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# Causality of Interest Rate, Exchange Rate and Stock Prices inThe Chicago Board Options and Exchange.

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***Abstract*** *This paper explores the Granger causality test and the bivariate as well as the multivariate co-integration test to determine the interactions between interest rates, exchange rates, and the composite stock volatilities of different traded contracts under the Chicago Board Options and Exchange. Using the daily sector data for all observed variables from the St.Louis Fed over the period of 2007-2017 and introducing the method of simple vector autoregression, this study examines various aspects of the integration where the current and the previous values of volatility indices, interest rates, and exchange rates have shown significant Granger causality effects to the return behavior of those volatility indices, interest rates, and exchange rates. The estimated result indicates that, under the absence of any long-run relationships, interest rates have more unidirectional and bi-directional causal effects with the stock market volatility indices than in comparison with the exchange rates, whereasboth are identified as significant determinants of stock price volatility.*

***Keywords:****Stock Volatility, Granger Causality, Exchange Rate, and Interest Rate. JEL category: JEL: C21, C22*

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## I. Introduction

The relative rate at which the price of a security moves up and down is generally known as Stock Volatility. It is calculatedby annualizing the standard deviation of a daily change in price. A highly volatile stock has the price that moves up and down rapidly over a very short period. On the other hand, the stock whose price does not show almost any recurrent changes then it is termed as low volatility.The following are some of the indicators that have been developed over the years, such as the S&P 500 Volatility Index, the NASDAQ Volatility Index, the Russell 2000 Volatility Index, etc. to track the status of broad market volatility and help investors decide when to buy or sell stocks.

Most of the time stock prices move up and down, even sometimes trending higher and lower, instead of moving straight line.Salimullah (2016) finds interest rate and foreign exchange rate risks are two significant economic and financial factors that affect the common stock value. The interest rates indirectly affect the valuation of the stock prices, and stock volatility directly creates a shift between the money market and capital market instruments.[1] The performance of the stock market can reflect the overall performance of a country's economy. When the stock market is doing well, it may imply that the economy is experiencing high growth.

Gul and Ekinci (2006) explain the advances in the stock market that affect the exchange rate through liquidity and wealth effects; a rise in the interest rate increases the opportunity cost of holding cash balances and the reduction in money demand creates an excess supply of credit and stimulates a decrease in stock prices. Md-Yusuf and Rahman (2012) argue that foreign exchange rates are a major source of macroeconomic uncertainty that affects stock volatility. In earlier research, Ibrahim (2000) lays out the interactions between Malaysian stock prices and the exchange rates using multivariate co-integration and the Granger causality test. He found that exchange rates and the stock prices have no long-run relationship by themselves, but in the presence of money supply and the foreign reserves these two variables showed co-integration; hence, Granger causes Malaysian stock volatility quite significantly. The general framework of this research is closely connected to those ideas and therefore, extended by including several short-term interest rates and foreign exchange rates for the United States.

This paper deals with the variables from the Chicago Board Options Exchange (CBOE) Global Markets—the largest U.S. options exchange with respect to annual trading volume—that calculates and updates

[1]The higher interest rates cause businesses and consumers to spend more on servicing debt. This makes borrowings from money and capital market more expensive and the availability of capital to investment goes down. As a result, the stock prices also move downward and thus, tends to create a change between borrowing and lending of short-term assets and long-term assets.

several volatility indices implied by option prices, the exchange rates, and the interest rates. The three measures of market expectations of volatility indices are the CBOE Volatility Index: VIX, the NASDAQ 100 Volatility Index, and the S&P 500 3-Month Volatility Index. In the case of exchange rates, some influential rates of worldwide controlling currencies are most connected with U.S. business and exchange have been chosen. These are Japan/U.S. Foreign Exchange Rate (¥/$), Mexico/U.S. Foreign Exchange Rate (₱/$), and Canada/U.S. Foreign Exchange Rate (C$/$). For the case of interest rates, the daily rates of Three-Month Treasury Bill: Secondary Market Rate, Three-Month Commercial Paper minus Federal Funds Rate, and One-Year Treasury Constant Maturity Rate have been taken as measures of effective rates. All of these data sets were collected as a daily form of data from the St. Louis Fed over the period between 2007 and 2017. There would be other effective comparative measurements of interest rates that can be found at the St. Louis Fed website, but they cannot be used accurately in this study because they are recorded as quarterly or monthly.

This study explores the causality between stock market volatility, exchange rate risk, and the interest rate uncertainty (risk). The motivation of this study is to find out whether it is the exchange rate or the interest rate that causes the stock price volatility to become more sensitive. The findings of this paper show that under the co-integrating relationship ₱/$ currency exchange rates share a common trend and form a stationary relationship in the long-run with the CBOE VIX volatility and NASDAQ 100 stock price volatilities. However, in the case of multivariate co-integration, the stock volatilities exhibit long-run relationship with the series of the exchange rates, but their relationships are exogenously weak and do not move together to restore the equilibrium.

On the other hand, having no long-run relationship between the stock volatilities and interest rates, more unidirectional and bi-directional causal relationships have been generated between them as compared to that of the exchange rates. This has been supported by the idea in which more positive changes in interest rates, sales and profits of the investor will decline, and stock prices will drop because firms or investors will lose their international competitiveness. Obviously, interest rate volatility influences the value of the stock since the future cash flows of the firm will change and affect their investment plan on stock or bond.

The rest of this paper is organized as follows. Section 2 deals with the related literature and the ex-ante discussion. Section 3 presents the data analysis and outlines the empirical methodology. Section 4 presents the results and findings of the paper. Finally, section 5 contains some concluding remarks.

## II. Related Literature and Ex-Ante Discussion

**2.1 *Related Literature***

Internationalization of stock markets, liberalized capital flows, and huge foreign investment in the U.S. equity markets have led stock and foreign exchange markets to become increasingly interdependent. Kutty (2010) examines the correlation of Mexico's stock prices and exchange rates. The paper uses the Granger causality test and exhibits how stock prices lead exchange rates in the short-run, and there is no long-run relationship between these two variables. That finding corroborates the results of Bahmani-Oskooee and Sohrabian's (1992) conclusion about the existence of a long-term relationship between exchange rates and stock pricesbut contradicts the findings of Kutty (2010).

Dimitrova (2005) shows in a separate paper there could be a link between the stock market and exchange rates, and this might explain fluctuations in bothmarkets. Focusing on the U.S. and the U.K. over the period from January 1990 through August 2004,the findings of the paper state that firms' stock prices and the stock market condition may react to changes in the exchange rates situation. On the contrary, changes in stock prices may influence the movements in the exchange rates via firms' portfolio adjustments or outflow of capital. Neih and Lee (2001) examine the relationship between stock prices and exchange rates for the G7 countries using basic co-integration tests and vector error correction models (VECM) from 1993 to 1996. Their paper did not evaluate for dual causality between the variables and end up with the conclusion that there is no long-run relationship between the stock prices and the exchange rates in G7 counties.

The causality between Nifty returns and Indian Rupee/U.S. Dollar Exchange Rates has been widely examined by Agarwal et al. (2010). They find that the correlation between Nifty returns and exchange rates were negative. They employ the Granger causality test to carry out further investigation for the causal relationship between the two variables and their findings highlighted a kind of unidirectional relationship between Nifty returns and exchange rates, running from the former toward the latter. Muradoglu et al. (2000) investigate the causal relationship between market returns, exchange rates, interest rates and inflation rates for nineteen emerging markets from 1976 to 1997.They explain how the scope of the importers competitiveness in domestic markets will increase, which would lead to the growth in profit and stock prices. Their findings supported that the interactions between implied stock volatilities and macroeconomic variables was mainly linked to the size of the stock market.[2]

In a different study, Çifter and Ozuna (2007) examine the impact of changes in the interest rates on the stock returns by applying the Granger causality test to the daily rates of the Istanbul Stock Exchange 100 index and the compounded rate of interest. Their findings come up with a proof of interest rate Granger causes ISE 100 index starting with nine days' time-scale effect and specifies that the effects of interest rates on stock return increase with a higher time scale. Their research augmented the rationale of this current study. The study conducted by Ibrahim (2000) has formulated an idea that is closely related to this present study. He applies standard co-integration and Granger tests to investigate the interactions between exchange rates and the stock market index for Malaysia. The results established two opposite scenarios: There is no long-run relationship between the stock market indices and the exchange rates and there is evidence for co-integration when the model extends to include broader money supply and foreign reserves.

Another study is conducted by Muktadir-al-Mukit (2012) where he took the volatility of the market index at the Dhaka Stock Exchange (DSE) and finds that, both in the long-run and in the short-run, interest rates are ranked first in terms of the Granger causes of market volatility index. Using the Johansen co-integration test, he showed that in the long-run, exchange rates have a positive impact and interest rates have a negative causal impact on stock price where all the coefficients are found statistically highly significant. The interest rate and the exchange rate have negative impacts on the stock market index in the long-run as well as the short-run, providing some useful insights into the effects on the stock market index of Malaysia, as shown in the research conducted by Thang (2009). The findings of his paper reveal that exchange rates and stock prices demonstrate a high relationship when returns in asset markets are lower and volatility is higher. To search for both the long-run and short-run impacts, Thang uses the standard econometrics time series model as the Johansen Juselius (JJ) co-integration test, the VECM, and the Granger causality test. The author discloses about a negative impact of interest rates and the stock market index.

### 2.2 *Ex-Ante Discussion*

The Granger causality testing procedure requires one set up while testing two equations. In each equation, the current value of one observed variable ($x_t$ or $y_t$) is formulated as an equation of the other variable(s) with all the different time lag and the previous lagged values of its own level one. Granger (1988) develops a relatively simple test that defined causality as follows: a variable $y_t$ is said to Granger causes $x_t$, if $x_t$ can be predicted with greater accuracy by using the past values of the variable $y_t$, all other terms remain unchanged. The thought process behind the Granger test is that– if previous values of variable $y_t$ significantly influence current values of variable $x_t$, then it can be said that $x$ causes $y$ and vice-versa. For instance, this study begins with the model by taking the three volatility indices of different measurements as dependent variables and then running the simple vector autoregression model to see whether the interest rates and the exchange rates have any Granger causality effects on the volatility indices.

Consider two time-series variables, $y_t$ and $x_t$ that are interrelated. Their combinations yield a sequence of equations that describe a system in which each variable is a function of its own lag, and the lag of the other variable. Together the equations constitute a system known as a vector autoregression (VAR). The following example includes the maximum lag of order two, so we have a VAR(2):

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \varepsilon_t \quad (1)$$

$$x_t = \lambda_0 + \lambda_1 y_{t-1} + \lambda_2 y_{t-2} + \delta_1 x_{t-1} + \delta_2 x_{t-2} + \mu_t \quad (2)$$

If $y$ and $x$ are stationary, then equations (1) and (2) can be estimated by using the least squares method. On the other hand, if $y$ and $x$ are non-stationary in their levels but stationary in their first difference, then the difference operators can be used, and the following system of equations can then be estimated:

$$\Delta y_t = \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \beta_1 \Delta x_{t-1} + \beta_2 \Delta x_{t-2} + \Delta\varepsilon_t \quad (3)$$

$$\Delta x_t = \lambda_1 \Delta y_{t-1} + \lambda_2 \Delta y_{t-2} + \delta_1 \Delta x_{t-1} + \delta_2 \Delta x_{t-2} + \Delta\mu_t \quad (4)$$

[2]The superiority of the information content of implied volatility over historical volatility measure in various markets has been extensively documented by other researchers. (see among others, Blair, Poon and Taylor, 2001; Poon and Granger, 2003; Christensen and Prabbala, 1998; Jorion, 1995).

To make things simple, equation (3) and (4) are considered to test the following null hypotheses. The null hypothesis in this case is $H_0$: $x_t$ does not cause $y_t$; i.e.($x_t \nRightarrow y_t$).

$$Unrestricted regression: \Delta y_t = \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \beta_1 \Delta x_{t-1} + \beta_2 \Delta x_{t-2} + \Delta\varepsilon_t$$
$$Restricted regression: \Delta y_t = \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \Delta\varepsilon_t$$

From these two regression equations, the joint F-statistic will be calculated. If the calculated F-statistic is high enough at a lowest level of significance, then we can reject $H_0$ and conclude that $x_t causes y_t$ ($x_t \Rightarrow y_t$). The second form of equation is used to test another null hypothesis. $H_0$: $y_t$ does not cause $x_t$; i.e. ($y_t \nRightarrow x_t$).

$$Unrestricted regression: \Delta x_t = \lambda_1 \Delta y_{t-1} + \lambda_2 \Delta y_{t-2} + \delta_1 \Delta x_{t-1} + \delta_2 \Delta x_{t-2} + \Delta\mu_t$$
$$Restricted regression: \Delta x_t = \delta_1 \Delta x_{t-1} + \delta_2 \Delta x_{t-2} + \Delta\mu_t$$

A second F-statistic is calculated from the above two regressions. If the F-statistic is found higher than the critical F-value, then we can reject $H_0$ and conclude that $y_t causes x_t$ ($y_t \Rightarrow x_t$).

In each equation, the current value of one variable ($x_t$ or $y_t$) is a function of the previous time lag of other variables, and its own values in previous time periods ('lagged' values). Recall that the purpose of this study is to find out whether there is any long run relationship between interest rates, exchange rates, and volatility indices and how these variables Granger causes each other. The regression procedure is designed for the possible causal interactions between nine variables: three are volatility indices of different measurement, three for representative exchange rates, and three for interest rates.

To capture these interactions, this paper employs co-integration *viz-a-viz* Granger causality approaches. The co-integration approach will capture the long-run co-movements or equilibrium relationship between those three different sets of variables. The Granger causality tests, on the other hand, shed light on the short-run dynamics of the variables concerned. Enders (1995) argues that co-integration between a set of variables does not necessarily imply the presence of the equilibrium relationship generated by market forces. The relationship of the variables can be causal or behavioral, or it can be characterized by a simple reduced-form relationship among other similar variables with common trends. The evidence for the relationship between the two variables may be persuasively obtained, the bivariate framework usually employed in many studies may or may not be enough.

The bivariate and multivariate framework for co-integration and causality testing, therefore, extend the analyses of this paper by investigating their potential relationship and creates the motivation towards the fact findings about what indices may receive considerable policy attention. The basic idea of co-integration relates closely to the concept of unit roots. For the set of above macroeconomic variables of interest, it may be the case that the variables in question are non-stationary, i.e. $I(1)$ when taken individually, or there exists a linear combination of the variables that is stationary without taking the difference, i.e. the system of equations will be $I(0)$.[3] This paper uses the Engle-Granger (EG) co-integration test to see whether two or more series are co-integrated i.e. two or more series are themselves non-stationary up-to certain order but tend to move together through time. Let us begin with the simple bivariate VAR(p) model:

$$y_t = \alpha_1 + \beta_1 x_t + \sum_{i=1}^{k} c_i\, y_{t-i} + \sum_{i=1}^{k} d_i\, x_{t-i} + \varepsilon_{1t} \qquad (5)$$

$$x_t = \lambda_1 + \delta_1 y_t + \sum_{i=1}^{k} e_i\, y_{t-i} + \sum_{i=1}^{k} h_i\, x_{t-i} + \varepsilon_{2t} \qquad (6)$$

Assume that $\varepsilon_{1t}$ and $\varepsilon_{2t}$ are uncorrelated white-noise error terms. For testing the presence of a unit root and to see the case of any autocorrelation in the observed series, Dickey and Fuller (1979) proposed alternative regression equations known as Augmented Dickey-Fuller (ADF) Test. The ADF test is performed by estimating the following model:

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{k} \gamma_i\, \Delta y_{t-i} + u_t \qquad (7)$$

[3]A subset of the variables is individually integrated of order 1. In another sense the variables are non-stationary in their levels, but their first differences are stationary. An $I(0)$ variable indicates the series is stationary.

The EG two-step co-integration test for bivariate and multivariate case is represented by applying the ordinary least squares (OLS) technique into the above bivariate VAR equationsand then to include simply the ADF unit root tests on the residuals estimated from the step-one co-integrating regression.[4]If the variables are found co-integrated, the residuals from the equilibrium regression can be used to estimate the error correction model (ECM) model and used to analyze the long-run and short-run effects of the variables as well as to see the adjustment coefficient. For the multivariate case, this study also performs the EG test for co-integration and estimating the co-integrating vectors which are also more straightforward.

## III. Empirical Framework and Specification

3.1 *Data Description*

As previously stated, this paper uses the common data series from the Federal Reserve Bank of St. Louis website, namely St. Louis Fred economic data. Daily time point data ranging from December 2007 to December 2017 has been collected. The selected volatility indices are based on the common stock prices of the top publicly traded American company's equities or stocks. Three CBOE's volatility indices are: ($i$) VIXCLS, widely known as the first benchmark volatility index of Chicago Board Options Exchange, measures the market's expectation of future volatility. It is considered as the world's premier barometer of equity market volatility; ($ii$) VXVCLS, the implied volatility index on stocks constructed using Standard and Poor's 500 index options, widely known as S&P 500 3-Month Volatility Index; ($iii$) VXNCLS, the implied volatility index on domestic and international non-financial securities based on their market capitalization, with certain rules capping the influence of the largest components, popularly known as NASDAQ 100 Volatility Index. Under the CBOE Global Markets, these three vital indices mainly created as a suite of market expectations of volatility conveyed by the options prices based on all the major U.S. broad-based stock indices.

Three predominant currency exchange rates that control the world's most trading volumes to the United States, have been chosen. These are,₱/$ Foreign Exchange Rate (ticker symbol-DEXMXUS), ¥/$ Foreign Exchange Rate (ticker symbol-DEXJPUS), and C$/$ Foreign Exchange Rate (ticker symbol-DEXCAUS). China/U.S. (¥/$) foreign exchange rate has been opted out because China has a strictly controlled currency policy which regulates their trading activity with the U.S. by controlling the daily movements of the yuan on the forex market. Unlike the others they follow an exchange rate adjustment system which can be identified as 'crawling peg.'

The interest rate variables that have been used in this research are the three widely utilized short-term interest rates. These are the daily rates of 3-Month Treasury Bill: Secondary Market Rate (ticker symbol-DTB3), 3-Month Commercial Paper Minus Federal Funds Rate (ticker symbol- CPFF), and 1-Year Treasury Constant Maturity Rate (ticker symbol-DGS1). DTB3 is the interest rate on a three-month U.S. Treasury bill that is often used as one of the risk-free rates for U.S. based investors. CPFF is the spread of interest rate calculated by taking the difference between 3-Month AA rated Financial Commercial Paper Rate and Effective Federal Funds Rate and DGS1 is the index based on the average yield of various Treasury securities maturing at one-year period. This study considers two government regulated interest rates as the useful proxies because the capital market usually operates on the belief that there is virtually no chance of the U.S. government defaulting on its obligations. Only the daily data for the interest rate has been downloaded from the FRED website. Therefore, other potential interest rates cannot be chosen because some of their values have been recorded either as a monthly, quarterly, or yearly basis. This restriction technique ends up with a total of 2,416 observations.

Table 1 summarizes and provides different statistical information about the data series used in this sample study. The preliminary analysis for all data series reveals that interest rate volatilities are highly persistent (according to their standard deviation) indicating that the values cluster closely to their average value. The spread between 3-month commercial paper and the federal funds rate (CPFF) has the lowest mean value ($\mu = 0.17$) as well as a lower standard deviation ($\sigma = 0.283$) as compared to the other two interest rates. The average mean value for all of the three interest rates is $\mu = 0.38$ and the standard deviation is $\sigma = 0.512$ (almost 51%). The one-year constant maturity rate is one of the most widely used indexes and is often used by lenders as a reference point for adjustable rate for mortgages. The mean and standard deviation for one-year constant maturity rate is found 0.60 and 0.663 respectively from this sample study.

All the three option indices VIXCLS, VXNCLS and VXVCLS have much higher levels of implied volatility with the average mean of $\mu = 20.59$ and the standard deviation $\sigma = 8.405$ (almost 840%). The higher standard deviation means stock returns for the companies vary substantially from their average stock returns which can be considered as the reflection of revealing high levels of investor anxiety. The CBOE volatility index VIXCLS itself has the shortest level of maturity with$\mu = 19.50$but S&P 500 3-Month Volatility Index has the lowest level of implied volatility with $\sigma = 7.705$. A sharp shift took place recently in

[4]The null hypothesis for the ADF test will be $H_0$: $\delta = 0$ ( $y_t \sim I(1)$ ) against $H_a$: $\delta < 0$ ( $y_t \sim I(0)$ ) .

the S&P 500 Index options as the credit crisis unfolded. The mean and standard deviation for the exchange rate DEXCAUS is found $\mu = 1.13$ and $\sigma = 0.132$ or 13% respectively. However, the overall measure of the market expectations by the two near-term volatility indices CBOE NASDAQ 100 Volatility and CBOE S&P 500 3-Month Volatility are quite different than expected since they are based on some normalization scheme under CBOE. DEXJPUS has the highest mean and standard deviation with $\mu = 99.40$ and $\sigma = 13.619$ or 136%, over the class of three selected exchange rates. Nevertheless, the trend of exchange rate for Japan and Canada indicates an exchange rate appreciation against the U.S. dollar in this contemplated period. The mean and standard deviation for the exchange rate between Mexico and U.S. DEXMXUS is found $\mu = 14.35$ and $\sigma = 2.727$ shows a moderate depreciation in the past few years ascompared to the other two exchange rates. Other key statistics such as the lag length, minimum or maximum values, skewness, and kurtosis of the data sets are also displayed in Table 1 and are self-explanatory.

3.2 *Model Identification*

As noted earlier, the EG test is a two-step procedure that involves an OLS estimation for a prespecified co-integrating regression and a unit root test of the residuals saved from this step. The null hypothesis of no co-integration is rejected if it is found that the residuals are non-stationary. The EG test procedure for bivariate and multivariate co-integration is shown by estimating the so called co-integrating regression of the following form. Equation (8) exhibits the first step of this test:

$$spv_{1,t} = \beta_1 + \beta_2 \ xrt_{2,t} + \beta_3 \ xrt_{3,t} + \beta_4 \ xrt_{4,t} + u_t \qquad (8)$$

where $spv_t$ is the measurement for the stock price volatilities, $xrt_t$ is the exchange rate measurement. In the above regression it is assumed that all the variables are $I(1)$ and might be co-integrated to form a stationary relationship as well as a stationary residual term. This equation represents the assumed economically meaningful steady state or equilibrium relationship among the variables. If the variables are found co-integrating, they will share a common trend and form a stationary relationship in the long run. The second step in this procedure is to test for a unit root in the residual process to obtain the co-integrating regression. For this purpose, equation (9) for the estimated residual sequence is constructed.

$$\Delta\hat{u}_t = \alpha + \pi\hat{u}_{t-1} + \sum_{i=1}^{k} \gamma_i \, \Delta\hat{u}_{t-i} + v_t \qquad (9)$$

Under the null of no co-integration, the estimated residual will be $I(1)$ because $spv_t$ is $I(1)$, and all the parameters will be zero in the long run. Finding the optimal lag length is extremely important for the residual process to become the white noise.[5] If the unit root null hypothesis for the residuals is rejected then a significant $\pi$ implies $spv_t$ and $xrt_t$ are co-integrated. This means that the integrated variable $spv_t$ co-integrates at least with one of the variables on the right-hand side. The estimated results might end up with a few co-integrating relationships between stock volatilities and the exchange rates. Once a co-integrating relationship is established then the next step is to see whether the stock price volatilities are weakly exogenous or hang together to restore the equilibrium with the exchange rates. The following equation (10) will estimate the ECM:

$$\Delta spv_{1,\ t} = \sum_{i=1}^{k} \delta_i \Delta spv_{1,\ t\ -\ i} + \sum_{i=1}^{k} \gamma_i \Delta xrt_{1,\ t\ -\ i} - \pi(spv_{1,\ t\ -\ 1} - \beta_1 - \beta_2 xrt_{1,\ t\ -\ 1}) + \Delta \varepsilon_{1,t} \qquad (10)$$

where $\pi$ is the adjustment co-efficient that needs to be tested. If $\pi$ is found significant then there would be a long-run equilibrium relationship that exists between stock volatility and the exchange rate with a short-run dynamic adjustment mechanism. This implies that having some co-integration relationship, stock price volatility will not appear to be weakly exogenous and thus moves together to restore the equilibrium with exchange rates. On the other hand, the time series of the interest rates are found stationary i.e.$irt_t \sim I(0)$ and the series for the stock volatilities are found to be non-stationary i.e. $spv_t \sim I(1)$. Therefore, there would be no genuine long run relationship to exist between them and hence, no co-integration will exist between interest rate and stock price volatility. As $irt_t$ will be constant over time, $spv_t$ will increase over time.

One of the important characteristics of VAR models is that they allow us to test the direction of causality. Causality in econometrics refers to the ability of one variable to predict (and therefore cause) the other. The standard methodology this paper uses is the two-way Granger causality test, which is an indistinct but

[5] In fact, different standard statistical programming software and their applicable packages usually do the maximum work to generate the optimal lag length.

familiar application of the $F$-test. As previously stated, an ADF test for unit root will identify whether a series is non-stationary or a random walk process. If a time series is stationary, the causality test is performed by using their level values, but in contrast if the time series are found non-stationary, then the transformation of the series is done by taking the first differences.

The number of lags is usually chosen by using some information criterion such as Akaike Information Criterion (AIC). Any particular 'lagged' value of a variable will be retained in the regression if it is significant according to the specific $t$-test and hence, the other 'lagged' values of the variable will jointly add an explanatory power to the model according to an $F$-test. For the bivariate case, the directions of causation will be examined based on the following empirical models:

$$\Delta spv_{1,\ t} = \alpha_1 + \sum_{i=1}^{k_1} \delta_{1,i} \ \Delta spv_{1,\ t\ -\ i} + \sum_{i=1}^{k_2} \gamma_{1,i} \Delta xrt_{1,\ t\ -\ i} + \varepsilon_{1,t} \quad (11)$$

$$\Delta spv_{2,\ t} = \alpha_2 + \sum_{i=1}^{k_1} \delta_{2,i} \Delta spv_{2,\ t\ -\ i} + \sum_{i=1}^{k_2} \gamma_{2,i} \ \Delta irt_{2,\ t\ -\ i} + \varepsilon_{2,t} \quad (12)$$

where $irt_t$ is the measurement of the interest rate. The stock price volatilities and the exchange rate variables are expressed in their first differences. $\varepsilon_{1,\ t}$ and $\varepsilon_{2,\ t}$ are both uncorrelated white-noise error terms. The null hypothesis of no Granger causation from $xrt$ to $spv$ and also from $irt$ to $spv$ that is $\sum\gamma_{1,\ i} = 0$ or $\sum\gamma_{2,\ i} = 0$, will be tested by using the lower level of significance for the $F$-statistic. The reverse causation from $spv$ to $xrt$ and $spv$ to $irt$ will be evaluated by reversing the role of $spv$, $xrt$, and $irt$ in equations (11) and (12). In this case, four alternative patterns of causality can be possible: $(i) spv_t$ causes $xrt_t$ (unidirectional Granger causality from $spv$ to $xrt$), $(ii) xrt_t$ causes $spv_t$ (unidirectional Granger causality from $xrt$ to $spv$), $(iii)$ there would be a bi-directional causality (causality among the variables), and finally $(iv)$ the two variables will be independent (no causality).

The appropriate causality model that allows us to test and statistically detect the cause and effect relationship among multivariate case, is expressed by the following VAR(p) models:

$$\Delta spv_{1,\ t} = \alpha_1 + \sum_{i=1}^{k_1} \delta_{1,i} \Delta spv_{1,\ t\ -\ i} + \sum_{i=1}^{k_2} \gamma_{1,i} \ \Delta xrt_{1,\ t\ -\ i} + \sum_{i=1}^{k_3} \lambda_{1,i} \ \Delta irt_{1,\ t\ -\ i} + \varepsilon_{1,t} \quad (13)$$

$$\Delta xrt_{2,\ t} = \alpha_2 + \sum_{i=1}^{k_1} \delta_{2,i} \Delta spv_{2,\ t\ -\ i} + \sum_{i=1}^{k_2} \gamma_{2,i} \Delta xrt_{2,\ t\ -\ i} + \sum_{i=1}^{k_3} \lambda_{2,i} \ \Delta irt_{2,\ t\ -\ i} + \varepsilon_{2,t} \quad (14)$$

$$\Delta irt_{3,\ t} = \alpha_3 + \sum_{i=1}^{k_1} \delta_{3,i} \Delta spv_{3,\ t\ -\ i} + \sum_{i=1}^{k_2} \gamma_{3,i} \Delta xrt_{3,\ t\ -\ i} + \sum_{i=1}^{k_3} \lambda_{3,i} \ \Delta irt_{3,\ t\ -\ i} + \varepsilon_{3,t} \quad (15)$$

where $\varepsilon_{1t}$, $\varepsilon_{2t}$, and $\varepsilon_{3t}$ are again uncorrelated white-noise error terms and $spv_t$ and $xrt_t$ are integrated of order one while $irt_t$ is integrated of order zero. From the above sets of equations, the joint significance of the coefficients of 'lagged' independent variables will be evaluated to uncover the directions of causation between any pairs of the variables. If the coefficients of 'lagged' $xrt_t$ terms in equation (13) are statistically different from zero as a group and the coefficients of 'lagged' $spv_t$ terms in equation (14) are also statistically different from zero, but at the same time if the coefficients of 'lagged' $irt_t$ are not statistically different from zero both in equation (13) and (14) then two-way Granger causality will be seen between $xrt_t$ and $spv_t$. That means $xrt_t$ and $spv_t$ will have a bi-directional Granger causality. However, if the the coefficients of 'lagged' $irt_t$ are statistically different from zero in equation (13) but are not statistically different from zero in equation (14) then $irt_t$ will cause $spv_t$ in one direction and the reverse direction will be absent (unidirectional causality).

By the same token, if the 'lagged' terms of $irt_t$ in equation (14) are statistically different from zero as a group, and the 'lagged' $xrt_t$ terms in equation (15) are also statistically different from zero with a significant 'F-statistic' then it can be concluded that $irt_t$ and $xrt_t$ will resulting a bi-directional Granger causality. Again, if the sets of 'lagged' $spv_t$ terms in equation (14) are not statistically different from zero but the sets of 'lagged' terms of $spv_t$ in equation (15) are statistically different from zero as a group then for a significant F-value, a unidirectional causality will be exhibited between $irt_t$ and $spv_t$. Finally, if both sets of 'lagged' $irt_t$ terms and 'lagged' $spv_t$ terms are not statistically different from zero for an insignificant F-value in either equations (14) and (15) then it can be concluded that $xrt_t$ is independent of $irt_t$ and $spv_t$ (no causality).

## IV. EMPIRICAL RESULTS AND FINDINGS

4.1 *Co-integration Analysis*

The results for the bivariate and multivariate co-integration tests are reported in Tables 3 and 4. The co-integration test depends on the ADF unit root test of the selected variables. The unit root test results for all the respective variables are shown in Table 2. The three interest rates are found to be stationary in their levels.

Table 3 presents the results of co-integration for bivariate case. In this study, the bivariate EG test of co-integration between the stock volatility indices and the exchange rates are performed because they have a unit-root non-stationary process. The null hypothesis of no co-integration between the stock volatilities and the Mexico-U.S.$ exchange rates cannot be rejected in some cases. Table 3 reports the estimated coefficient from the co-integrating regression between different stock price volatilities measurement and the three exchange rates. Almost all the coefficients are found to be statistically significant. It also shows the unit root test results for the estimated residuals from those co-integrating regression. It reports the error-correction estimation results through the adjustment coefficient only when the two series are found co-integrated. The null hypothesis of unit root in the estimated residuals of a co-integrating regression between the ₱/$ exchange rate and the CBOE VIX volatility index is rejected at better than 1% level. It means that these two series are co-integrated or move together in the long run.

However, the null hypothesis of no co-integration cannot be rejected for S&P 500 3-month volatility index with the ₱/$ exchange rate but is rejected for NASDAQ 100 volatility index. The unit-root hypothesis cannot be rejected for the estimated residuals from those two co-integrating regressions. Besides, all other exchange rates and the stock price volatilities illustrate zero co-integration or having no long-run relationship between them. The error-correction estimation for the co-integrating regression of CBOE VIX volatility index and CBOE NASDAQ 100 volatility index with the ₱/$ rate are shown as an adjustment coefficient value of the residuals. In both cases the coefficients are found statistically significant; that means the CBOE VIX volatility variable is not weakly exogenous and moves together to restore the equilibrium with ₱/$ rate. In summary, the results of this paper suggest that stock price volatilities exhibit zero co-integration with several other exchange rates but provides the evidence of co-integration with the ₱/$ rate when investigated in a bivariate context.

Table 4 presents the co-integration result for the multivariate case. In the multivariate framework there seems to be a long-run relationship between the stock price volatility indices and the exchange rate measures. But the statistically insignificant error correction estimation shows that S&P 500 3-month volatility index and NASDAQ 100 volatility index are weakly exogenous to the exchange rates and will not move together to restore the equilibrium in the long-run. Nevertheless, the finding of multivariate co-integration rules out the possibility of non-causality between the variables, since the presence of co-integration suggests that there must be at least one direction of causation in the Granger sense. The following two sections examine the issue in detail.

4.2 *Results from Bivariate Causality Test*

This section investigates the empirical results produced by the bivariate Granger causality tests. Table 5 generates some stimulating results of the short-run interactions between stock price volatility and exchange rate. The null hypothesis for this test is that the stock volatility index does not cause exchange rate and vice-versa. The null hypothesis of no causation from the CBOE VIX stock price volatilities (VIXCLS) to the ₱/$ exchange rates is rejected at less than 1% level of significance. In contrast, the null hypothesis of no causation from the ₱/$ exchange rates to the S&P 500 3-month volatility (VXVCLS) and NASDAQ 100 (VXNCLS) stock volatility cannot be rejected. However, for the cases of C$/$ and ¥/$ exchange rates the changes in the stock prices have predictive power for those exchange rate changes. This paper documents unidirectional causality from the ¥/$ exchange rate and bi-directional causality from C$/$ exchange rate to those of the stock price volatilities; most of them are found to be highly statistically significant at 1% to 5% level of significance. These findings, however, may not be convincing as the regressions may suffer from omitted variable bias or fail to account for the possibility of another variable driving both the exchange rates and the stock price volatilities.

Table 5 shows that CBOE VIX volatility index and ¥/$ foreign exchange rate have a unidirectional causal relationship. However, CBOE S&P 500 3-month volatility index establishes a bi-directional causality with ¥/$ exchange rate. Both relationships are found to be significant at a large value of F-statistic. Nevertheless, the positive and negative sign of causality are also determined by the significant value of the long-run multiplier (LRM). In the case of interest rates, the stock volatilities produce significant amount of unidirectional and bi-directional Granger causality with those preferred rates. Table 6 shows that almost every selected interest rate exhibits at least one unidirectional causality over stock prices although many of their relationships postulate a negative causality sign. This means that the stock price volatilities Granger cause interest rates negatively.

Table 6 reports that the daily rates of 3-Month Treasury Bill (DTB3) shows a bi-directional Granger causality with all of the three CBOE volatility index, but it shows a negative causal relationship with the VIXCLS and VXVCLS. The spread between 3-month commercial paper and federal funds rate (CPFF) produce a feedback relationship for causality with VXVCLS. But VIXCLS, VXVCLS and VXNCLS indices show zero unidirectional causality for 1-year treasury constant maturity rate (DGS1); an index that is mostly used to set the cost of variable-rate loans such as adjustable rate mortgages. All the other test results of statistical significance or zero Granger causality have been ascertained from Table 6 by their respective lowest reported F-statistic and the corresponding probability values. Accordingly, it can also be predicted, at the same time, the causality sign of the test results by their LRM multiplier values and its significance from the corresponding probability values. The empirical results from those two tables produce two different bivariate flow charts. Figure 1 incorporates the stock volatility and the exchange rate variables with a node; each node exhibits a causal relationship and the arrow sign represents the direction of the causality. C$/$ exchange rate shows bi-directional Granger causality and ¥/$ exchange rate also displays two-way Granger causality with VXVCLS volatility index. Both are connected by two oppositely directed nodes. The interesting thing is that VXVCLS volatility index exhibits bi-directional Granger causality with the other two volatility rates. Finally, ¥/$ dollar rate shows a two-way Granger causality with C$/$ dollar rate.

Figure 2 captures several bi-directional Granger causality and more unidirectional causality between interest rate and the stock price volatility. DTB3 rate establishes bi-directional Granger causality with all three stock volatilities VIXCLS, VXNCLS and VXVCLS. CPFF has two-way Granger causality with VIXCLS and VXVCLS volatility index. Two-way Granger causality is evident from VXVCLS to volatility indices VIXCLS and VXNCLS. DGS1 shows unidirectional causality to all three volatility indices. The feedback causality from those three indices towards DGS1 are absent in this case.

4.3 *Results from Multivariate Causality Test*

Table 7 illustrates causality results for the multivariate case. In the Granger sense, the results confirm the previous bivariate findings that the stock price volatilities are causally linked to the effective interest rates with feedback effects. In the case of the DTB3 interest rate, there is bi-directional Granger causality with VIXCLS, VXVCLS and VXNCLS. The F-values for the joint significance test are found to be statistically significant and the sign of the causal relationship is determined by the significant values of LRM. Additionally, both the CPFF spread rate and the DGS1 turn out to be Granger caused by VIXCLS, VXVCLS and VXNCLS volatility index. But in return, those two interest rates do not Granger cause the three volatility indices of the interest. However, there is no evidence for feedback relationship from VIXCLS to CPFF and the DGS1 to VIXCLS.

The results appear to indicate that VIXCLS Granger causes the ₱/$ dollar exchange rate. But this causality is found to be statistically insignificant in the opposite direction. Additionally, the null hypothesis that there is no causation from VIXCLS and VXVCLS to that of ¥/$ and C$/$ exchange rates respectively, is not rejected in both cases. This means the ¥/$ rate and C$/$ rate is an insignificant indicator for VIXCLS and VXVCLS volatility indices. Similarly, there is no causality from the VXNCLS to ₱/$, ¥/$, C$/$ rate. Only a feedback relationship for causality is established for VXVCLS and ₱/$ rate. The F-statistic is high enough to reject the null at 1% level of significance in both cases. These results indicate that the ChicagoBoardOptions and Exchange market is ceremoniously efficient. The findings of this study are also more or less consistent with some findings of Kim (2003) and Soenen and Hennigar (1988). Moreover, their results indicate that the importance of interest rate regulation and monetary policies could be more effective in explaining the movements of the U.S. equity market.

For the multivariate case, Figure 3 produces a total of six bivariate Granger causalities. DTB3 shows three bi-directional Granger causality with VIXCLS, VXVCLS and VXNCLS. ₱/$ratesproduce the bivariate causality with VXVCLS. DGS1 has created a feedback causal relationship with ₱/$ rate. ¥/$ foreign exchange rate unidirectionally causes VXVCLS and VXNCLS. ₱/$ rate creates a bi-directional causality with DTB3. However, the flow chart reveals that C$/$ rate has a unidirectional Granger causality to VXNCLS and VXVCLS. On the other hand, CPFF has a unidirectional Granger causality to ₱/$ rate and ¥/$ rate. VXVCLS has a unidirectional causal relationship with DGS1 interest rate but there is a one-way Granger cause from VIXCLS to DGS1. However, DGS1 shows a two-way Granger causality effect with ¥/$ rate. In summary, it is apparent that three interest rates produce more bi-directional Granger causality in terms of the numbers with stock volatilities than in comparison with exchange rates. The findings of this study, therefore, substantiate that interest rate has discernible causal impact on stock price volatilities but exchange rates, although created few causal relationships, cannot be identified as noticeable factors.

## V. Conclusion

This research empirically examines the dynamics between the volatility of stock returns, the movement of dollar exchange rates, and interest rates in terms of the extent of interdependence and causality. The standard co-integration test and Granger procedure has been applied to investigate the interactions between three major exchange rates (in terms of the U.S. trade-volumes), three important representative interest rates and three stock market indices for the Chicago options market. Daily data sets from December 2007 to December 2017 have been used. The results from the bivariate models indicate no long-run relationship between the stock volatility indices and ¥/$ and C$/$ exchange rates but there is evidence of long-run relationships between VIXCLS, VXNCLS and the ₱/$ currency exchange rate. However, there is some indication for co-integration when the models are extended to include all the exchange rates and the stock volatilities. On the other hand, co-integrating relationships between the stock volatilities and the interest rate cannot be possible because the interest rate variables are found stationary in nature.

However, the absence of co-integration in bivariate cases subsequently exhibits a few Granger causalities in between exchange rates and the stock market volatilities. The empirical findings from the causality tests reveal strong statistical evidence by establishing severalunidirectional and bi-directional causal relationships between the stock price volatility and the interest rate. First, there is a unidirectional causality from all the three stock price volatilities to the 3-month treasury bill. Additionally, a feedback effect from the 3-month treasury bill to the stock volatilities is also observed. Second, three stock volatility indices and the exchange rates are Granger caused by the one-year treasury constant maturity rate and the three-month commercial paper rate minus federal funds rate. There is also evidence of bi-directional causality between the CBOE S&P 500 3-month volatility index and the ₱/$ exchange rate. The extent of unidirectional causal relationships with stock volatility indices with the other exchange rates is insufficient when compared to the interest rates.

Finally, this study presents more significant unidirectional as well as bi-directional causalities from interest rates to stock returns and other significant unidirectional causalities from exchange rates to stock returns. However, in the opposite cases the feedback effect of exchange rates mostly did not exist. The findings of this paper suggest that the ₱/$ rate might play an important role in the U.S. stock market in the short-run. The changes in the exchange rate reflects the international competitiveness of United States' exports, one of the factors in U.S. growth rate over the past two decades. Additionally, the results focus on the fact that the stock price volatility at the Chicago Options Market is driven considerably by government-based interest rates regulations. These changes in interest rates mainly reflect the presence of any short-run bi-directional causal link from DTB3 and CPFF in the Chicago Options and Equity market.

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## APPENDICES

**TABLE 1**:*Summary Statistics (2007-2017).*

| Variables† | Mean | Std. Dev. | Min. | Max. | Skewness | Kurtosis | Lag Length |
|---|---|---|---|---|---|---|---|
| VIXCLS | 19.497 | 8.8746 | 9.14 | 80.06 | 2.29 | 7.73 | 18 |
| VXNCLS | 21.168 | 8.6342 | 10.31 | 79.16 | 2.35 | 8.39 | 18 |
| VXVCLS | 21.118 | 7.7056 | 11.85 | 64.35 | 1.82 | 7.45 | 18 |
| DTB3 | 0.3734 | 0.5867 | -0.02 | 3.29 | 2.28 | 5.20 | 20 |
| CPFF | 0.1690 | 0.2831 | -0.53 | 2.91 | 4.79 | 29.55 | 20 |
| DGS1 | 0.5988 | 0.6625 | 0.08 | 3.49 | 1.79 | 2.62 | 17 |
| DEXMXUS | 14.3543 | 2.7271 | 9.92 | 21.89 | 1.05 | 12.56 | 20 |
| DEXJPUS | 99.4039 | 13.6198 | 75.72 | 125.58 | -0.41 | 4.69 | 19 |
| DEXCAUS | 1.1279 | 0.1318 | 0.94 | 1.46 | -0.25 | 8.38 | 10 |

Note: Number of Observations are 2,416; †all of the variables are measured in their levels; VIXCLS means CBOE Volatility Index: VIX; VXNCLS means CBOE NASDAQ 100 Volatility Index; VXVCLS means CBOE S&P 500 3-Month Volatility Index; DEXMXUS stands for ₱/$ Foreign Exchange Rate; DEXJPUS means ¥/$ Foreign Exchange Rate; DEXCAUS means C$/$ Foreign Exchange Rate; DTB3 stands for 3-Month Treasury Bill: Secondary Market Rate; CPFF stands for 3-Month Commercial Paper Minus Federal Funds Rate; DGS1 stands for 1-Year Treasury Constant Maturity Rate.

**TABLE 2:***Unit Root Test.*

| ADF Test | | |
|---|---|---|
| Variables† | *Tau*-Statistics in level | *Tau*-Statistics after difference |
| VIXCLS | -2.21881 | -23.95152 |
| VXNCLS | -2.10924 | -21.30651 |
| VXVCLS | -2.51276 | -19.03378 |
| DEXMXUS | 1.24498 | -30.6357 |
| DEXJPUS | -0.133204 | -13.4615 |
| DEXCAUS | 0.691829 | -24.1448 |
| DTB3 | -4.50269 | - |
| CPFF | -3.73479 | - |
| DGS1 | -3.94405 | - |

Note: †three stock price volatilities and the three exchange rate variables are found to be first difference stationary, i.e. they are I(1); the three interest rate variables are found I(0) at their levels.

TABLE 3:*Co-integration Tests (Bivariate Case).*

| Engle-Granger Test | | | |
|---|---|---|---|
| Variables | Coefficient | Test-statistic for Residuals | Adjustment Coefficient |
| (a)VIXCLS, DEXMXUS | -1.1005*** | -3.9841* | -0.0234*** |
| | (-15.77)† | (0.052)‡ | (-2.786)† |
| VIXCLS, DEXJPUS | -0.1996*** | -2.5947 | |
| | (-14.80) | (0.196) | |
| VIXCLS, DEXCAUS | -6.4481** | -2.6815 | |
| | (-2.41) | (0.179) | |
| (b) VXVCLS, DEXMXUS | -0.9134*** | -2.8892 | |
| | (-15.27) | (0.139) | |
| VXVCLS, DEXJPUS | -0.1999*** | -2.8277 | |

| | | | |
|---|---|---|---|
| | (-17.65) | (0.157) | |
| VXVCLS, DEXCAUS | -5.9372** | -2.6134 | |
| | (-3.74) | (0.232) | |
| (c) VXNCLS, DEXMXUS | -1.0037*** | -3.4231** | -0.0213** |
| | (-14.83) | (0.039) | (-2.556) |
| VXNCLS, DEXJPUS | -0.1578*** | -2.6836 | |
| | (-11.97) | (0.169) | |
| VXNCLS, DEXCAUS | -4.1666** | -2.6627 | |
| | (-2.94) | (0.156) | |

Note: †figures inside the parentheses indicate t-ratio for the entire column; ‡figures inside the parentheses indicate the asymptotic p-value for the entire column; the null hypothesis for testing residuals is that estimated residuals has a unit root; *significant at 10% level, **significant at 5% level, ***significant at 1% level.

**TABLE 4:** *Co-integration Tests (Multivariate Case).*

| Engle-Granger Test | | | | |
|---|---|---|---|---|
| Variables | | Coefficient | Test Statistics for Residuals | Adjustment Coefficient |
| (a) VIXCLS | DEXMXUS | -5.6129*** | -5.62805 | -0.02867*** |
| | | (-49.53)† | (0.001)‡ | (-2.58)† |
| | DEXJPUS | -0.6441*** | | |
| | | (-42.20) | | |
| | DEXCAUS | 143.071*** | | |
| | | (49.66) | | |
| (b) VXVCLS | DEXMXUS | -4.7561*** | -4.91534 | -0.01463 |
| | | (-51.57) | (0.003) | (-1.95) |
| | DEXJPUS | -0.6068*** | | |
| | | (-48.87) | | |
| | DEXCAUS | 125.502*** | | |
| | | (53.53) | | |
| (c) VXNCLS | DEXMXUS | -5.4311*** | -5.37601 | -0.02534 |
| | | (-48.20) | (0.006) | (-1.29) |
| | DEXJPUS | -0.5773*** | | |
| | | (-38.05) | | |
| | DEXCAUS | 136.955*** | | |
| | | (47.81) | | |

Note: †figures inside the parentheses indicate t-ratio for the entire column; ‡figures inside the parentheses indicate the asymptotic p-value for the entire column; the null hypothesis for testing residuals is that estimated residuals has a unit root;*significant at 10% level, **significant at 5% level, ***significant at 1% level.

**TABLE 5:** *Bivariate Causality Results (Stock Volatility and Exchange Rate).*

| Null Hypothesis* | F-Value | Pr (F≥f) | Long Run Multiplier (LRM)† | Pr(≥LRM)‡ |
|---|---|---|---|---|
| VIXCLS dnc DEXMXUS | 3.6035 | 0.000*** | 1.00E-04 | 0.332 |
| DEXMXUS dnc VIXCLS | 2.4197 | 0.058* | 139.577 | 0.407 |
| VXVCLS dnc DEXMXUS | 0.8489 | 0.279 | 1.00E-03 | 0.049 |
| DEXMXUS dnc VXVCLS | 0.1577 | 0.138 | 135.504 | 0.417 |
| VXNCLS dnc DEXMXUS | 3.4884 | 0.006*** | 1.00E-04 | 0.024 |
| DEXMXUS dnc VXNCLS | 1.2649 | 0.159 | 93.7300 | 0.388 |
| VIXCLS dnc DEXCAUS | 5.7695 | 0.000*** | 0.84240 | 0.493 |
| DEXCAUS dnc VIXCLS | 6.5271 | 0.040** | 0.03127 | 0.017 |

| | | | | |
|---|---|---|---|---|
| VXVCLS dnc DEXCAUS | 6.0528 | 0.000*** | 0.00312 | 0.041 |
| DEXCAUS dnc VXVCLS | 5.8241 | 0.001*** | 3144.694 | 0.309 |
| VXNCLS dnc DEXCAUS | 0.1056 | 0.579 | 0.003 | 0.493 |
| DEXCAUS dnc VXNCLS | 4.3491 | 0.000*** | 0.0958 | 0.039 |
| VIXCLS dnc DEXJPUS | 2.9811 | 0.000*** | -0.002 | 0.000 |
| DEXJPUS dnc VIXCLS | 0.294 | 0.587 | -2.377 | 0.449 |
| VXVCLS dnc DEXJPUS | 3.0822 | 0.000*** | -0.003 | 0.057 |
| DEXJPUS dnc VXVCLS | 4.0521 | 0.044** | 0.0006 | 0.037 |
| VXNCLS dnc DEXJPUS | 3.6385 | 0.000*** | -0.003 | 0.032 |
| DEXJPUS dnc VXNCLS | 0.0755 | 0.784 | -1.074 | 0.485 |

Note: dnc means does not cause; †LRM is used to find out the specific sign of the causality; ‡pr(LRM) is the probability value when the null of LRM is not different from zero; ⋆all the variables are measured in their first differences; *significant at 10% level, **significant at 5% level, ***significant at 1% level.

**TABLE 6:***Bivariate Causality Results (Stock Volatility and Interest Rate).*

| Null Hypothesis⋆ | F-Value | Pr (F≥f) | Long Run Multiplier (LRM)† | Pr(≥LRM)‡ |
|---|---|---|---|---|
| VIXCLS dnc DTB3 | 3.2528 | 0.002*** | -0.0046 | 0.027 |
| DTB3 dnc VIXCLS | 9.3967 | 0.003*** | 0.0043 | 0.078 |
| VIXCLS dnc CPFF | 5.8332 | 0.001*** | -0.0024 | 0.053 |
| CPFF dnc VIXCLS | 8.7911 | 0.000*** | 0.0061 | 0.021 |
| VIXCLS dnc DGS1 | 0.5595 | 0.583 | -0.0713 | 0.437 |
| DGS1 dnc VIXCLS | 3.9987 | 0.001*** | 0.0039 | 0.037 |
| VXVCLS dnc DTB3 | 2.0408 | 0.061** | -0.0478 | 0.041 |
| DTB3 dnc VXVCLS | 7.0199 | 0.000*** | 0.0003 | 0.048 |
| VXVCLS dnc CPFF | 5.5638 | 0.000*** | -0.0048 | 0.052 |
| CPFF dnc VXVCLS | 9.3164 | 0.003*** | 0.0080 | 0.027 |
| VXVCLS dnc DGS1 | 0.4336 | 0.283 | -0.0743 | 0.957 |
| DGS1 dnc VXVCLS | 2.3444 | 0.002** | 6.7477 | 0.426 |
| VXNCLS dnc DTB3 | 1.8918 | 0.025** | -0.000 | 0.043 |
| DTB3 dnc VXNCLS | 8.1392 | 0.000*** | 5.6498 | 0.387 |
| VXNCLS dnc CPFF | 0.7555 | 0.361 | 0.0011 | 0.483 |
| CPFF dnc VXNCLS | 8.2831 | 0.000*** | 24.8066 | 0.255 |
| VXNCLS dnc DGS1 | 0.0482 | 0.286 | -0.0818 | 0.389 |
| DGS1 dnc VXNCLS | 3.8616 | 0.000*** | 0.0009 | 0.032 |

Note: dnc means does not cause; †LRM is used to find out the specific sign of the causality; ‡pr(LRM) is the probability value when the null of LRM is not different from zero; ⋆only the stock volatilities variables are measured in their first differences; *significant at 10% level, **significant at 5% level, ***significant at 1% level.

**TABLE 7:***Multivariate Causality Results.*

| Null Hypothesis⋆ | F-Value | pr (F≥f) | Long Run Multiplier (LRM)† | pr(≥LRM)‡ |
|---|---|---|---|---|
| VIXCLS dnc DEXMXUS | 2.3219 | 0.023** | 2.00E-04 | 0.065 |
| VIXCLS dnc DEXCAUS | 0.7995 | 0.287 | 0.1097 | 0.429 |
| VIXCLS dnc DTB3 | 3.2589 | 0.001*** | -0.0046 | 0.044 |
| VXVCLS dnc DEXMXUS | 2.6705 | 0.000*** | 1.00E-04 | 0.026 |
| VXVCLS dnc DEXCAUS | 0.0812 | 0.694 | 0.000 | 0.254 |
| VXVCLS dnc CPFF | 5.5677 | 0.000*** | -0.0043 | 0.044 |

| | | | | |
|---|---|---|---|---|
| VXVCLS dnc DGS1 | 2.4259 | 0.024** | -0.0174 | 0.451 |
| VXNCLS dnc DEXJPUS | 0.4541 | 0.385 | -0.0037 | 0.225 |
| VXNCLS dnc DTB3 | 2.8774 | 0.014** | 0.0049 | 0.037 |
| VXNCLS dnc CPFF | 5.7779 | 0.000*** | 0.0014 | 0.049 |
| VXNCLS dnc DGS1 | 2.0465 | 0.062** | -0.0083 | 0.041 |
| DEXMXUS dnc VXVCLS | 3.5928 | 0.000*** | 198.248 | 0.361 |
| DEXMXUS dnc VXNCLS | 0.6302 | 0.383 | 72.0766 | 0.346 |
| DEXJPUS dnc VXNCLS | 2.9465 | 0.000*** | 0.00128 | 0.049 |
| DEXCAUS dnc VXVCLS | 2.6824 | 0.029** | 1655.61 | 0.414 |
| DEXCAUS dnc VXNCLS | 2.8983 | 0.015** | 0.00239 | 0.049 |
| DTB3 dnc VIXCLS | 9.3403 | 0.000*** | 0.00046 | 0.048 |
| DTB3 dnc VXNCLS | 8.1121 | 0.001*** | 0.00079 | 0.008 |
| CPFF dnc VIXCLS | 8.7873 | 0.000*** | 26.7801 | 0.114 |
| DGS1 dnc VXVCLS | 2.3437 | 0.001*** | 6.8468 | 0.4324 |
| DGS1 dnc VXNCLS | 3.8416 | 0.000*** | 6.7591 | 0.3361 |

Note: dnc means does not cause; †LRM is used to find out the specific sign of the causality; ‡pr(LRM) is the probability value when the null of LRM is not different from zero; *stock price volatilities and the exchange rates variables are measured in their first differences; *significant at 10% level, **significant at 5% level, ***significant at 1% level.

**FIGURE 1:***Flow Chart of Bivariate Granger Causality (Stock Volatility and Exchange Rate.)*

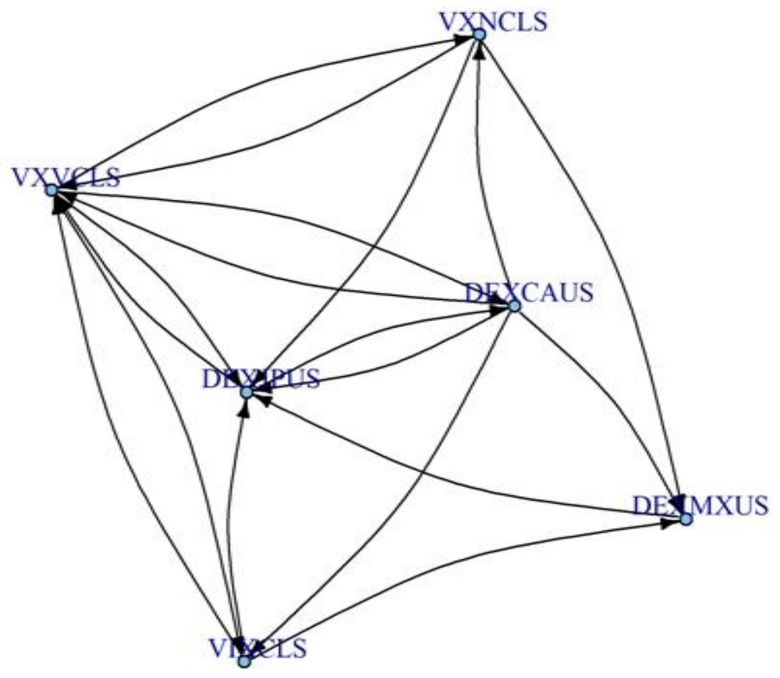

**FIGURE 2:***Flow Chart of Bivariate Granger Causality (Stock Volatility and Interest Rate.)*

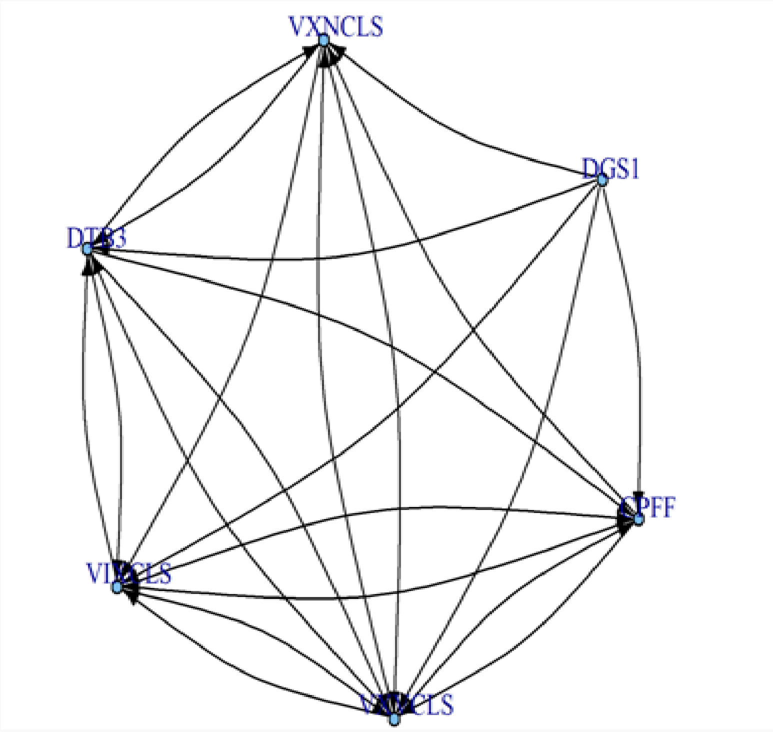


**FIGURE 3:***Flow Chart of Multivariate Granger Causality (Stock Volatility, Exchange Rate and Interest Rate.)*