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The Interactions among Gold, Oil, and Stock Market: Evidence from S&P500

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Abstract

The inter-relationship between financial and commodity markets is one of the most challenging issues for investors. The volatility in one market might affect the price index of the other market. The aim of this paper is to test whether gold price, oil price, gold price volatility (GVZ) and oil price volatility (OVX) have significant effect on stock market price index (GSPC) or not. In order to carry out the task, due to the properties of the data, the ARDL co-integration approach has been used to check the long–run relationship among OVX and GVZ; as proxies of oil and gold market volatility indexes; and S&P500 market price index. Obtained results indicate the presence of long-run equilibrium among the variables under investigation and reveal that S&P500 stock market price index converges to its long-run equilibrium level by 1.2% speed of daily adjustment by contribution of oil and gold market prices and their volatilities.

Keywords: Gold price; Oil price; Stock price; ARDL; Bounds test

1. Introduction

Oil and gold prices have extensive economic impacts on financial activities, and all sectors of US economy. This impact is directly apparent in consumption, industrial production and investment in both real and financial sectors; where volatilities of oil and gold influence the stock price, and create some implications in the capital market of the US and indirectly exhibit itself in inflation and unemployment (Ebrahim et al., 2014).

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Crude oil price is influenced by geopolitical and weather related factors, which may create unexpected shifts in supply and demand and lead to volatility in oil price. Understanding the volatility of crude oil price is very critical, because it may create uncertainty in all sectors of the economy, and lead to instability in the economy for both oil exporting and importing countries. The oil price volatility exposes industrial producers and consumers at risk; they cannot offer their goods and services in fair price, because of the dependency of these industries to oil and oil products (Pindyck, 2003). The oil price volatility also affects derivative markets, because the value of a commodity is based on a contingent claim affected by the volatility (Narayan and Narayan, 2007). Also, oil price volatility results in higher inflation and unemployment rates.

Gold is a precious metal considered as a commodity and a monetary asset. It acts like a source of wealth, a unit of value and medium of exchange (Goodman, 1956). Also, gold is a mean of investment which is highly liquid and a valuable metal used to make jewelry (Ciner, 2011). Traditionally, gold has been an indicator of future inflation, acted as a hedge against inflation, an important asset in portfolio allocation and has shown its role in crises, because gold creates a hedge to diversify the increasing risk in the market during the crises. Central banks and international financial institutions retain a large amount of gold for diversification, and economic security (Kaufmann and Winters, 1989).

Despite the importance of gold for currency hedging and trading, volatility of gold price may lead to negative consequences in financial markets, because an increase in the gold price volatility lead to an unsafe investment condition, while lower gold price volatility lead to safe investment condition (Baur, 2012). Thus, it is essential to learn about gold price volatility, for derivative valuation, hedging decisions, financial markets and the overall economy (Ewing and Malik, 2013). An increase in gold volatility is an alert for investors and producers of the gold industry and exposes them to risk. So, understanding the gold price volatility enhances our understanding of financial markets (Tully and Lucey, 2007) and enables us to have a better view of the whole economy.

The stock market is influenced by several interconnected factors such as economic, political, and social developments and there is a complex connection among these factors. The stock price is affected by macroeconomic variables, including gold price, crude oil price, gold and oil price volatilities, the inflation rate, and the exchange rate. The aim of this paper is to investigate the long-run relationship among oil price, gold price, oil price volatility index, gold price volatility index, and S&P price index by applying bounds test.

The rest of the article is structured as follows. Next section reviews related literature surrounding the influence of oil price, gold price, and their volatilities on the stock market. Section 3 illustrates the data used in the study, and explains the methodology conducted. Section 4 and 5 provide empirical findings and conclusion respectively.

2. Literature review

There are many studies devoted to the relationship between oil price, gold price and macroeconomic variables (among others; Hamilton, 1983; Gilbert, 1984; Cunadoa and Gracia, 2005). In contrast, only a few studies have devoted to examining the relationship among oil price, gold price and financial markets.

Oil has an important place for US economy, and volatility in oil price lead to changes in stock prices (Hamilton, 1983). In efficient market oil price and stock price are contemporaneously correlated, that is, if oil price increases, it would lead to a decline in the stock price of companies which consume oil in their operation (Gilbert, 1984). In inefficient market, changes in oil price would adjust with the lag of changes in stock price (Mork et al., 1994). A study done by Jones and Kaul (1996) for the period of 1947 to 1991 found that there is no impact of oil price on real stock returns. Huang et al. (1996) investigated the influence of crude oil prices on stock returns of the oil companies. They examined three oil companies' stock prices by applying the VAR model, and found the relationship between one-day lead of oil futures returns and stock returns. Ciner (2001) draws attention to the impact of oil price on real stock returns, using the non-linear connection; he found that variability in the crude oil price affects the stock index returns. Papapetrou (2001) studied the relationship among oil price, real stock price, real economic activity, and interest rates in Greece, by applying a multivariate VAR model, the results shown that changes in the oil price

significantly explain changes in the stock price return. Masih et al. (2011) reported that the volatility of oil price determines real stock returns.

Cai et al. (2001) examined the relationships among GDP, inflation and gold price and argued that GDP and inflation have a strong impact on volatility of gold price returns. Capie et al. (2005) claim that gold is a hedge against foreign exchange volatility. Baur and McDermott (2010) explored the impact of gold price on financial market for 1979-2009 period, the result illustrated that gold acts as a hedge, and a safe haven, in the stock market of the U.S. and most European countries. The research of Batten et al. (2010) found a significant impact of gold price volatility on the financial market returns. Mensi et al. (2013) studied the correlation and volatility transmission across commodities such as gold, oil, and equity market. The results of their study revealed that S&P500 price affects the gold and oil price volatility. Bhunia (2013) inspected the relationship of domestic gold price and stock price return, using Granger test and found the bidirectional causality between gold price and stock price return. Arouri et al. (2015) made use of VAR-GARCH model to investigate the effect of gold price volatility on the stock market returns in China for the period of 2004-2011; their results demonstrated evidence of significant impact of gold price volatility on China's stock market return.

3. Data and methodology

3.1. Data

Data for Euro Brent crude-oil spot price (in US dollars per share) were collected from the United States Energy Information Administration (USEnergy, 2014). Market index based on the daily adjusted close price for S&P500 (GSPC) was extracted from the Yahoo Finance website (S&P500Dow, 2014). The gold historical spot prices were acquired from London PM Fix (US dollar per ounce) (PMfixLondon, 2014). Volatility indexes for gold (GVZ) and oil (OVX) series, which have been available since 2008 were obtained from the CBOE official website (CBOE, 2014). The study covered daily prices and indexes from the beginning of January 2013 to the end of November 2014, inclusive of 484 observations for each time series.

The descriptive statistics for natural logarithm form of variables are mentioned in the table below.

Table 1. Descriptive statistics of variables (2013-2014).

	LGSPC	LGOLD	LGVZ	LOIL	LOVX
Mean	7.475189	7.209881	4.574123	4.656457	3.575448
Median	7.491453	7.185190	4.577542	4.683519	3.513931
Maximum	7.635019	7.439083	4.706101	4.778283	4.235844
Minimum	7.245962	7.046299	4.188745	4.275137	3.235536
Std. Dev.	0.094771	0.093469	0.078795	0.084443	0.181123
Skewness	-0.315649	1.102378	-1.337457	-1.985353	0.699796
Kurtosis	2.003540	3.303008	5.713910	7.100909	2.885141
Jarque-Bera	27.94537	99.46791	291.6195	654.3947	39.60530
P-Value J-B	0.000001	0.000000	0.000000	0.000000	0.000000
Sum	3603.041	3475.163	2204.727	2244.412	1723.366
Sum Sq. Dev.	4.320124	4.202228	2.986327	3.429831	15.77942
Observations	482	482	482	482	482

Jarque-Bera test demonstrates neither of the variables is normally distributed. Standard deviation illustrates that the changes in the volatility of oil (OVX) is approximately two times that of gold (GVZ), however; changes in the standard deviation of oil and gold price index and S&P500 market index are very close to each other.

The correlation among these five variables is reported in the table 2. The correlation table displays a strong negative correlation between changes in the gold price and changes in S&P500 market price index, and a moderate or quite weak correlation among other variables.

Table 2. Correlation matrix

	LGSPC	LGOLD	LGVZ	LOIL
LGOLD	-0.810657			
LGVZ	0.272484	-0.469789		
LOIL	-0.468552	0.416255	-0.028614	
LOVX	-0.409351	0.384410	0.022349	0.034837

3.2. Methodology

3.2.1. Model specification

According to the literature review and theories, the econometric model in this regard considers crude oil price, gold price, and oil price volatility and gold price volatility as the independent variables and stock market price as the dependent variable. The model is specified as:

$$GSPC = f(Oil, Gold, OVX, GVZ) \qquad (1)$$

Where, GSPC is the S&P500 market price index. We consider GSPC in the study because it contains 500 large companies from a vast number of industries picked based on market capitalization and high liquidity (Chen et al., 2004). Oil is the Brent crude-oil spot price. West Texas Intermediate (WTI) and Brent are the global benchmarks for crude oil. We consider Brent in this study, because two-thirds of all crude oil contacts reference Brent all around the world (Milonas and Henker, 2001). Gold is the gold international spot price. OVX is used as a proxy for oil price volatility. This newly published crude oil volatility index is used in other recent studies, such as (Ji and Fan, 2012; Nikkinen and Sahlstrom, 2004; Krylova et al., 2009; Wang, 2009). Also GVZ is used as a proxy for gold price volatility, instead of using traditional price series. We consider OVX and GVZ as index series because they imply market uncertainty based on both historical volatility information and investors' expectation over future market conditions (Poon and Granger, 2003; Ji and Fan, 2012). The natural logarithms of the variables are used to have a better economic interpretation.

$$\ln(GSPC_t) = \beta_0 + \beta_1 \ln(Oil_t) + \beta_2 \ln(Gold_t) + \beta_3 \ln(OVX_t) + \beta_4 \ln(GVZ_t) + \epsilon_t \qquad (2)$$

3.2.2. Unit root test

Financial time series might show trending behavior in the mean. Stationarity and unit root tests can be applied to investigate integration properties of the series. Unit root tests have different power and size properties. Phillips and Perron (1988) test is considered as one of appropriate method for checking the integration order of the variables. PP is a nonparametric statistical method deals with autocorrelation and heteroscedasticity in the disturbance terms. Table 3 provides the output of Phillips and Perron unit root test.

3.2.3. Co-integration test

When a nonstationary series is regressed on another nonstationary time series, the result might be a spurious regression. Co-integration test is to investigate the existence of long-run equilibrium relationship among variables

which are integrated at least in first difference I(1). If the time series variables are integrated at different levels (I(0) and I(1)), investigating for co-integration is only conductible with ARDL (autoregressive distributed lag) method.

The ARDL modified model is given by following equation:

$$\Delta y_t = \alpha_0 + \alpha_i \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \varepsilon_t \tag{3}$$

The bounds test which is proposed by Pesaran et al. (2001) illustrates in five different models; considering different conditions on trend and intercepts (Nieh and Wang, 2005):

Model 1: no intercept, no trend;

$$\Delta y_t = \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy} y_{t-1} + \pi_{yX,X} X_{t-1} + \varepsilon_t \tag{4}$$

Model 2: restricted intercept, no trend;

$$\Delta y_t = \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy}(y_{t-1} - \mu_y) + \pi_{yX,X}(X_{t-1} - \mu_X) + \varepsilon_t \tag{5}$$

Model 3: unrestricted intercept, no trend;

$$\Delta y_t = c_0 + \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy} y_{t-1} + \pi_{yX,X} X_{t-1} + \varepsilon_t \tag{6}$$

Model 4: unrestricted intercept, restricted trend;

$$\Delta y_t = c_0 + \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy}(y_{t-1} - y_y t) + \pi_{yX,X}(X_{t-1} - y_x t) + \varepsilon_t \tag{7}$$

Model 5: unrestricted intercept, unrestricted trend;

$$\Delta y_t = c_0 + c_1 t + \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy} y_{t-1} + \pi_{yX,X} X_{t-1} + \varepsilon_t \tag{8}$$

Where, Δ is the difference operator, y_t is dependent variable, X_t are independent variables, Z_t are the lags of variables $Z = f(X_t, y_t)$, t is the trend term, ε is the disturbance.

Then the model should be checked for serial correlation and stability. To test the co-integration, the null hypothesis must be considered as $\pi_{yy} = \pi_{XX} = 0$ (no co-integration) that is tested by Wald test which should be rejected in term of long-run relationship between variables. The critical values of F-statistics came from Narayan (2005). Significant F test implies a co-integration. Table 5 will display ARDL co-integration results.

3.2.4. Error correction mechanism

The last step of our research methodology is the error correction mechanism (ECM) developed by Engle and Granger (1987). Error correction model estimates the speed at which an endogenous variable returns to equilibrium after any change in exogenous variables and show how to reconcile the short-run behavior of a time series economic variable with its long-run behavior (Pesaran, et al., 2001). Given VAR model the ECM would be calculated from the below equation:

$$\Delta y_t = \alpha' \Delta X_t + \sum_{j=1}^{p-1} \beta_j' \Delta Z_{t-j} + \pi_{yy} y_{t-1} + \pi_{yX,X} X_{t-1} + \gamma ECT_{t-1} \tag{9}$$

Where, γ is the estimated coefficient of ECT_{-1} (the first lag of error correction term) and ECT are the residuals of the estimated model. Next section would discuss about the empirical results of applying the mentioned techniques on time series data and model.

4. Empirical results

   This section presents the empirical results found for the variables employed in this study. The data estimations and tests of the model have been conducted by EVIEWS 8 software. Before following formal tests of stationarity, it's necessary to plot the logarithmic form of time series variables, as we have done in figure 1. These graphs clarify the nature of the series.

(a)   LGOLD
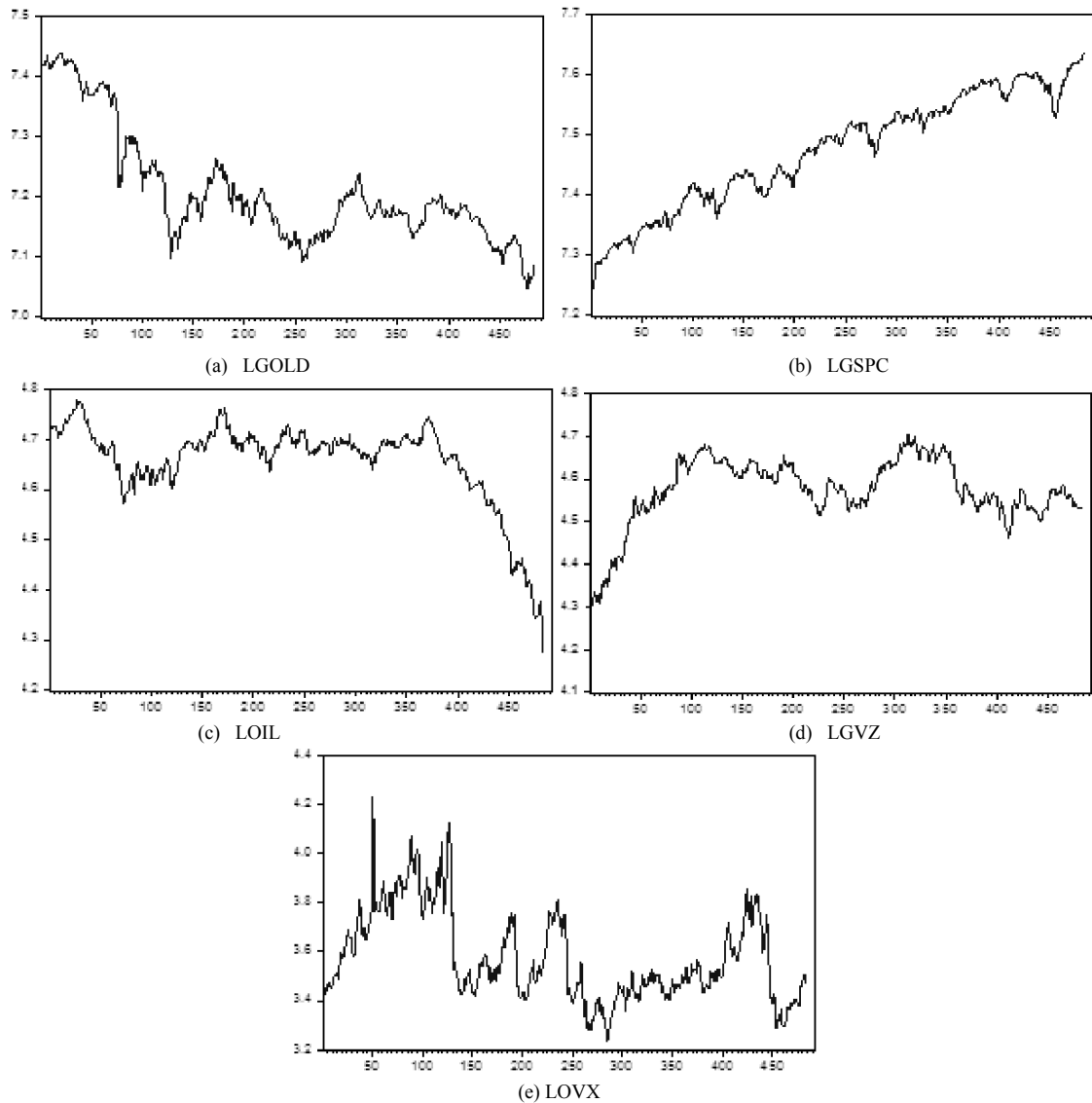
(b)   LGSPC

(c)   LOIL

(d)   LGVZ

(e) LOVX

Fig. 1. Time series plots of the logarithmic form of variables

   The LGOLD time series shown in figure 1.a has downward trend, in other words, over the period of study LGOLD has been decreasing. The mean of LGOLD has been changing, suggesting perhaps the series is non-stationary. This is also true for LOIL displayed in figure 1.c. The LGSPC time series illustrated in figure 1.b is

increasing over time with an upward trend, the mean of the variable is changing, proposing possibly LGSPC is non-stationary. However, figure 1.d and 1.e looks stationary, since the mean of time series LGVZ and LOVX appear to remain constant during the time. This overview is a starting point for the formal test of stationarity.

To check stationarity of the time series formally Augmented Dickey-Fuller Test and Phillips and Peron Test have been conducted. Table 3 indicates the results of ADF and PP unit root tests; illustrating that stock price, crude oil price, gold price are non-stationary at level. However; in the first difference form they become stationary, in other words, they are integrated of order one, I(1). While oil price volatility (OVX) and gold price volatility (GVZ) are stationary at level (I (0)).

Table 3. Unit root tests results.

Panel A. Phillips and Perron Test at Level				
Variables	Test statistics	Prob.	Test statistics	Prob.
LGSPC	-1.56	0.499	-4.19	0.004
LOIL	-2.50	1.000	-1.39	1.000
LGOLD	-1.88	0.339	-2.35	0.404
LGVZ	-5.18*	0.000	-4.78*	0.000
LOVX	-3.16**	0.022	-3.73**	0.021
Panel B. Phillips and Perron Test at First Difference				
Variables	Test statistics	Prob.	Test statistics	Prob.
LGSPC	-23.33*	0.000	-23.33*	0.000
LOIL	-19.90*	0.000	-20.08*	0.000
LGOLD	-20.98*	0.000	-20.98*	0.000
LGVZ	-	-	-	-
LOVX	-	-	-	-

Note: *, **, *** represent for significant level at 1%, 5% and 10%, respectively.

Consequently, co-integration test is used to figure out whether there is co-integration, any long-term relationships, among S&P500 market stock price, gold price, crude oil price and the volatility of gold and volatility of crude oil. Because the variables are integrated at different levels (I (0) and I (1)), the ARDL was used to investigate the long-run relationship. ARDL optimal lag structure test, based on Akaike (AIC) and Schwartz Information Criterion proposed ARDL (1, 4, 1, 1, 1) as an appropriate ARDL model. Then the model was estimated and serial correlation and stability diagnostic CUSUM test were conducted. No serial correlation was found and the model was stable.

Thus, the selected ARDL (1, 4, 1, 1, 1) model displayed as below.

$$\Delta \text{GSPC}_t = \beta_0 + \beta_1 LOIL_{t-1} + \beta_2 LGOLD_{t-1} + \beta_3 LOVX_{t-1} + \beta_4 LGVZ_{t-1} + \beta_4 \Delta LGSPC_{t-1} +$$
$$\sum_{j=1}^{4} \beta_{5j} \Delta LOIL_{t-j} + \beta_6 LOIL_{t-1} + \beta_7 \Delta LGOLD_{t-1} + \beta_8 \Delta LOVX_{t-1} + \beta_9 \Delta LGVZ_{t-1} \tag{10}$$

To check if the model is well specified, the joint hypothesis of $H_0: B_1 = B_2 = B_3 = B_4 = 0$ is rejected by the F-test (2.820), at 5% significant (0.016).

Co-integration has found in two of the models; in model 1 which is no intercept, no trend at 5% significance level and also in model 5 which is unrestricted intercept and unrestricted trend at 1% significance level based on F-statistics. This means LGSPC, LGOLD, LOIL, LGVZ, and LOVX are co-integrated and there is a long-run relationship among them. The results of ARDL co-integration tests are shown in table 4.

Table 4. ARDL Bounds test for co-integration.

	Unrestricted intercept With Deterministic Trend						Unrestricted intercept Without Deterministic Trend				
	F_{IV}	p_value	F_V	p_value$_V$	t_V	p_value	F_{III}	p_value$_{III}$	t_{III}	p_value	Conclusion
f_{gspc} = (gspc|loil, lgold, lovx, lgvz)	1.40	0.219	3.12*	0.008	0.85	0.512	1.04	0.391	2.56	0.026**	Reject null.

Note: According to Schwartz (SBC) Information Criterion lag of ARDL was selected as (1,4,1,1,1) for different scenarios of the co-integration test: FIII denotes the F-stat of the model with unrestricted intercept and no trend, FV is the F-stat of the model with unrestricted intercept and trend, FIV represents the F-stat of the model with unrestricted intercept and restricted trend and tV and tIII are the t ratios for testing model (3) and model (2) with deterministic trend and without deterministic trend.
*, **, *** represent for significant level at 1%, 5% and 10%, respectively.

Table 5 provides estimated long-run ARDL model coefficients. Results indicate that one percent increase in LOIL would lead to a decrease 18% in GSPC in the long-run. Only a small fraction of S&P500 companies are energy related, and most of these firms are service and industry related which are oil consumers. An increase in oil price would decrease the profit of oil consumer companies in the long-run, thus lead to a decrease in GSPC. One percent increase in changes of gold price (LGOLD) would decrease GSPC by 74% in the long-run; because gold is known as a traditional substitute for the stock market. An increase in gold price might cause the investors withdraw their money from the stock market, which leads to a decrease in stock index. One percent increase in gold market price volatility (LGVZ) would increase GSPC by 8.7% in the long-run, because when uncertainty increases in gold market some investors might prefer to move to stock market. Finally, one percent increase in oil market price volatility (LOVX) would decrease GSPC by 6.3% in the long-run. This result shows that uncertainty in oil price (higher volatility) would lead to a decline of stock market return in the long-run, because the volatility in oil price directly increases the production cost of the firms and indirectly decreases the companies' profit margin; consequently investors might become reluctant to invest in the stock market.

Table 5. Long-Run ARDL model coefficient (LGSPC is endogenous variable).

Variables	Coefficient	t-statistics
LOIL	-0.182099*	-5.60
LGOLD	-0.740878*	-19.95
LGVZ	0.087470**	-2.38
LOVX	-0.063409*	-4.20
C	14.29158	

Note: *, **, *** represent for significant level at 1%, 5% and 10%, respectively

The above estimation is necessary to determine ECM which can capture the short-run causality as well as the long-run equilibrium relations among time series variables.

Then, short-run model would be estimated as following equation:

$$\Delta GSPC_t = \beta_0 + \beta_1 \Delta LGSPC_{t-1} + \sum_{j=1}^{4} \beta_{2j} \Delta LOIL_{t-j} + \beta_3 LOIL_{t-1} + \beta_4 \Delta LGOLD_{t-1} + \beta_5 \Delta LOVX_{t-1} + \beta_6 \Delta LGVZ_{t-1} + ECT_{t-1}$$

(11)

Then stability test and serial correlation test are conducted and to solve serial correlation problem of the error correction model (D_LOIL (-4)) eliminated from the model.

In table 6 which depicts the estimated coefficient of the short-run model, the sign of the error correction coefficient in determination of LGSPC is negative (-0.0121) and is statistically significant at 10% significance level (t-stat=-1.952). ECT reveals that S&P500 stock market price index (GSPC) converges to its long-run level by 1.2% speed of daily adjustment by contribution of oil and gold market prices and their volatilities.

Table 6. Error correction short-run ARDL model (ΔLGSPC is endogenous variable).

Variables	D-LGSPC	t-statistics
ECT	-0.012127***	-1.952
D_LGSPC(-1)	-0.060502	-1.327
D_LOIL(-1)	-0.018348	-0.604
D_LOIL(-2)	-0.000101	0.003
D_LOIL(-3)	0.05307***	1.737
D_LGOLD(-1)	0.05307***	3.518
D_LGVZ(-1)	-0.013648	-0.534
D_LOVX(-1)	0.002705	0.478
C	0.000874	

Note: *, **, *** represent for significant level at 1%, 5% and 10%, respectively.

The above table exhibits some lags of independent variables which have a significant short-run effect on the stock market return. According to the mentioned table (D_LOIL (-3)) reveals that one percent increase in the first difference of three days ago of OIL price would increase today's LGSPC by 5.3%, and (D_LGOLD (-1)) exposes that one percent increase in the first difference of previous day GOLD price would increase today's LGSPC by 10.2%. The rests of the variables has no significant short-run effect on S&P100 stock price index.

At last Granger causality test has been conducted to explore the direction of any possible relationship among these variables. Results which are illustrated in table 7 explain that changes in oil price granger cause of S&P500 stock market price index, having a unidirectional causality. There is a bilateral causality between changes of gold price and S&P500 stock market price index. There is also another bilateral causality between changes of oil price volatility and S&P500 stock market price index. Changes in the oil price granger cause the changes in the gold price, having unidirectional causality. Also a bilateral causality is found between changes of oil price volatility and changes of gold volatility.

Table 7. Granger causality test results between GSPC, OIL, GOLD, OVX and GVZ**.**

Granger Causality H0	Lag	F-statistics	Prob.
LOIL ⇏ LGSPC	5	2.43787**	0.0338
LGSPC ⇏ LOIL	10	1.18692	0.2973
LGOLD ⇏ LGSPC	2	5.57651*	0.0040
LGSPC ⇏ LGOLD	1	3.34050***	0.0682
LOVX ⇏ LGSPC	1	3.45566***	0.0636
LGSPC ⇏ LOVX	1	2.98848***	0.0845
LGVZ ⇏ LGSPC	10	0.80851	0.6206
LGSPC ⇏ LGVZ	10	0.48640	0.8990
LGOLD ⇏ LOIL	10	0.90443	0.5289
LOIL ⇏ LGOLD	1	4.38397**	0.0368
LOVX ⇏ LOIL	10	1.02265	0.4230
LOIL ⇏ LOVX	10	0.79111	0.6375
LGVZ ⇏ LOIL	10	0.88720	0.5451
LOIL ⇏ LGVZ	10	1.17511	0.3056
LOVX ⇏ LGOLD	1	4.53892**	0.0336
LGOLD ⇏ LOVX	1	9.51752**	0.0022
LGVZ ⇏ LGOLD	10	1.05488	0.3963

LGOLD ⇏ LGVZ	10	0.73815	0.6885
LGVZ ⇏ LOVX	10	1.30159	0.2269
LOVX ⇏ LGVZ	10	0.80545	0.6236

Note: *, **, *** represent for significant level at 1%, 5% and 10%, respectively

5. Conclusion

Oil and gold prices and price volatilities have extensive impacts on economic and financial activities of the US. This paper investigated the long-run relationship between oil price, gold price, gold price volatility index and oil price volatility index on US S&P500 stock market price index.

The results imply that S&P500 stock market price index (GSPC) converges to its long-run level by 1.2% speed of daily adjustment by contribution of oil, and gold price and their volatilities. While all the variables have long-run impact on S&P500 stock market price index, the gold price has the highest impact on the stock price in long-run and short-run; which has important implications for investors. Investors can react against changes in the gold price, by considering that gold is a very good substitution of stock; because it's more available and they can hedge themselves against inflation, when changes in the gold price happen it has the highest impact in the stock market. In the short-run volatilities of oil and gold have no impact on S&P500 stock market. Investors may not be willing to transfer their money to the other markets in the short-run, while in the long-run they react to the volatilities of oil and gold prices. The findings also highlighted the short-run impact of changes in the oil price on the stock market, considering that 10% of S&P500 stock market belongs to energy sector companies (S&P500 energy, 2015). These companies' stock prices would increase by any increase in oil prices.

The extension to this study is to investigate the impact of the mentioned variables on each of the sectors in S&P500 stock market, means on industry stock, energy stock, and transportation stock sector, which leads to draw a very broad and valuable policy recommendation.

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