Discerning lead-lag between fear index and realized volatility

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Abstract

In theory, historical volatility gauges the fluctuations of underlying assets or securities by monitoring changes in price over predetermined time period, while implied volatility looks into the future in its attempts to forecast the movement of the asset's price based on current ones. Option trader tends to combine both volatilities with realized volatility serving as the baseline and implied volatility redefining the relative values of the options. Henceforth, the purpose of this study is twofold; first is to investigate the nature of lead-lag between the 'fear index' (VIX) and its corresponding realized volatility (RVI) of S&P 500 indices. Second, we examine the dynamic analysis of implied volatility transmission across inter-market correlation with newly adapted volatility indices from CBOE, VIX, OVX and GVZ to indicate which market is leading. Contrary to the popular perception, the paper finds that S&P 500 implied volatility is lagging its historical variance markedly, and surprisingly even its price index is leading the implied volatility as well. The study also concludes that Gold spearheads the market with stocks being the most sensitive to shocks. Our findings have clear policy implications for trading strategies and using volatilities in risk management.

Keywords: implied volatility, realized volatility, inter-market correlation, VIX, OVX, GVZ

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1.0 INTRODUCTION

In option trading, traders are involved in betting on an underlying asset's volatility, thus the importance of understanding these volatility matrices cannot be made more momentous. As a trader, it is vital to comprehend that one will be presented with two metrics of volatility; historical as well as implied volatility, and the combination of both metrics will directly influence an option's price. In theory, historical volatility gauges the fluctuations of underlying assets or securities by computing price changes over predetermined time period. It is looking back in time to see how much a stock price has fluctuated on daily basis over one-year period, for example. Implied volatility on the other hand, looks into the future as the name suggests; based on current prices, attempts to forecast the movement of the asset's price. It takes forward-looking analysis on options premium translated into probability, and the level of demand and supply of the option will drive the implied volatility reading. Option trader tends to combine both volatilities with realized volatility serving as the baseline and implied volatility redefining the relative values of the options.

In layman's term, implied volatility is the market expectation on the future realized volatility on the underlying asset over the remaining life of an option (Badshah, 2009). Major options exchange platform including the Chicago Board of Exchange (CBOE) and others have launched implied volatility indices covering main industry such as gold, crude oil and key-player stock markets to cater for the needs of the investors. The new indices give measurement of the option traders' consensus opinion on the future direction of the asset's volatility over the next 30 days, given that traders' opinion is considered professional judgments by the market. For example, the CBOE VIX is implying information of implied volatility for S&P 500 stock index while the CBOE VXN relays information principally for NASDAQ 100. Each implied volatility index often referred to as the 'investor's fear gauge' (Whaley, 2000) to illustrate the fear in the market expectations of the future price. Thus, this paper is trying to answer these main questions; (1) what is the nature of lead-lag relationship between fear index (implied volatility) and the historical volatility? (2) How closely are the volatilities linked in respect to the price of the option? (3) If such a relationship exists, why does the market need to rely on both indices, rather than focusing on one significant volatility?

With information from the data, it is discovered that S&P 500 implied volatility is lagging behind its historical volatility, which is contrary to the current understanding on the nature of their relationship. Price is also surprisingly leading the implied volatility, which will be further disclosed in the findings.

The paper is also trying to look into the degree of inter-market correlation, which benefits the investors with diversification availability in investment opportunity portfolio. With market integration developing robustly over the past decades due to economic integration through trade and investments, correlations among stock markets are also proven to increase across the globe (Bekeart, Harvey, & Lundblad, 2001). International investors may raise question on (4) is there any effect on the inter-market volatilities when one market experiences economic shocks, and if there is, how long does it take for the markets to get back into equilibrium? And finally (5) which market returns and shocks is leading others? It is in the interest of the paper to look for the long-run relationship amongst the markets and finds that Gold market leads the other volatilities and is least affected by any shock on other markets, while stock market has the most sensitive returns.

The study is built on previous literature by other researches on finding the relationship between the two volatilities but differs in two aspects. We study the S&P 500 volatilities using Auto Regressive Distributed Lag Model (ARDL), which has never been adopted before in this case and the after-effect of the inter-market co-integrations. Realized volatility index from S&P 500 also has not been used in previous literature as the authors tend to estimate the historical volatilities using mean and variance of the returns. The findings should help a trader in search of relationship between these volatilities and its global market correlation as well as helping policy maker play their role in controlling or improving stock markets across the borders. Potential investors can also be benefitted in decision making process to choose portfolio with the right economic outlook and anticipated changes in returns. The paper is also trying to analyze the kernel of implied volatility concerning different markets, which has yet to be explored thoroughly and for which only a few references can be found.

The rest of this paper is organized as follows. The issues that encourage this study and objectives of the study will be shown in Section 1 (Introduction). Section 2 provides a brief review on theoretical perspectives and past literature related to the issues. Section 3 discusses the data and methodology used throughout the research period. Empirical results will be discussed thereafter in Section 4 and an ending with conclusion remarks on policy implications in Section 5.

2.0 LITERATURE REVIEW

Since the 90s, it is established that implied volatility triumphed over realized or historical volatility when one in need to forecast the future returns' variance of an underlying asset (Christensen & Prabhala, 1998) (Dumas, Fleming, & Whaley, 1998). A similar paper also discussed on the S&P 500 implied and realized volatility dynamic by examining the measurement error in both volatilities and concluded that implied gave more information in forecasting realized and the latter has less explanatory power to the former (Shu & Zhang, 2000). Fleming also argues that the implied volatility dominates the historical volatility rate in terms of ex ante forecasting power, using employment of ARCH variation model when measuring the S&P 100 indices (Fleming, 1998). These papers consistently argue that implied volatility outperforms past or historical variances in forecasting future returns. Various method and analysis were conducted among the papers to justify their findings.

There are however, researches that found conflicting outcome. Day in his study concluded that implied volatility is biased and inefficient, where past volatilities give batter predicament on future variances beyond in what contained in implied (Day, 1992). Supporting Day's conclusion by using overlapping data with different sample period also gave out the same outcome. A much recent study also gives the same findings with the increasing availability of financial intra-day market data frequencies for volatility forcasting. Another study shows a convincing empirical result that realized volatility models produces more accurate forecasts compared to implied volatility (Koopman, Jungbacker, & Hol, 2005), again by evaluating S&P 100 index using GARCH methodology. However, the most striking results said that implied volatility to be a poor forecast of subsequent realized volatility, and virtually has no correlation altogether with future returns as it does not incorporate information passed through recent observed volatility (Canina & Figlewski, 1993). Prahbala and Christensen argues that the latter result was surprising and extreme, more so because the evidence pertains S&P 100 Index option which is regarded as the most active option market. The goal for this paper is to reaffirms the contradictory findings on S&P Indices as it can give a much clearer picture to other markets. With a new technique and broader and recent data range, the findings of this paper are anticipated to enlighten the situation.

The paper also tries to perform a scrutinize analysis on various implied volatilities from three different market; gold, crude oil and stock itself. Co-integration and linear or non-linear causality amongst these three markets has been discussed beforehand in few literatures fitting to flowing of information and emerging economies across the borders. Evidence from Indian market indicates the presence of co-integration relationship and positive non-linear impact of implied volatilities of gold and oil on the Indian stock markets (Bouri, Jain, Biswal, & Roubaud, 2017). The paper is extremely recent and thoroughly discuss on the variables. Luo and Qin presented another good argument in their paper on Chinese stock returns over oil price uncertainty. Evidence indicates that crude oil volatility index (OVX) shocks have significant impact on Chinese stock returns (Luo & Qin, 2017). The most exemplary literature did and empirical analysis of implied volatility index by fixing OVX as its dependent against other implied volatilities. The results verify the effectiveness of cross-market volatility portfolio strategy to hedge risk by indicating strong influenced of other volatilities on OVX. These papers show that there are overflowing effects of one-market returns to another thus indicating integration amongst the volatilities. It is the goal of an author to try and established on which market is leading in terms of shocks and returns.

3.0 DATA AND METHODOLOGY

3.1 Data Extraction

The study uses data from two sources, the CBOE and the S&P 500® databases.

The Chicago Board of Exchange (CBOE) is the world's largest option exchange platform that focuses on options contracts for individual entities, corporation indices and interest rates. Three implied volatility indices were extracted from the CBOE, namely;

i) **CBOE S&P 500 Implied Volatility Index (VIX),**

ii) **CBOE Crude Oil ETF Volatility Index (OVX), and**

iii) **CBOE Gold Volatility Index (GVX),**

on daily basis data from August 31st, 2010 to April 28th, 2017 (1,677 observations). CBOE VIX index is considered by many to be the premier barometer of equity market volatility. It is based on real-time prices of options on the S&P 500® Index and is designed to reflect investors' consensus view of 30-days in future for expected stock market volatility. Using the VIX methodology, CBOE OVX measures the market's expectation of 30-day volatility of crude oil prices od US Oil Fund options spanning its strike prices. The last index, CBOE GVZ also measures expectation of 30 days volatility but onto Gold Shares.

The S&P 500® is chosen to represent the option trading platform market for the study as it is widely regarded as the best single gauge of large-capital US equities. The index includes 500 top companies with approximately 80% coverage of available market capitalization. Using the same time frame observation, two indices are extracted;

i) **The S&P 500 Price Index (PI), and**

ii) **The S&P 500 Realized Volatility Index (RVI).**

The PI is self-explanatory while the RVI is the variations of the real-price of the option.

3.2 Methodology

The goal of the study is to study the relationship between the options' implied and realized volatility (1) and its effect towards pricing (2 & 3). The identified model will incorporate the other two implied volatilities to answer the $(4)^{th}$ and $(5)^{th}$ questions, which are looking into cross-market interrelationship. The functional form of the model is,

$\boldsymbol{PI = f(RVI, VIX, OVX, GVZ)}$ where,

PI = S&P 500 Price Index,

RVI = S&P 500 Realized Volatility Index,

VIX = CBOE S&P 500 Implied Volatility Index,

OVX = CBOE Crude Oil ETF Volatility Index, and

GVZ = CBOE Gold Volatility Index.

In proceeding with the research, a few test were ran and it is disclosed that the most suitable method to be adapted is by using the Autoregressive Distributed Lag Model (ARDL) method because of the stationary status of the data (variables contains a mixture of I(0) and I(1)) at the leveled form. Below are the required tests in completing this study.

i) **Unit Root Test:** To test whether the data are stationary or non-stationary at both Leveled and Differenced forms.

ii) **Lag Order Selection:** Determines the number of lag for the data

iii) **Bound Test:** *(ARDL approach to co-integration)* Examines the existence of long-run relationship among the variables,

iv) **Diagnostic Test:** Tests whether the models are well specified or not

v) **Error Correction Model (ECM):** Observes the lead-lag situation of the variables; which variables are endogenous and which are exogenous

vi) **Variance Decomposition (VDC):** Finds relative value of exogeneity and endogeneity

vii) **Impulse Response Function (IRF):** Graphical visual of VDC by way of tracing variables response towards shock.

4.0 EMPIRICAL RESULT

This section will report the findings of each test taken for the ARDL methodology approach in running the data.

4.1 Unit Root Test

Most time series data exhibit trending behavior non-stationarity in the mean value. Thus the first step to analyze time series data is to determine the most appropriate form of the variable within available data set to remove any trending comportment applicable. The most common trend removal is by first-differencing the data for I(1). For this study, two methods of unit root testing are used to justify the usage of ARDL instead of the ordinary regression (Ordinary Least Square Method) or the Vector Auto-Regression (VAR) model. Both methods, Augmented Dickey Fuller (ADF) test and Phillip-Perron (PP) test indicate whether the variables are stationary at level form, I(0) or in the first-differenced form, I(1). Both test correct autocorrelation problem but PP also adjusts for Heteroskedasticity issue using Newey-West adjusted variance method. The result from both test depends on each variable t-statistic value; if T-stat > Critical Value, the variables are stationary and if T-stat < Critical Value, then the variable is considered non-stationary. Both tests are performed on extracted data and the results as below;

Log (Level) Form, I(0)

VARIABLE		ADF	VALUE	T-STAT.	RESULT
PI	AIC	3	4708.3	-2.560	**Non-Stationary**
	SBC	1	4695.1	-2.675	Non-Stationary
VIX	AIC	5	2001.8	-5.062	**Stationary**
	SBC	1	1989.6	-6.019	Stationary
RVI	AIC	5	2097.4	-5.378	**Stationary**
	SBC	4	2077.1	-5.142	Stationary
OVX	AIC	5	2690.8	-2.401	**Non-Stationary**
	SBC	3	2680.9	-2.634	Non-Stationary
GVZy	AIC	5	2486.3	-4.429	**Stationary**
	SBC	3	2479.3	-4.628	Stationary

Critical Value = -3.4154

Table 1: ADF Test Result for Leveled Form

First-Differenced Form, I(1)

VARIABLE		ADF	VALUE	T-STAT.	RESULT
PI	AIC	4	4708.1	-19.728	**Stationary**
	SBC	2	4692.5	-23.663	Stationary
VIX	AIC	4	1989.4	-21.677	**Stationary**
	SBC	1	1974.1	-30.551	Stationary
RVI	AIC	3	2083.2	-16.867	**Stationary**
	SBC	1	2070.6	-24.934	Stationary
OVX	AIC	4	2680.0	-21.040	**Stationary**
	SBC	1	2664.5	-29.245	Stationary
GVZ	AIC	5	2470.6	-19.672	**Stationary**
	SBC	2	2457.8	-27.187	Stationary

Critical Value = -2.8637

Table 2: ADF Test Result for Differenced Form

From the tables, ADF Test in the Log (Level) Form shows a mixture of stationary and non-stationary data, with 2 variables are already stationary at its actual form, where its t-statistics value are significantly greater than the critical value. The above said variables are the realized volatility index (RVI), implied volatility index (VIX) and the gold volatility index (GVZ). On the other hand, all variables are deemed stationary at its first-differenced form as illustrated in Table 2. To further prove the result, PP Tests are run and the results illustrated below yield the same outcome as the ADF Test.

Log (Level) Form, I(0)

VARIABLE	T-STAT.	RESULT
PI	-2.883	**Non-Stationary**
VIX	-7.330	**Stationary**
RVI	-3.664	**Stationary**
OVX	-2.828	**Non-Stationary**
GVZ	-6.248	**Stationary**

Critical Value = -3.4154

Table 3: PP Test result for Leveled Form

First-Differenced Form, I(1)

VARIABLE	T-STAT.	RESULT
PI	-42.810	**Stationary**
VIX	-57.839	**Stationary**
RVI	-37.834	**Stationary**
OVX	-44.496	**Stationary**
GVZ	-51.564	**Stationary**

Critical Value = -3.2840

Table 4: PP Test result for First Differenced form

Thus, as our variables have combination of both I(0) and I(1), ARDL approach is the best method available to test the long run relationship among the variables; VAR requires stationary in I(0).

4.2 Lag Order Selection

To proceed with ARDL steps, order of the lag of the vector must be determined by performing test statistics and choice criteria of selecting the order. Using optimal order given by the highest value of Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and adjusted Likelihood Ratio (LR), the following results are obtained.

Optimal Order	AIC	SBC	Adjusted LR
3	13226.2		
1		13120.6	
1			279.3455 [.000]

Table 5: Lag Order of the VAR

The highest value of AIC gives the optimal order of three (3) while SBC inclines the first (1) order of VAR. By theory, AIC does tends to choose the higher lag order while SBC chooses the lower lag. Thus, it is consistent with our findings and the paper will still run both AIC and SBC while obtaining tests result, but when needed, AIC with lag order of 3 will be prioritized based on our nature of data. Having daily data gives us a bigger space to chose the higher lag.

4.3 Bound Test (ARDL approach to co-integration)

Differ from VAR approach, ARDL method uses bound test as a tool to discover any long-run relationship or co-integration among the variables chosen. It is important to note that the regression constructed while running the test must not indicate any prior information on the direction of the relationship. In other words, if the variables co-integrated, one may prove any theoretical relationship between them. The test is testing;

H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ - Long-run relationship does not exists

H_1: : $\delta_1 \neq \delta_2 \neq \delta_3 \neq 0$ - Long-run relationship exists

The result will give away an F-stats value to be compared with the 95% critical value of boundaries under unrestricted intercept and no trend (Pesaran, Shin, & Smith, 2001). If the F-stats obtained are lesser than the lower bound, then we cannot reject the null. If it is greater, then we can reject the null and say long-run relationship exists. If the stats are within the boundary, then the result is inconclusive. Outcome for bound test for this study is as tabled below.

MODELS	F-STATS	RESULT
F (PI | VIX, RVI, OVX, GVZ)	1.2522	**No Long-run relationship**
F (VIX | PI, RVI, OVX, GVZ)	4.6651	**Long-Run relationship exist**
F (RVI | PI, VIX, OVX, GVZ)	16.2745	**Long-Run relationship exist**
F (OVX | PI, VIX, RVI, GVZ)	1.2847	**No long-run relationship**
F (GVZ | PI, VIX, RVI, OVX)	3.5662	**Inconclusive**

95% Band (2.649, 3.805)

Table 6: ARDL approach for Co-integration

From table 6, we found a mixture of conclusion on the relationship among the variables. However, statistically speaking, from the two models above, [F (VIX| PI, RVI, OVX, GVZ) and F (RVI| PI, VIX, OVX, GVZ)], we can confirm that there is long-run relationship among the 5 chosen variables. This suggests that all the variables are moving together in a long run without restricting the degree and direction, and the bond among the variables is not spurious. The result indicates that each variable has information for the other and theoretical underpinning the variable subsists.

4.4 Diagnostic Test

Running diagnostic test helps to identify if the model is well specified or not. Correction for any problem is needed if any particular problem is detected. Tabled below is the result obtained for our data. If the p-value acquired is less than 5%, this indicates that the model suffers for that particular problem, and vice versa.

TEST	**F-STAT [p-Value]**	RESULT
Serial Correlation	0.039 **[0.844]**	**No**
Functional Form	0.485 **[0.486]**	**No**
Normality	**Not applicable**	**No**
Heteroskedasticity	68.836 **[0.000]**	**Problem detected**

Table 7: Diagnostic Test using Akaike Information Criterion

No major problem is serial correlation and functional form can be found from the model, and normality issues also not to be considered, as it is not applicable in our data. Notwithstanding, our test has detected Heteroskedasticity problem in the data use, which indicates that the standard deviations of a variable are non-constant, monitored over a period of time. It is expected from our data to lead to Heteroskedasticity problem as we are testing the variances themselves. Both implied and realized volatility are variances for each particular underlying assets and conditional Heteroskedasticity is often seen in finance; prices of stock as example (Akgiray, 1989). Thus, having S&P 500 price index as a variable would normally lead to this problem. However, we have considered for this setback in our first step, in finding the unit root test. Using the PP-test, we can carefully say that the results found have been corrected for Heteroskedasticity problem arises.

4.5 Error Correction Model (ECM)

With the findings that there exists long-run relationship between the indices, coefficients of each variable can be estimated using the Error Correction Model. Co-integration and error correction mechanism are exceptionally interrelated, where the former depicts on long-run correlation, the latter indicates any short run relation between the variables (Asteriou & Hall, 2007). To run ECM, the following regression models are constructed.

$$\text{DPIt} = a_0 \sum_{i=1}^{n} b_i DVIX_{t-i} + \sum_{i=1}^{n} c_i DRVI_{t-i} + \sum_{i=1}^{n} d_i DOVX_{t-i} + \sum_{i=1}^{n} e_i DGVZ_{t-i} + \mathcal{E}_{t-1}$$

$$\text{DVIXt} = a_0 \sum_{i=1}^{n} b_i DPI_{t-i} + \sum_{i=1}^{n} c_i DRVI_{t-i} + \sum_{i=1}^{n} d_i DOVX_{t-i} + \sum_{i=1}^{n} e_i DGVZ_{t-i} + \mathcal{E}_t - 1$$

$$\text{DRVIt} = a_0 \sum_{i=1}^{n} b_i DVIX_{t-i} + \sum_{i=1}^{n} c_i DPI_{t-i} + \sum_{i=1}^{n} d_i DOVX_{t-i} + \sum_{i=1}^{n} e_i DGVZ_{t-i} + \mathcal{E}_{t-1}$$

$$\text{DOVXt} = a_0 \sum_{i=1}^{n} b_i DVIX_{t-i} + \sum_{i=1}^{n} c_i DRVI_{t-i} + \sum_{i=1}^{n} d_i DPI_{t-i} + \sum_{i=1}^{n} e_i DGVZ_{t-i} + \mathcal{E}_{t-1}$$

$$\text{DGVZt} = a_0 \sum_{i=1}^{n} b_i DVIX_{t-i} + \sum_{i=1}^{n} c_i DRVI_{t-i} + \sum_{i=1}^{n} d_i DOVX_{t-i} + \sum_{i=1}^{n} e_i DPI_{t-i} + \mathcal{E}_t - 1$$

Running using both Akaike Information and Schwarz Bayesian criterions, the following is attained. The first two table gives the long-run coefficient for the indices, varies in preset dependent variable.

	Dependent Variable				
	PI	**VIX**	**RVI**	**OVX**	**GVZ**
LPI		-0.488* [.000]	0.607* [.001]	1.199* [.033]	0.061 [.817]
LVIX	-1.832* [.008]		1.851* [.000]	1.612* [.025]	0.620 [.052]*
LRVI	0.208 [.471]	0.143* [.028]		-0.152 [.699]	0.047 [.772]
LOVX	0.118 [.612]	0.188* [.001]	-0.105 [.301]		-0.118 [.417]
LGVZ	0.791* [.000]	0.311* [.001]	-0.114 [.448]	-0.005 [.992]	

**significant at 5%*

Table 8: Estimated Long-Run Coefficient based on AIC

	Dependent Variable				
	PI	**VIX**	**RVI**	**OVX**	**GVZ**
LPI		-0.493* [.000]	0.588* [.001]	1.271* [.005]	0.054 [.812]
LVIX	-1.980* [.002]		1.797* [.000]	1.771* [.001]	0.607 [.021]*
LRVI	0.350 [.173]	0.133* [.037]		-0.229 [.430]	0.038 [.783]
LOVX	0.153 [.436]	0.194* [.001]	-0.089 [.375]		-0.111 [.383]
LGVZ	0.834 [.068]	0.312* [.001]	-0.079 [.594]	0.002 [.995]	

**significant at 5%*

Table 9: Estimated Long-Run Coefficient based on SBC

The given result for both criterion give away VIX as the dependent variable with all variables are significant at 5% critical value, which is in line with the bound test which give positive long-run relationship between the variables. This gives indication that implied volatility is led by other variables including its realized volatility. To further check on this, ECM is determined. The p-value of ECM will give endogeneity and exogeneity of the variables. Exogenous variable is a leader variable which may or may not depend on other variables while endogenous variable is a follower which depends more to other variables rather than itself. The null hypothesis for this test is the variable is considered to be exogenous if the p-value is higher than the critical value. If it is the other way round, we will reject null hypothesis, and therefore deemed the variable endogenous.

	Dependent Variable				
	PI	**VIX**	**RVI**	**OVX**	**GVZ**
dPI		-5.528* [.000]	0.847* [.008]	-1.137* [.000]	0.383 [.122]
dVIX	-0.103* [.000]		0.267* [.000]	0.184* [.000]	0.300* [.000]
dRVI	0.006* [.012]	0.100* [.000]		0.040* [.023]	0.002 [.772]
dOVX	-0.020* [.000]	0.162* [.000]	0.091* [.026]		0.123* [.000]
dGVZ	0.004 [.145]	0.183* [.000]	-0.008 [.445]	0.088* [.000]	
ECM (-1)	-2.1911 [.029]	-6.5627 [.000]	-9.0668 [.000]	-2.9988 [.003]	-4.5112 [.000]
RESULT	**Endogenous**	**Endogenous**	**Endogenous**	**Endogenous**	**Endogenous**

***significant at 5%**

**significant at 5%*

Table 10: ECM based on AIC

	Dependent Variable				
	PI	**VIX**	**RVI**	**OVX**	**GVZ**
dPI		-5.519* [.000]	0.039* [.001]	-1.148* [.000]	0.002 [.812]
dVIX	-0.102* [.000]		0.213* [.000]	0.192* [.000]	0.259* [.000]
dRVI	0.001 [.132]	0.098* [.000]		-0.004 [.408]	0.002 [.783]
dOVX	-0.019* [.000]	0.163* [.000]	-0.006 [.367]		0.117* [.000]
dGVZ	0.003* [.010]	0.185* [.000]	-0.005 [.593]	0.080* [.000]	
ECM (-1)	-2.6053 [.009]	-6.766 [.000]	-9.75 [.000]	-3.9463 [.000]	-5.2326 [.000]
RESULT	**Endogenous**	**Endogenous**	**Endogenous**	**Endogenous**	**Endogenous**

**significant at 5%*

Table 11: ECM based on SBC

Tables 10 and 11 above indicate the outcome of ECM for both AIC and SBC. Both test directed to the same conclusion, which led to conclusion that all variables included in the model are endogenous. This means that all variables are dependent upon each other depending on the direction and degree of dependency. Both tables also agree with the previous result and gave away second regression as the most suitable and all indices are significant at 95% confidence interval. The coefficient of dPI exhibits the expected negative sign (price of stocks decreases with an expected increment in its own volatility and volatility of other key commodities) and denotes that the variables need roughly 50% speed adjustment correction after 3 months from when shocks are taken place. Other volatilities are positively correlated with VIX, which is also as expected, as variations in stock's option will give the same effect to other affected or correlated market.

4.6 Variance Decomposition (VDC)

The next step in analysing ARDL approach is to determine the relative value of ECM result. ECM gave us the absolute value of the variables, which concludes endogeneity in all indices, thus, variance decomposition is important to reconfirm the result as well as rank the variables accordingly to its dependency. In other words, this step will capture which variable is the most endogenous and which is the most exogenous.

VDC decomposes the variance of the forecast error of a variable in proportion attributable to a shock in each variable in the system. The relative exogeneity or endogeneity is determined by ranking the variables based on percentage of self-dependency of its own past shock. The most exogenous variable is predominantly explained by its own shock and least explained by other variables. Two method of decomposing variance are used; orthogonolized and generalized VDC. The only difference is that orthogonalized VDC is biased to the first order of the variable in the computed VAR. To this method, ordering is crucial thus assumes that when one variable is shocked, others will be switched off. However, setting all other errors to zero may stipulate a misleading picture of the actual dynamic relationships between the variables. Generalized VDC to the contrary, drops the assumption thus ordering is not important. The following two tables demonstrate the outcome of the tests.

	Horizon 10						
	DPI	**DVIX**	**DRVI**	**DOVX**	**DGVZ**	**TOTAL**	**RANKING**
DPI	**48.09%**	32.69%	1.50%	12.53%	5.18%	100%	**4**
DVIX	31.64%	**45.94%**	2.42%	12.46%	7.53%	100%	**5**
DRVI	3.53%	6.01%	**85.79%**	3.26%	1.41%	100%	**1**
DOVX	15.39%	16.50%	1.68%	**61.05%**	5.38%	100%	**3**
DGVZ	8.00%	11.91%	1.07%	6.64%	**72.38%**	100%	**2**
	Horizon 50						
	DPI	**DVIX**	**DRVI**	**DOVX**	**DGVZ**	**TOTAL**	**RANKING**
DPI	**48.09%**	32.69%	1.50%	12.53%	5.18%	100%	**4**
DVIX	31.64%	**45.94%**	2.42%	12.46%	7.53%	100%	**5**
DRVI	3.53%	6.01%	**85.79%**	3.26%	1.41%	100%	**1**
DOVX	15.39%	16.50%	1.68%	**61.05%**	5.38%	100%	**3**
DGVZ	8.00%	11.91%	1.07%	6.64%	**72.38%**	100%	**2**

Table 12: Generalized VDC using AIC

	Horizon 10						
	DPI	**DVIX**	**DRVI**	**DOVX**	**DGVZ**	**TOTAL**	**RANKING**
DPI	**97.88%**	0.32%	0.68%	0.91%	0.22%	100%	**1**
DVIX	67.79%	**31.16%**	0.43%	0.57%	0.05%	100%	**5**
DRVI	4.03%	3.09%	**92.61%**	0.23%	0.04%	100%	**2**
DOVX	24.83%	3.59%	0.41%	**70.74%**	0.42%	100%	**4**
DGVZ	10.88%	5.84%	0.24%	1.37%	**81.67%**	100%	**3**
	Horizon 50						
	DPI	**DVIX**	**DRVI**	**DOVX**	**DGVZ**	**TOTAL**	**RANKING**
DPI	**97.88%**	0.32%	0.68%	0.91%	0.22%	100%	**1**
DVIX	67.79%	**31.16%**	0.43%	0.57%	0.05%	100%	**5**
DRVI	4.03%	3.09%	**92.61%**	0.23%	0.04%	100%	**2**
DOVX	24.83%	3.59%	0.41%	**70.74%**	0.42%	100%	**4**
DGVZ	10.88%	5.84%	0.24%	1.37%	**81.67%**	100%	**3**

Table 13: Orthogonalized VDC using AIC

As both AIC and SBC gave similar outcome in the ECM, we proceeded with AIC for this step to keep it simple. As you can see from the table, it is clear that orthogonalized

VDC is biased towards the ordering. The tests differs in raking the most exogenous variable (realized volatility in generalized but price index in the other) but the gave the same rank to our implied volatility, which is the most endogenous. As financial market is very sensitive towards any changes in price or financial instruments, shocks can be seen almost immediately and effectively translated across the market. After 10-days, all of the shocks are in or nearing equilibrium and stay coherent over time, until another shock is introduced, proven by the 50-day horizon table. The results are still consistent 50 days later.

Due to its biasness nature, this study chooses to proceed with generalized VDC. The result shows that variance of the realized volatility is 85% dependable on its own past after 10 days. Implied volatility (VIX) however, being the most endogenous, only 46% explained by its own past and much more affected by other variables. Price is expected to be endogenous due to its market nature. Thus, it is safe to conclude that in the case for S&P 500, its realized volatility (RVI) is leading the implied volatility (VIX) and also the price index (PI). Price is also exogenous to the fear index, which is in contrary to the argument made by Badshah in his 2016 paper.

We are also with intention in looking into the endogeneity of all three implied variances (stocks, gold and crude oil) as our sub-purpose to see which market is more stable and leading the other. Our result is as expected, without drawing in assumption during the test. Being the most stable market, gold is the most exogenous among the three markets followed by crude oil and stock options. As expected, gold is highly likely to be independent of other markets with high dependency of its own past. Stock being the most sensitive market will have the biggest shock if any turmoil were to occur.

4.7 Impulse Response Analysis (IRF)

To clearly see the result of shocking the variable and its effect depending on its exogeneity or endogeneity, impulse response analysis is arranged. IRF maps out the dynamic response path of a one-period standard deviation shock of a variable to another and to itself. The response is illustrated graphically to give the visual impression of the dynamic correlation within the whole system. Hence, one may say that IRF is VDC represented in graph format, thus can better illustrate the shock consequence.

Akin to VDC, IRF can also be tested through two method; orthogonalized and generalized IRF. Hence, the biasness of orthogonalized VDC carries thru hence leading to problematic assumption in IRF, which stress on shock affected only one variable at a single time. Such assumption is precarious as it is only applicable if and only if the variable is independent and stands on its own without explanation from others. Figures below are illustration of our results.

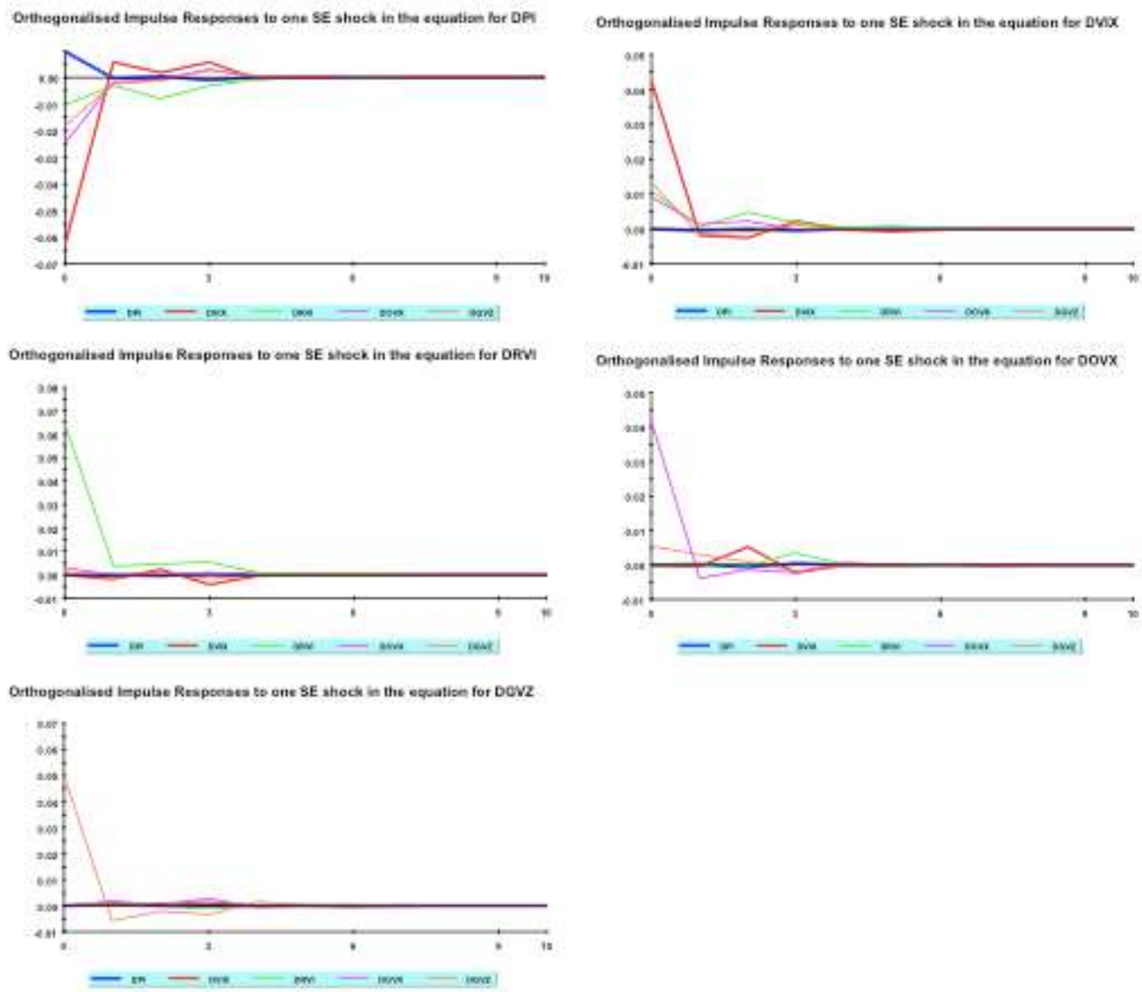

Figure 1: Orthogonalized IRF

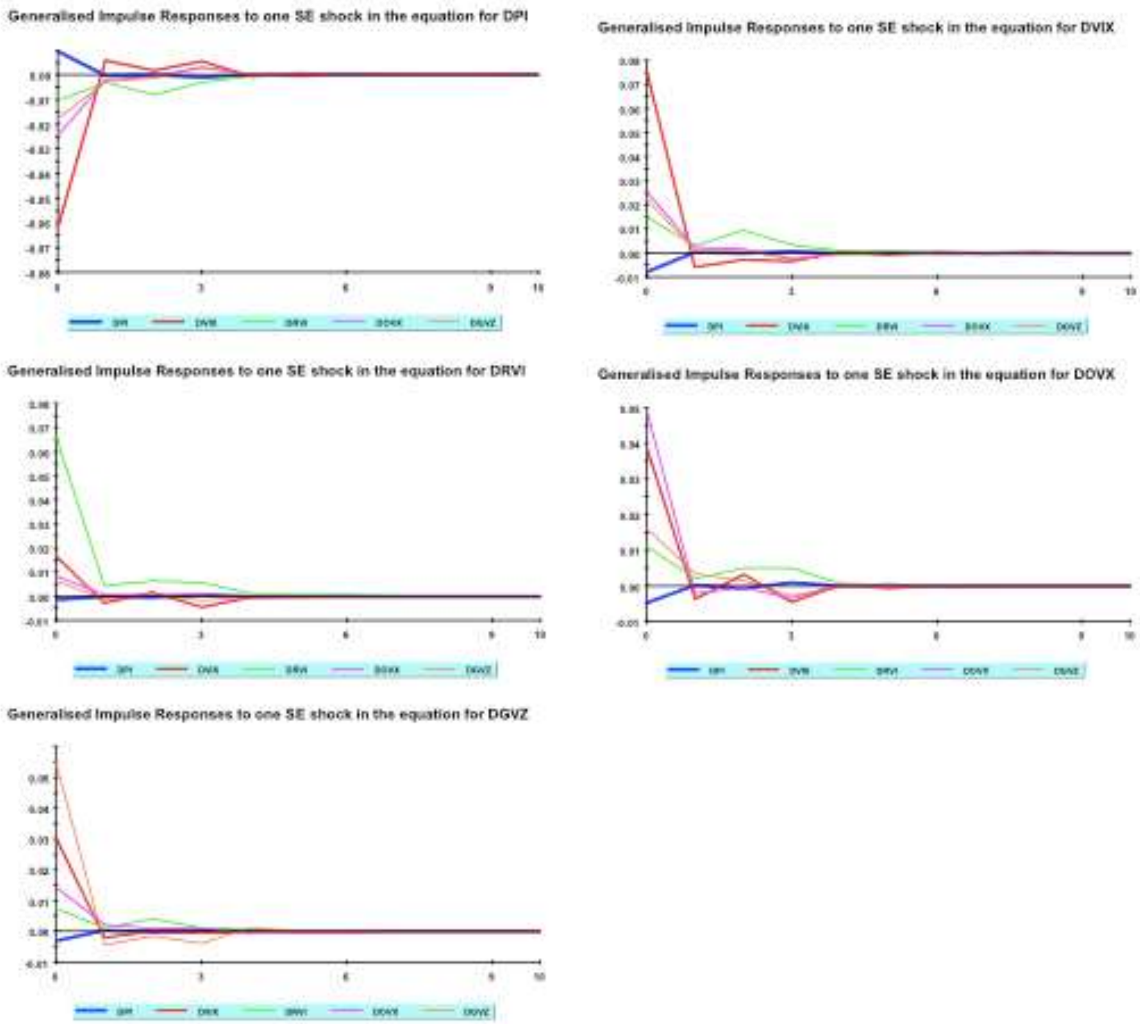

Figure 2: Generalized IRF

Figure 1 depicts Orthogonalized Impulse Response Function for all variables by shocks each variable to see dynamic relationship. The results are quite similar to the generalized IRFs as shown in Figure 2. When the impulse shock is for all other variables, DVIX takes the biggest or second biggest risk while others fluctuates around the zero line. DVIX shock also tends to take the longest time to dies out in all shocks response which is I line with our findings in above testing.

5.0 CONCLUSION AND POLICY IMPLICATIONS

Great deals of researches have been conducted to look into the relationship between implied volatility, historical and realized volatility, yet no uniformity can be screened out from the findings. Some sides on implied volatility leads other volatilities, as it is 'the market' expectation on returns while others including this paper, empirically suggesting that it is realized volatility that is more independent as it relies heavily on its own past. One striking cause that can be pointed out is the difference in methodology adopted in the studies on top of the different datasets and markets that the researches chose to underpin in their respective study.

For this literature, we find that realized volatility is the leader in the volatilities for S&P 500 stock options market, over its implied volatility represented by the VIX. Without any estimation, the outcome should be true to its nature. The paper also abled to lay out the cross market relationship between gold, crude oil and stocks in search for the market that can be controlled and the controller. Gold, being a single independent market, triumphs with the least effect on shocks of other variable and responded only to its own shocks.

It is in the interest of the author that policy maker may be able to use the study in laying out implication of the outcome for trading strategies, hedging portfolios, pricing of derivatives and risk management. It is also the goal for a better investment route in inter-markets portfolio with the spill over from the fear index to developed and emerging markets as one market uncertainty interacts differently with other markets' return in its own direction and degree. Thus, a more rounded and sound policy can be reformed to cater for this need.

BIBLIOGRAPHY

Akgiray, V. (1989). Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecasts. *The Journal of Business* , 62(1), 55-80.

Asteriou, D., & Hall, S. (2015). *Applied Econometrics: A Modern Approach Using Eviews and Microfit* Revised Edition, London, Palgrave Macmillan.

Badshah, I. U. (2009). Asymmetric Return-Volatility Relation, Volatility Transmission and Implied Volatility Indexes, SSRN-id 1344413.

Badshah, I. U. (2016). Volatility Spillover from the Fear Index to Developed and Emerging Markets. *Emerging Markets Finance and Trade* (forthcoming).

Bekeart, G., Harvey, C., & Lundblad, C. (2005). Does Financial Liberation spur Growth? *Journal of Financial Economics,* 77(1), 3-55.

Bouri, E., Jain, A., Biswal, P., & Roubaud, D. (2017). Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. *Resources Policy , 52*, 201–206.

Canina, L., & Figlewski, S. (1993). The Informational Content of Implied Volatility. *Review of Financial Studies , 6*, 659—681.

Christensen, B., & Prabhala, N. (1998). The relation between implied and realized volatility. *Journal of Financial Economics , 50, 125-150*

Day, T. E. (1992). Stock market volatility and the information content of stock index options. *Journal of Econometrics , 52* (1), 267-287.

Dumas, B., Fleming, J., & Whaley, R. E. (1998).Implied volatility functions: Empirical tests, *Journal of Finance* ,53(6), 2059-2106.

Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices . *Journal of Empirical Finance , 5* (4), 317–345.

Koopman, S. J., Jungbacker, B., & Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance , 12* (3), 445–475.

Luo, X., & Qin, S. (2017). Oil price uncertainty and Chinese stock returns: New evidence from the oil volatility index. *Finance Research Letters , 20*. 29-34,

Pesaran, M., Shin, Y., & Smith, R. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics , 16*. 289-326

Shu, J., & Zhang, J. (2000). The Relation between Implied and Realized Volatility of S&P 500 Index. In *Wilmott magazine,* January 83-91

Whaley, R. (2000). The Investor Fear Gauge. *Journal of Portfolio Management , 26* (3), 12-17