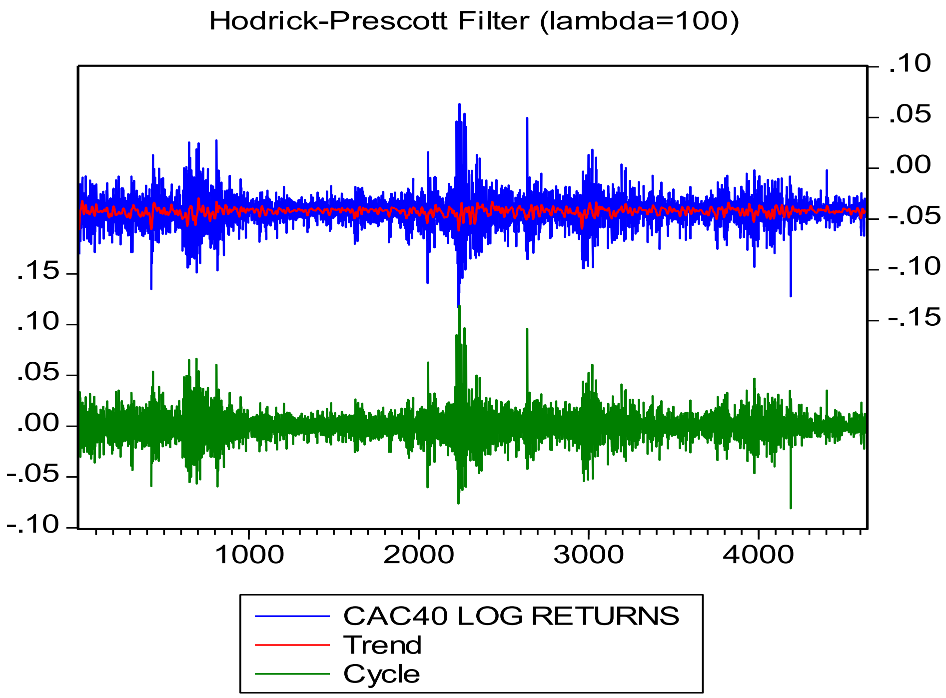
Dependent variable: FTSE_100_LOG_RETURNS

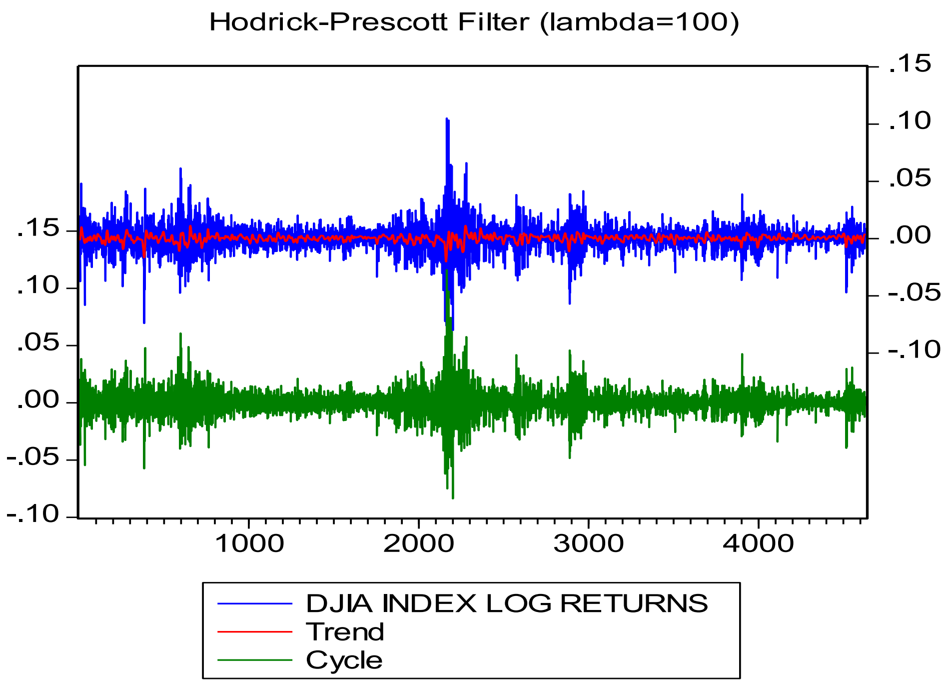
Excluded	Chi-sq	df	Prob.
CAC40	2.377869	2	0.3045
DJIA	14.85797	2	0.0006
S&P TSX	10.99466	2	0.0041
All	28.88600	6	0.0001

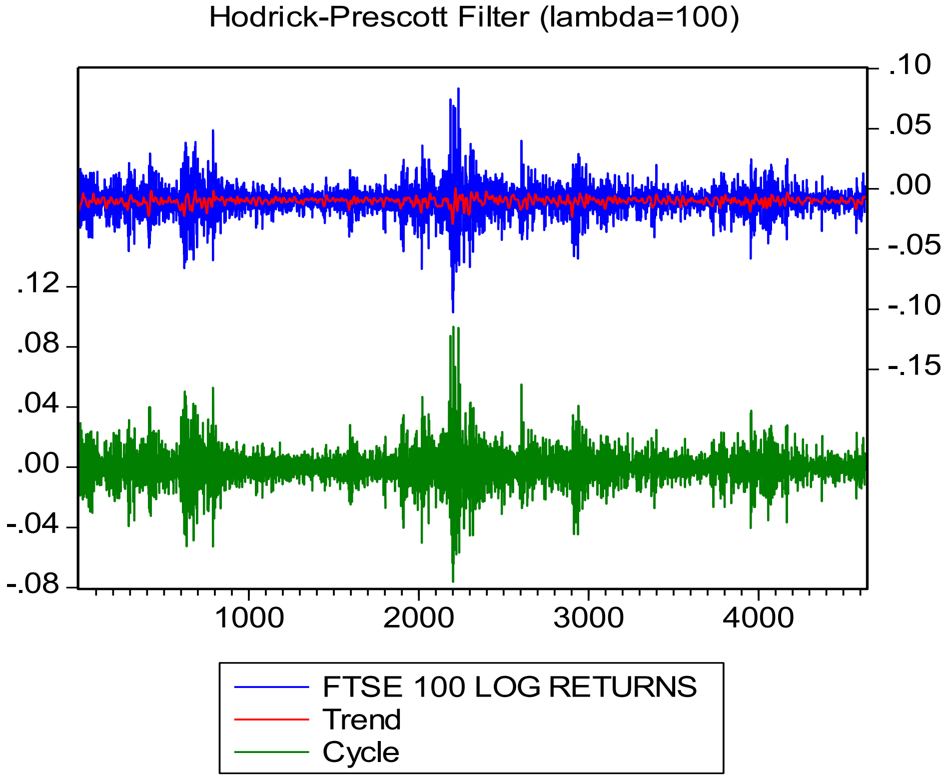
Dependent variable: S_P_TSX_COMPOSITE_LOG_RE

Excluded	Chi-sq	df	Prob.
CAC40	11.46282	2	0.0032
DJIA	15.11686	2	0.0005
FTSE100	0.872606	2	0.6464
All	27.16066	6	0.0001

Source: Author's computation using selected stock market indices







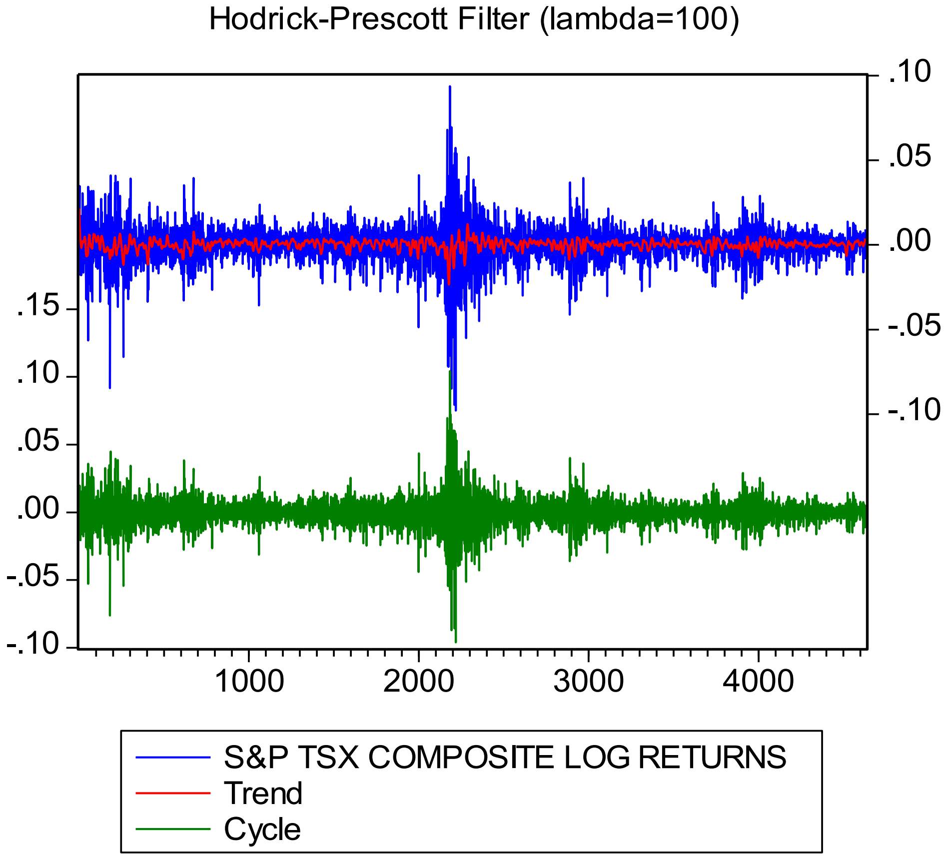


Figure no.6 : Hodrick – Prescott Filter

Source: Own computations based on selected financial data series

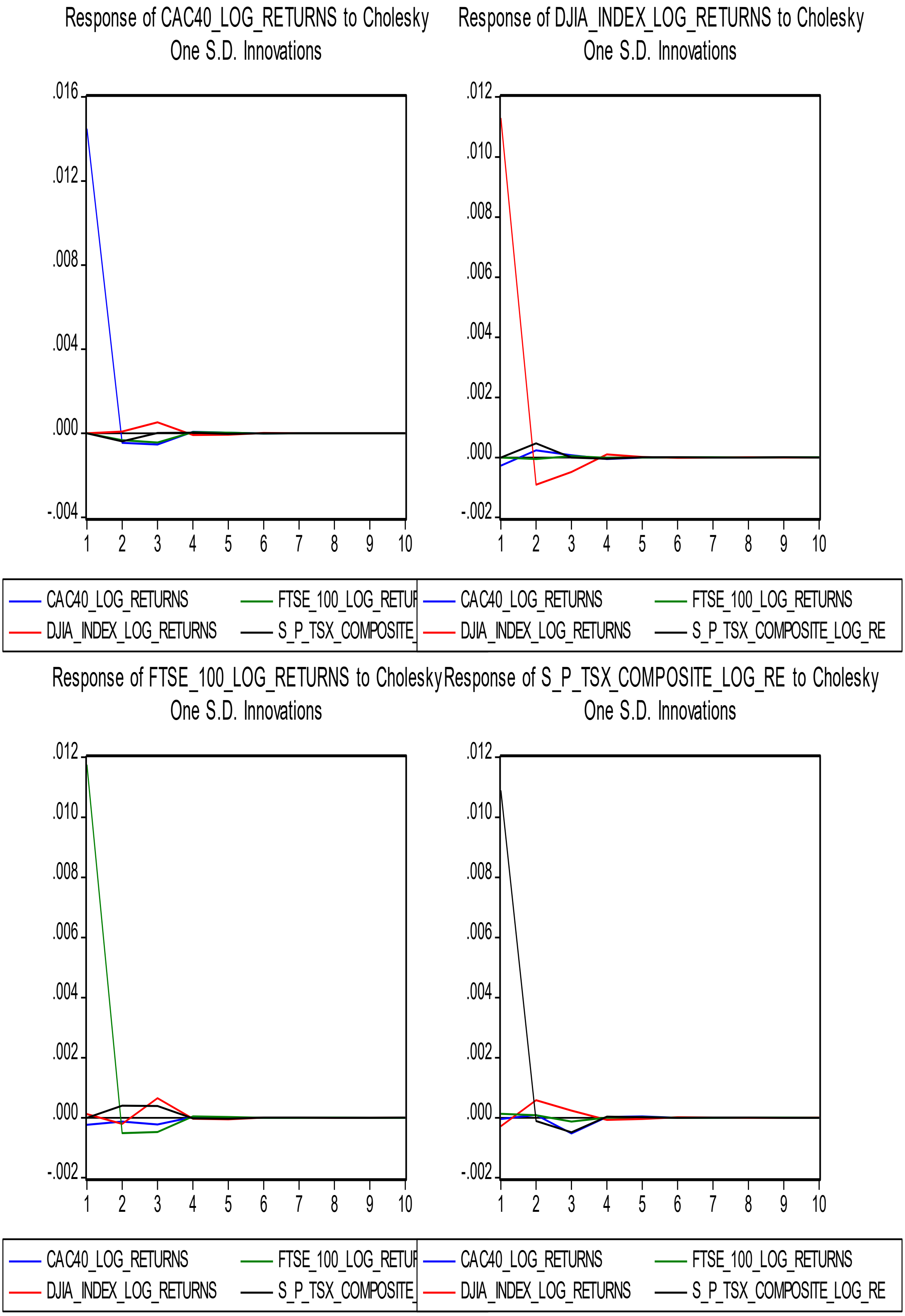


Figure no. 7 Impulse Response Analysis to Cholesky One S.D. Innovations
Source: Own computations based on selected financial data series

Table no.5 Symmetric and Asymmetric GARCH models property

Variable	USA-DIJA index	UK – FTSE100 index	France-CAC40 index	Canada-S&P TSX index
Constant	0.000577033	0.00035761	0.000500	0.000429394
Omega	1.68455e-06	1.66614e-06	2.01215e-06	6.89966e-07
Alpha	0.110151	0.108481	0.0959039	0.0809410
Beta	0.876582	0.879436	0.896163	0.913484

Source: Author's computation using selected indices

Data processing considered after white-noise process and found significant result at degree of 1% considering VCV robust method. Conditional mean equation results merely zero as first log difference considered for white-noise process. Conditional variance equation indicates risk factor almost eight times higher than positive probability. Economic stability plays vital role in movement of stock market and the same assessed by investor community to determine value of probable risk factor. US economy is based on asset based funding. It means funding that based on market value of asset hold by individuals. This may be one of reason that creates changes in financial market which followed by all connected countries regardless developing or developed countries. However, this paper identifies new changes in financial market transmitting pattern which is no longer following shadow effect of US economy. Such independence behavior of financial market makes new formation of individual transmitting patterns.

4. Conclusions

The empirical results based on data distribution revealed particular values for Skewness and Kurtosis. Statistically, skewness is a measure of asymmetry of the distribution of a financial data series around its means but the skewness of a symmetric distribution is zero. Taking into account the financial implications of efficient markets hypothesis it is obvious that in the case of normal distribution, the skewness is null. Positive skewness highlights that the distribution has a long right tail, while negative skewness implies that the distribution has a long left tail. Kurtosis measures the peakedness or flatness of the distribution of a return financial data series. The kurtosis of a normal distribution is 3, but if the kurtosis exceeds 3, the distribution is peaked (Leptokurtic) relative to the normal. In addition, if the kurtosis is less than 3, the distribution is flat (Platykurtic) relative to normal. The empirical results revealed that in all four selected cases, respectively for DIJA index (USA) is -0.111698, for S&P TSX index (Canada) is -0.654185, for FTSE 100 index (UK) is -0.142394 and for CAC 40 index (France) is -0.0362980 indicate the existence of negative skewness which implies that the distribution has a long left tail. The kurtosis exceeds 3 in all four cases, respectively for DIJA index (USA) is 8.39606, for S&P TSX index (Canada) is 9.79679, for FTSE 100 index (UK) is 6.41107 and for CAC 40 index (France) is 5.07496 so that the distribution is peaked (Leptokurtic) relative to the normal.

The Augmented Dickey-Fuller test was applied in order to determine the stationarity of selected financial time series. The empirical results obtained based on continuously compounded returns indicate that the null hypothesis H_0 is rejected in all four cases because t_{test}_ADF< t_{critic} (1%, 5%, 10 %) which implies that all the analyzed time series are stationary. We also can use the formula Prob (0 %) < test levels (1%, 5%, 10 %) which leads to the same conclusion that all the analyzed time series are stationary (see Table 2).

The BDS test was performed in order to determine whether the residuals are independent and identically distributed. The null hypothesis is rejected if the BDS test statistic is greater than or less than the critical values. The level of significance, respectively, a of 5 % (if a = 0.05, the critical value = ±1.96) is considered in this hypothesis testing. In the case of continuously compounded returns, the null hypothesis was rejected in all four cases (see Table 3).

GARCH (1, 1) model allows series returns to remain in conditional variances and each of them depend on previous legs that reflects on rest of series returns. Thus, hypothetically it estimates effect of previous volatility on present day volatility. Moreover, before implementing GARCH (1, 1) it is necessary to test white noise process to confirm stationarity in series returns of selected developed markets. ADF test result indicates significant level at degree of 1% and confirms series return stationary. Volume creates shocks and that appears as sketches in historic events of stock markets. Detail study of such outcome helps to understand that how different events and news create changes in volatility. General approach remains unchanged when high volume appears as reaction with response to different news events. Dow Jones Industrial Average (DIJA) considered as indicator that representing US financial markets, that is also one of the strongest and developed financial markets considering data from January 2000 to June 2018 counting 4639 daily observations.

Transmitting pattern of DIJA represents the movements of lower, higher, average, medium-lower, and medium-higher magnitude volatility shocks. This time range captures journey of index from merely hundred thousand points to breaching twenty five thousand points and absorption of negative impact resulting market index trending below 8500. In case such prediction for negative shocks pre-identified, it could have generated best ever value return for attempt. Nevertheless, previous studies indicate that greater volatility always results from negative news impacts and which always remain difficult to predict. However, some of part can even be possible to predict being ordinary investor by living in environment. More challenging part is how the rest of investors react on such news and for how long impact will be carried forward. Data processing is processed through generalized autoregressive conditional heteroskedasticity models that derived volatility magnitudes.

According to Engle [1982] traditional econometric models assume a constant one-period forecast variance and therefore in order to generalize this implausible assumption, it was implemented a new class of stochastic processes called autoregressive conditional heteroscedastic (ARCH) processes. Bollerslev [1986] has generalized ARCH model by including lagged valued of the conditional variance. Practically, GARCH models are much more permissive considering a wider range of behavior patterns for more persistent volatility. The most general form of the model is GARCH (1, 1) where GARCH stands for Generalized Autoregressive Conditional Heteroscedasticity. Moreover, a GARCH model or in other words a Generalized ARCH model represents an extension of the ARCH model which otherwise is very similar to an ARMA model. According to Brooks [1996] such a generalization of the ARCH model, such as GARCH model can be perceived as ARCH model of infinite order and concluded that it is highly unlikely that a GARCH model of order greater than one in the autoregressive and moving average components would be required, since by definition, a GARCH (1,1) model implies an infinitely long memory with respect to past innovations.

The results of VAR Granger Causality tests/Block Exogeneity Wald Tests indicate that all variables in the model can be treated as endogenous considering that remaining variables have significant impact on them jointly, but not always individually). Engle and Granger [1987] have provided a very interesting econometrical approach. Chi-square statistics and probability values of pairwise Granger causality/block exogeneity Wald test results between the endogenous variables.

The authors selection of the four developed stock markets was not random. The four developed economies selected for empirical analysis are linked by very tight economic and financial relations. The United States of America (USA) and Canada are a part of North American continent, and comprise nearly 80% of the entire land area. In other words, USA and Canada are neighbors and share a common past but also very attractive economic collaboration projects. On the other hand, France and United Kingdom (UK) are also neighbors share a very controversial common past. The continued cooperation and international trade between France and the UK are very important especially in the context of globalization. The European Union (EU) consists of 28 member states but France and United Kingdom (UK) are two of the founding countries. Moreover, Moreover, all four countries are full members of NATO. Consequently, the stock markets behaviour reflects all this important aspects as empirical analysis has demonstrated during the long-time period from January 2000 to June 2018.

Stock price movements exhibit certain stylised facts such as the following : volatility clustering, financial leverage effects, heavy tailed empirical distribution, leptokurtosis, unconditional time-varying moments, asymmetric volatility effects, conditional heteroskedasticity and various other deviations from normality. The investment benefits arising from international diversification of portfolios are significant especially in the context of globalization. Selected developed financial markets react with similar pattern while responding to other market behavior with different degree of leverage effect in volatility variables. Descriptive statistics indicates leptokurtosis effect for all selected financial markets with high degree of standard deviation that will make investment with high uncertainty. Generalized autoregressive test indicates results at significant degree of 1% that assures that GARCH (1, 1) model by Bollerslev [1986] fitted considering normal distribution and robust as VCV method.

Selected stock markets i.e. US, UK, France and Canada react based on a similar pattern revealed by GARCH model that confirms the existence of persistent volatility, high degree of shocks and uncertainty in transmitting patterns. With reference to GARCH outcome it confirms that DJIA - Dow Jones Industrial Average – index (US) is one of most positive approach for having better good news impact and having higher probability for much safer investment. Whereas S&P TSX index (Canada) provides significant possibility for higher degree of changes in volatility and degree of risk during considered period i.e. from January, 2000 to June 2018. Despite of having higher degree of risk factor, S&P TSX index (Canada) has breached upside down with degree of changes and has higher market recover capability from negative shocks. FTSE 100 index of UK secured second rank for second positive market that indicates less degree of higher magnitude shocks in normal market transmitting patterns. Moreover, The impulse responses for the selected period from January 2000 to June 2018 are quite relevant.

A future extended version of this research paper will focus on investigating long-term co-movements, dynamic causal linkages and international contagion patterns between developed and emerging capital markets based on international portfolio diversification.

5. Bibliography

[1] Abimanyu, Y., et. all, International Linkages to the Indonesian Capital Market: Cointegration Test, *Capital Market and Financial Institution Supervisory Agency*, Ministry of Finance of Indonesia, 2008.

[2] Ahmed, A.E.M.; Suliman, S.Z. Modeling stock market volatility using GARCH models evidence from Sudan, *Int. J. of Bus. and Soc. Scien.*, Special Issue, 2011, 2 (23), 114-128.

[3] Balios, D.; Xanthakis, M. International interdependence and dinamic linkages between developed stock markets, *South Eastern J. of Econ*., 2003, 105-130.

[4] Bollerslev, T. Generalized autoregressive conditional heteroskedasticity. *J. Econom.*, 1986, 31, 307–327.

[5] Brooks, C., Testing for Non-Linearity in Daily Sterling Exchange Rates, *Applied Financial Economics*, 1996, 6, 307–317.

[6] Dickey, D.A., Fuller, W.A., Distribution of the estimators for autoregressive time series with a unit root, *J. Am. Stat. Assoc*., 1979, 74, 427-431.

[7] Engle, R.F., Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation, *Econometrica*, 1982, 50(4), 987-1008.

[8] Engle R. F.; Granger C. W. J., Cointegration and Error Correction: Representation, Estimation and Testing, Econometrica, 1987, 55, 251-276.

[9] Eun, C.S.; Shim, S., International Transmission of Stock Market Movements, *J. of Financial and Quantitative Analysis*, 1989, 241-256.

[10] Granger, C. W. J. Investigating Causal Relations by Econometric Models and Cross-spectral Methods, *Econometrica*, 1969, 37 (3), 424–438.

[11] Hassan, S.A. A Time Series Analysis of Major Indexes Using GARCH Model with Regime Shifts, *Int. J. of Fin. Res.*, 2017, 8 (4), 127-133, ISSN 1923-4023, E-ISSN 1923-4031.

[12] Li, X.; Ma, J.; Chen, Z.; Zheng, H. Linkage Analysis among China's Seven Emissions Trading Scheme Pilots, *Sustainability*, 2018, 10(10), 3389; https://doi.org/10.3390/su10103389.

[13] Lim, C.M.; Sek, S.K. (2013) Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia, *Proc. Econ. and Fin., Elsevier*, 2013, 5, 478 – 487.

[14] Lin, Z. Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models, *Fut. Gener. Comp. Syst. J.*, Elsevier Science Publishers B. V. Amsterdam, The Netherlands, 2018, 79 (P3), 960-972, ISSN: 0167-739X, doi>10.1016/j.future.2017.08.033.

[15] Mathur, S.; Chotia, V.; Rao, N.V.M. Modelling the Impact of Global Financial Crisis on the Indian Stock Market through GARCH Models, *Asia-Pacific J. of Manag. Res. and Innov.*, 2016, 12 (1), 11-22, ISSN: 2319-510X, Online ISSN: 2321-0729.

[16] Miralles-Marcelo, J.L.; Miralles-Quirós, J.L.; del Mar Miralles-Quirós, M. Multivariate GARCH models and risk minimizing portfolios : The importance of medium and small firms, *The Spanish Rev. of Fin. Econ.*, 2013, 11, 29–38.

[17] Pretorius, E. (2002) Economic determinants of emerging stock market interdependence, *Emerging Markets Review*, 3(1), pp. 84-105.

[18] Ruan, L. Research on Sustainable Development of the Stock Market Based on VIX Index, *Sustainability*, 2018, 10(11), 4113; https://doi.org/10.3390/su10114113.

[19] Sariannidis, N.; Giannarakis, G.; Litinas, N.; Konteos, G. A GARCH Examination of Macroeconomic Effects on U.S. Stock Market : A Distinction Between the Total Market Index and the Sustainability Index, *Euro. Res. Stud.*, 2010, XIII (1), 129-142.

[20] Singh, G.S.P. Chinese and Indian Stock Market Linkages with Developed Stock Markets, *Asian J. of Fin. & Account.*, 2010, 2(2).

[21] Srinivasan, P. Modeling and Forecasting the Stock Market Volatility of S&P 500 Index Using GARCH Models, *The IUP J. of Behav. Fin.*, 2011, VIII (1), 51-69.