Interrelationships Between Crude Oil Price Shocks, Stock Market, and Foreign Exchange Market: Evidence from USA Market

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This study investigates the inter-relationships between three different markets – the stock market ($S\&P_{500}$), the Brent oil market, and the foreign exchange market (FX), during different Brent oil price shock periods. We examined mean-reverting properties for Brent oil prices and the volatility relationships between the three markets using the constant conditional correlations (CCC) model, the dynamic conditional correlations (DCC), and the time-varying conditional correlations (VCC). We found evidence that there are arbitrage opportunities in the Brent oil markets and that there are volatility relationships between the three markets. The paper also concluded that there is a long-run dynamic equilibrium between Brent oil, FX, and $S\&P_{500}$.

Keywords: VAR, FX, VEC, VECM, Oil Shocks, $S\&P_{500}$, Co-integration, Market Efficiency, IRF, Granger Causality, Volatility, Nonparametric tests

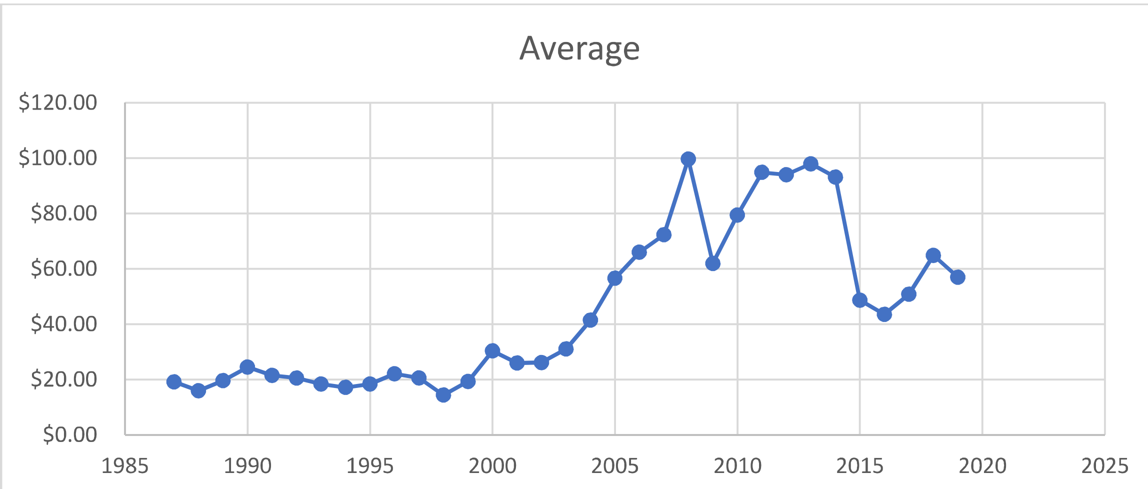
INTRODUCTION

According to the National Bureau of Economic Research (NBER), the US economy went to a recession, among other periods, from November 1973 to March 1975, January 1980 to July 1980, July 1990 to March 1991, and December 2007 to June 2009. A characteristic feature of these four recessions over the last 40 years is that unusually high oil prices accompanied them. The 1973 oil crisis started in October 1973 when the Arab oil producers initiated an oil embargo. This action has been regarded to have a persistent economic activity since it was followed by several years of inflation and recessionary economic activity. Also, the second oil crisis in the U.S occurred in 1979-1980 as a result of the Iranian revolution in 1979 and the Iran-Iraq war in 1980. The resulting spike in the oil prices in the early 1980s is widely believed to have been a significant factor in the recession of the early 1980s.

Moreover, the Iraqi invasion of Kuwait in August 1990 led to the oil price to increase from $17 per barrel in July 1990 to $36 per barrel in August 1990. Again, the oil price spike was followed by the 1990-1991 recession. More recently, the 2007-2008 global financial crisis was associated with another oil price peak at $147.30 in July 2008.

We defined oil price shocks as any increase or decrease in oil prices from year to year that is above $\pm$30%. The reason we did so was to follow the same percentage increase or decrease in oil prices that corresponded with significant economic events. Therefore, we identified the following dates to have oil price shocks 1991-1992,1997-1998, 1999-2000, 2003-2005, 2007-2009, and 2014 -2016.

FIGURE 1
SHOWS THE DIFFERENT PERIODS WHERE OIL PRICES EITHER INCREASED OR DECREASED BY ±30%. THEREFORE, WE IDENTIFIED THE FOLLOWING DATES TO HAVE OIL PRICE SHOCKS 1991-1992,1997-1998, 1999-2000, 2003-2005, 2007-2009, AND 2014 -2016.



The purpose of this study is to investigate the inter-relationships between three different markets – the stock market (S&P$_{500}$, the Brent oil market, and the foreign exchange market (FX), during those Brent oil price shock periods. The contribution of this study is unlike the existing literature that examines either the relation between oil prices and stock prices (e.g., Narayan and Sharma, 2011) or between oil prices and exchange rates (e.g., Aloui, Ben Aïssa, and Nguyen, 2012), this study attempts to link the two streams of literature by examining the co-movements between the stock prices, Brent oil prices, and foreign exchange rates. Second, this article is the first attempt to explore the market interdependencies between the three classes of assets during oil price shocks. Third, we used non-parametric measures to investigate the robustness of our findings.

LITERATURE REVIEW

Our work is related to three different strands of literature. One stream focuses on examining the relationship between oil prices and stock prices. The second strand examines the relationship between oil prices and the exchange rate. The third one investigates the relation between stock prices and exchange rate prices. This study links these three strands of literature together by examining the relationship between Brent oil prices, exchange rate prices, and stock prices.

The Literature on the Relationship Between Oil Prices and Stock Prices

Chortareas et al. (2011) investigate the long-run linkage between stock prices and exchange rates in the Middle East and North Africa (MENA) countries using cointegration analysis. They find that cointegration appears only for the period following the 1999 oil price shock. Arouri and Nguyen (2011) use Vector Autoregressive - Generalized Autoregressive Conditional Heteroscedasticity (VAR-GARCH) approach to examine the extent of volatility transmission, portfolio designs, and hedging effectiveness in oil and stock markets in Europe and the U.S. at the sector-level. They provide evidence of significant volatility spillover between oil and sector stock returns. They find unidirectional spillover from oil markets to stock markets in Europe, but bidirectional spillover in the United States.

Chan et al. (2011) use the Markov switching model to examine the linkage between U.S. stocks, bonds, oil, gold, and real estate assets across periods of economic expansion and economic decline. The results show that there is a flight from quality during periods of calm (i.e., from gold to stocks), at the same time, there is a flight to quality during periods of tension (i.e., from stocks to bonds).

The Literature on the Relationship Between Oil Prices and Exchange Rates

The second strand of research investigates the relationship between oil prices and the exchange rate. Amanoa and Nordenc (1998) investigated the cointegration between the price of oil and the US real exchange rate. They find that a strong causality relation between oil price shocks and the US real effective exchange rate over the post-Bretton Woods period. Amanoa and Nordenc (1998) documented that oil prices may have been the dominant source of real exchange rate shocks.

Huang and Tseng (2010) examine whether exchange rate dynamics affect oil price disturbance. They apply a two-step regression approach by using auxiliary regression and separate the dynamics of oil price disturbance from the three observed oil prices that are retested against the effective exchange rate of the U.S. dollar index. Using a dataset covering twenty years, Huang and Tseng (2010) document that there is a two-way causal relationship between these two variables. Exchange rate fluctuations significantly affect oil supply dynamics and vice versa.

Wanget et al. (2010) examine the impact of Brent oil price fluctuations, gold prices, and exchange rates of the U.S. dollar against many currencies on the stock price indexes of the U.S., Germany, Japan, Taiwan, and China. They find that there are long-term relationships among these variables. However, there is no long-term relationship among the oil price, gold price, and exchange rate and the U.S. stock market index. They find that the exchange rate between the U.S. dollar and the New Taiwan (NT) Dollar affect the Taiwanese stock prices. They also find that the Brent oil price has an impact on the exchange rates, and the gold price affects the exchange rate, although gold prices and the Taiwanese stock prices are not correlated.

Moreover, Korhonen and Juurikkala (2009) examine the determinants of equilibrium real exchange rates in a sample of oil-dependent countries. Using data from 1975 to 2005 about OPEC countries, they find that the price of oil has a statistically significant positive impact on real exchange rates in oil-producing countries. These countries heavily export Brent oil, oil products, and natural gas. Korhonen and Juurikkala show that higher oil price leads to the appreciation of the real exchange rate. That long-run elasticity of the real exchange rate concerning the oil price is typically between 0.4 and 0.5.

In a more recent study, (Mohammadi and Parvar 2012) examine the long-run relation and short-run dynamics between oil prices and real exchange rates in a sample of 13 oil-exporting countries using threshold and momentum threshold autoregressive models (TAR and M-TAR) models. They find that oil prices have a long-run impact on the exchange rates in the 13 countries. However, there is no short-term causal relation between real oil prices and actual exchange rates. Furthermore, Salles (2012) investigates the relationship between Brent oil price models and exchange rates through a cointegration test. Using a daily closing exchange rate of the U.S. dollar to euro from January 2005 to March 2009, Salles does not find any evidence on the cointegration between oil prices, returns, and exchange rates. Aloui et al. (2012) study the extreme co-movement between Brent oil prices and five U.S. dollar exchange rates using a copula-GARCH approach. Over the 2000–2011 period, they find that the rise in the oil price is found to be correlated with dollar depreciation. Their results remain unchanged when considering alternative GARCH-type specifications and different crisis periods.

The Literature on the Relationship Between Stock Prices and Exchange Rates

Traditional models of the open economy document that there is a relationship between the stock market performance and the exchange rate behavior. Dornbusch and Fischer (1980) find that changes in exchange rates have an impact on firms' competitive advantages. Moreover, Oskoonee and Sohrabian (1992) find evidence of short-run bidirectional causality between the Standard and Poor's ($S\&P_{500}$) price index and the effective exchange rate of the U.S. dollar. Abdala and Murinde (1997) examine four emerging countries - India, Korea, Pakistan, and the Philippines – and they find evidence of short-run causality and long-run relationship between stock prices and exchange rates in India and the Philippines only. Also, Huang et al. (2000) and Hatemi and Roca (2005) examine various Asian countries, and they find that there is a change in causality relation between exchange rates and stock prices before and during the 1997-1998 Asian crisis.

Lee and Nieh (2001) examine both short-run co-movements and long-run equilibrium relationships between stock prices and exchange rates for the G7 countries. Although Lee and Nieh find evidence of some degree of short-run causality, their findings suggest that there is no long-run equilibrium relationship between the two variables. Doong et al. (2005) do not find evidence of cointegration for Indonesia, Korea, Malaysia, Philippines, Thailand, and Taiwan, although bidirectional Granger causality was detected in all the countries except Thailand.

Using monthly data from January 1980 to December 1998, Phylaktis and Ravazzolo (2005) and Khursheed, Ali, et al. (2014) investigate the long-run relationship between stock prices and exchange rates, and the channels through which exogenous shocks affect these markets. More recently, Bartram and Bonda (2012) examine the relationship between exchange rate exposures in the return of nonfinancial firms from 37 countries, including the United States. They find that there is a direct relationship between the realized gain to the size and sign of the exchange rate change.

Data and Sample

This study uses price data on three different variables – oil prices, stock prices, and exchange rate prices. The data are obtained from the Federal Reserve Economic Data (FRED). The Brent oil price indices are measured in dollars per barrel using market prices on West Texas Intermediate Brent oil. The stock prices are estimated as the $S\&P_{500}$ stock price index. The exchange rate prices are the trade-weighted US dollar index (TWEXBMTH), which is a weighted average of the foreign exchange value of the US dollar against the currencies of a broad group of major US trading partners.

The sample period runs from January 1986 till November 2016. To address the interrelations among oil, currency, and the stock market, we focus on oil price shocks, and we identified the following dates to have oil price shocks: 1991-1992,1997-1998, 1999-2000, 2003-2005, 2007-2009, and 2014 -2016. Those rates depend on the percentage increase or decrease in oil prices of more than $\pm$30%.

Table 1 shows the preliminary summary statistics as well as the correlation matrix of the three variables in the study – Brent oil prices, $S\&P_{500}$ index prices, and foreign exchange prices (measured by the trade-weighted US dollar index (TWEXBMTH)). Table 1 shows that oil prices are negatively correlated with the foreign exchange rate prices (correlation coefficient = -0.51), and positively correlated with the $S\&P_{500}$ index price (correlation coefficient = + 0.59).

TABLE 1
SUMMARY STATISTICS AND CORRELATION MATRIX:
ENTIRE SAMPLE PERIOD 01/02/1986:12/31/2016

	OIL	SP	FX
Mean	72.29	1,097.12	102.91
Median	61.36	1,571.86	133.53
Maximum	296.72	3,195.27	175.68
Minimum	22.25	523.89	135.51
Std. Dev.	58.16	1,213.89	18.07
Skewness	3.02	(0.15)	0.22
Kurtosis	8.65	4.35	2.90
Jarque-Bera	2,431.91	933.48	149.66
Probability	-	-	-
	-	-	-
Sum	310,066.46	8,189,917.16	1,035,832.83
Sum Sq. Dev.	665,205.87	2.09	1,220,916.99
	-	-	-
Observations	9,319.00	9,319.00	9,319.00
	OIL	SP	FX
OIL	1.0000	0.5912	-0.5112
SP	0.5912	1.0000	-0.4495
FX	-0.5112	-0.4495	1.0000

METHODOLOGY

To examine oil price shocks and their interrelationships with foreign exchange market (FX) and the stock market ($S\&P_{500}$), we wanted first to investigate the idea of whether oil prices are mean-reverting because if oil prices are mean-reverting, then they do not follow a random walk and hence, oil price shocks provide arbitrage opportunities. Unit root test is the method used to detect the existence of random walk, and due to the nonlinearity and structural breaks of the data because of oil price shocks, we used the unit root test with a Fourier function as proposed by (Bahmani et al., 2016). The following equation for the Fourier function for unit root test removes the effect of possible structural breaks of oil prices.

$$y_t = Oil_t - \alpha - \beta t - \sum_{1=1}^{m+1} \theta_1 \, DU_{1,t} - \sum_{1=1}^{m+1} \rho_1 DT_{1,t} - \gamma_1 sin \left(\frac{2\pi kt}{T}\right) - \sum_{k=1}^{n} \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \quad (1)$$

Y_t represents oil prices adjusted for the effect of structural breaks, and Oil_t represents the log of oil price. Table 2 shows that we can reject the null hypotheses of unit root and conclude that oil prices are mean-reverting and that they do not follow a random walk, and thus arbitrage opportunities are present.

Table 2: Shows the results for the Fourier function for unit root test.

$$y_t = Oil_t - \alpha - \beta t - \sum_{1=1}^{m+1} \theta_1 \, DU_{1,t} - \sum_{1=1}^{m+1} \rho_1 DT_{1,t} - \gamma_1 sin \left(\frac{2\pi kt}{T}\right) - \sum_{k=1}^{n} \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \quad (1)$$

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TABLE 2
UNIT ROOT TEST

Index	SSR	K^	F(k^)	# Of Lags Δy_t	Lμ(k^)
BRENT	1.5889	1	15.6172***	10	-26.511

Oil is an asset, and it is essential to determine the volatility spillover of that asset to other assets, especially in the context of this paper. M-GARCH models strongly depend on the definition of the matrix of conditional correlations as such M-GARCH models operate under the assumption that correlations are independent of time. The constant conditional correlations (CCC) model (Bollerslev 1990) allows a straightforward computation of the correlation matrix. However, if correlations vary over time, the models such as the dynamic conditional correlations (DCC) (Engle 2002) and the time-varying conditional correlations (VCC) (Tse and Tsui 2002) are more appropriate to compute the returns variations according to the following formulas:

$$\rho_{12,t} = \frac{= q_{12}(1-a-b)+a(\varepsilon_{1,t-1}\,\varepsilon_{2,t-1})+bq_{12,t-1}}{\sqrt{= q_{11}(1-a-b)+a\varepsilon^2_{11,t-1})\ \ (q_{22}1-a-b)+a\varepsilon^2_{22,t-1}+bq_{22,t-1}}} \tag{2}$$

In the bivariate case, the conditional correlation coefficient of Tse and Tsui (2002) is defined as:

$$\rho_{12,t} = (1-\theta_1-\theta_3)\rho_{12,t-1} + \theta_3 \frac{\sum_{s=1}^{S}\varepsilon_{1,t-s}\varepsilon_{2,t-s}}{\sqrt{(\sum_{s=1}^{S}\varepsilon^2_{1,t-s})\ (\sum_{s=1}^{S}\varepsilon^2_{2,t-s})}} \tag{3}$$

$$d_{ij}^{gH} = \frac{\sigma_{ij}\sum_{h=0}^{H-1}(e_i^T\varphi_h\sum_u e_j)^2}{\sum_{h=0}^{H-1}(e_i^T\varphi_h\sum_u\varphi_h^T e_i)}\ .100 \tag{4}$$

Table 3 panel A reports the parameter estimates for the conditional variance models of each market, where (γ)is the estimated constant term for each conditional variance, and (δ) and (θ) represent the estimated own Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) parameters, respectively. The estimated (δ) and (θ) parameters for each market are significantly different from zero, suggesting the existence of individualized ARCH and GARCH effects. The CCC, DCC, and VCC models all reveal volatility persistence.

Table 3 Panel B reports the corresponding conditional correlations between various pairs of markets. In all the estimated models, all the estimated conditional correlations are significantly different from zero. The statistically significant positive coefficient on the conditional correlation between exchange rate volatility and oil price volatility in all the models suggests that an increase in oil price volatility is associated with increased volatility of the exchange rate. Consistent with the literature, the estimated constant conditional correlation between $S\&P_{500}$ and oil price volatility is positive, suggesting that both markets are exposed to common shocks as well.

TABLE 3
ESTIMATED COEEFICIENTS FOR CONDITIONAL CORRELATIONS OF CCC, DCC, AND VCC MODELS

Table 3. Estimated coefficients for conditional correlations of CCC, DCC, and VCC models.						
		CCC		DCC		VCC
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
	Panel A-— GARCH Results					
(γ) Exchange rate retum	0.000 ***	0.003	0.000 ***	0.001	0.000 ***	0.001
(δ) Exchange rate return	0.150 ***	0.002	0.340 ***	0.000	0.468 ***	0.000
(θ) Exchange rate retum	0.245 ***	0.000	0.856 ***	0.000	0.431 ***	0.000
(γ) S&P index	0.000**	0.011	0.001**	0.013	0.002**	0.137
(δ) S&P index	0.055 **	0.030	0.053 **	0.015	0.093 **	0.014
(θ) S&P index	0.753 ***	0.020	0.661 ***	0.002	0.871 ***	0.000
(γ) Brent oil price index	0.006***	0.017	0.004***	0.186	0.001***	0.152
(δ) Brent oil price index	0.121 ***	0.09	0.111 ***	0.005	0.182 ***	0.004
(θ) Brent oil price index	0.201 ***	0.000	0.584 ***	0.009	0.734 ***	0.000
Panel B— -Conditional correlation results						
ρ (Exchange rate return, S&P index)	0.153 **	0.001	0.134	0.321	0.183 **	0.032
ρ (Exchange rate retum, Brent oil index)	0.083***	0.025	0.081	0.583	0.556***	0.063
ρ (S&P index, Brent oil index)	0.189 ***	0.008	0.145 *	0.081	0.563 **	0.012

Vector Autoregressive (VAR) Model

This paper uses the VAR system to capture the linear interdependencies among the three-time series of Oil, FX, and S&P$_{500}$. VAR models generalize the univariate autoregression (AR) models. All the oil returns, S&P$_{500}$ returns, and foreign exchange returns in a VAR are treated symmetrically; each variable has an equation explaining its evolution based on its lags and the lags of all the other variables in the model. Therefore, the relation between the stock market, Brent oil market, and the foreign exchange market can be examined by estimating the following three vectors autoregressive (VAR) system:

$$Oil_{i,t} = \lambda_0 + \sum_{i=1}^{I} \alpha_i \, Oil_{i,t-1} + \sum_{j=1}^{J} \beta_j \, FX_{i,t-j} + \sum_{k=1}^{K} \eta_k S\,\&\,P_{i,t-k} + \varepsilon_{i,t} \tag{5}$$

$$FX_{i,t} = \alpha_0 + \sum_{i=1}^{I} \alpha_i \, FX_{i,t-1} + \sum_{j=1}^{J} \beta_j \, Oil_{i,t-j} + \sum_{k=1}^{K} \eta_k S\,\&\,P_{i,t-k} + \varepsilon_{i,t} \tag{6}$$

$$S\,\&\,P_{i,t} = \lambda_0 + \sum_{i=1}^{I} \alpha_i \, S\,\&\,P_{i,t-1} + \sum_{j=1}^{J} \beta_j \, FX_{i,t-j} + \sum_{k=1}^{K} \eta_k Oil_{i,t-k} + \varepsilon_{i,t} \tag{7}$$

where $(FX_{i,t})$ represent the daily foreign exchange returns; (Oil_{it}) is the daily return on oil prices, and $(S\,\&\,P_{i,t})$ represents the daily returns on the S&P$_{500}$ index.

Vector Autoregressive (VAR) Results

Tables 4 shows the results of estimating the relation between the Brent oil market, stock market, and foreign exchange market using the Vector Autoregressive (VAR) model as determined by equations 5, 6, and 7. The results show that the coefficient of regressing Brent oil prices on the S&P$_{500}$ price index (with two levels) is positive and significant. Also, the results show that the relation between oil prices and foreign exchange prices is negative and significant. All that means that oil price shocks remain mostly positive shocks that then translates into higher returns on the stock markets while negative returns on the FX markets

TABLE 4
VAR ESTIMATES OF THE RELATIONSHIP BETWEEN OIL PRICES, S&P500 PRICES, AND FX PRICES

	OIL	SP	FX
OIL(-1)	0.828347	0.133897	-0.00386
	0.05394	0.31917	-0.00351
	[13.925]	[1.2596]	[-1.6453]
OIL(-2)	0.005489	0.100739	-0.00429
	0.03866	0.06214	-0.00193
	[1.1253]	[1.5863]	[-1.6146]
SP(-1)	0.00118	0.236171	-0.0071
	0.00491	0.04651	-0.00067
	[2.5643]	[11.5453]	[-5.3356]
SP(-2)	0.011093	0.01973	-0.00683
	0.00455	0.03239	-0.00088
	[2.5686]	[2.7865]	[-3.5865]
FX(-1)	-0.18768	-1.0312	-0.243365
	-0.01594	-0.55866	-0.02282
	[-2.86723]	[-0.48654]	[-2.01756]
FX(-2)	-0.11911	-0.42889	-0.000273
	-0.02179	-0.77158	-0.04962
	[1.06747]	[-1.192875]	[-1.55846]
C	1.869318	12.07191	1.428465
	-7.2168	-74.6911	-0.60197
	[-0.7868]	[-2.54000]	[-1.2585]
R-squared	0.549231	0.446543	0.935345
Adj. R-squared	0.283267	0.760653	0.018553
Sum sq. resids	1380.041	59252.34	46.42134
S.E. equation	1.132432	1.958334	0.440237
F-statistic	157.5698	5618.291	4723.265
Log likelihood	-691.591	-633.424	-138.597
Akaike AIC	1.168798	8.692153	0.793607
Schwarz SC	2.226095	7.850276	1.273865
Mean dependent	72.67784	202.7402	51.33736
S.D. dependent	28.59135	12.59407	2.91141

Impulse Response Function (IRF)

The problem with the variance-covariance estimated from the VAR model is that errors are unlikely to be diagonal, which means that it is difficult to shock one variable while holding other variables constant. Therefore, we use the Impulse Response Function (IRF) to measure the response of oil prices to a lagged unit impulse in S&P_{500} index prices, while holding the FX prices constant. Conversely, we focus on examining the impact of the impulse in FX prices on oil prices, while maintaining the S&P_{500} index prices constant.

Impulse Response Function (IRF) Results

Taken together, the results of the correlation matrix in Table 1, and the results of the VAR system in Table 4 show that S&P_{500} index prices and Brent oil prices move together while Brent oil prices and FX prices move in the opposite direction. The problem with VAR results, in general, is that it is difficult to shock one variable while holding the other variables constant. We proceed to the second empirical test, therefore, by using the impulse response function (IRF). The result of our interest is the response of FX prices to the oil shock prices and S&P_{500} index (i.e., FX is the response, while oil shock prices and S&P_{500} are the impulses). Table 5 shows the results of the impulse response function up to three lags. Table 5 shows that the long-run responses of FX prices to Brent oil shock are significant

TABLE 5
IMPULSE RESPONSE FUNCTION ESTIMATES OF THE RELATIONSHIP BETWEEN OIL PRICES, S&P500 PRICES, AND FX PRICES

Response of OIL: Period	OIL	SP	FX
1	4.1559	0.0000	0.0000
	(0.1192)	0.0000	0.0000
2	3.2288	0.9902	(0.1859)
	(0.2013)	(0.1906)	(0.0565)
3	4.1699	0.6077	(0.0662)
	(0.2397)	(0.2161)	(0.0561)
Response of SP: **Period**	**OIL**	**SP**	**FX**
1	6.30482	27.83211	0.00000
	(2.38266)	(0.89065)	0.00000
2	3.12538	24.49104	(0.76269)
	(1.68765)	(2.61226)	(1.30383)
3	6.59033	24.00906	(0.62586)
	(2.32039)	(1.47981)	(1.20027)

Response of FX: Period	OIL	SP	FX
1	0.31651	0.12087	(0.93133)
	(0.05176)	(0.05178)	(0.02642)
2	0.46132	0.38715	0.54132
	(0.06755)	(0.05520)	(0.03515)
3	0.23974	0.24422	(0.53704)
	(0.06822)	(0.04232)	(0.04978)

Cointegration and Causality

We turn our attention now to investigate the cointegration and causality relationship among Brent Oil, FX, and S&P$_{500}$ during the times of oil price shocks. To analyze the strength and direction of causality, we employ the Vector Error Correction Model (VECM), Granger causality, and VEC Granger Causality/Wald tests. Based on Table 2, where we rejected the null hypotheses of unit root, then the process is stationary. Therefore, the results of the unit root test indicate that Johansen's cointegrated test can be conducted for all the variables. Johansen's cointegration technique has been the most widely used (Narang & Singh, 2012; Samanta & Zadeh, 2011). If two or more non-stationary series combine to form a stationary series, the given series are said to be cointegrated. The kth order VAR model used to conduct Johansen's test is given below in Equation (8).

$$\Delta Y_t = \mu + \pi y_{t-1} + \sum_{i=1}^{k-1} \tau_i \Delta Y_{t-1} + \varepsilon_t \tag{8}$$

Table 6 shows that the three variables are cointegrated with one cointegrating relation in the pre-oil price shock, while during the oil price shock, there is a conflict between the results of the Trace and Maximum Eigen tests. The previous analysis suggests one cointegrating relation, while the latter test indicates that there are two cointegrating relations at a 10% level of significance. When such a conflict occurs, we defer to the Trace statistics (Johansen & Juselius, 1990). Therefore, we can say that the select variable series have one cointegrating equation during the price oil shock. However, we cannot reject the null hypothesis of r = 0 in the post-price oil shock. Thus, we conclude that there is a long-run equilibrium between Brent oil, FX, and S&P$_{500}$ before and during the shock period, but not after the shock period, which shows a dynamic relationship between all these variables.

TABLE 6
JOHANSEN'S COINTEGRATION RESULTS

Period	Null Hypothesis	Eigenvalue	Trace Test		Max Eigenvalue Test	
			Statistics	P-value	Statistics	P-value
Pre- Oil Price Shock	r = 0 (none)	0.026560	0.84601	0.01225*	13.36617	0.0326*
			(56.21973)		(14.12216)	
	r < 1 (at most 1)	0.034520	11.78819	0.0628	9.25378	0.7245
			(14.33304)		(7.706730)	
	r ≤ 2 (at most 2)	0.001450	5.45376 (4.75098)	0.1282	3.725293 (1.44411)	0.6452
	r < 3 (at most 3)	0.002560	2.246398	0.0522*	3.772847	0.0335*
			(5.362801)		(3.667037)	
During- Oil Price Shock	*r* = 0 (none)	0.055860	50.63469	0.0000*	8.14941	0.0026*
			(23.48634)		(10.06678)	
	r < 1 (at most 1)	0.068300	24.23326	0.1648	6.66590	0.0328*
			(14.64461)		(19.148301)	
	r < 2 (at most 2)	0.017530	3.968429	0.6110	3.941511	0.9210
			(5.58989)		(0.95901)	
	r < 3 (at most 3)	0.003650	0.360503	0.1913	0.509113	0.2241
			(1.347568)		(2.803513)	
Post- Oil Price Shock	r = 0 (none)	0.089630	5.21805	0.4781	14.07196	0.7925
			(3.82292)		(6.99417)	
	r < 1 (at most 1)	0.009353	16.32706	0.3586	4.02571	0.5556
			(18.37953)		(7.610222)	
	r < 2 (at most 2)	0.007896	7.16262	0.6574	1.430381	0.3896
			(5.52005)		(12.71842)	
	r < 3 (at most 3)	0.024300	1.576010	0.1898	1.502825	0.1955
			(2.784139)		(3.757252)	

Research indicates that cointegrated variables bear a long-run equilibrium relationship; however, they may suffer disequilibrium in the short run. The VECM is employed to find any such disequilibrium and the speed of correction or adjustment to put the variables back on long-run equilibrium trajectory. Both long- and short-run causality can be studied using VECM. According to equation (9), If β is found to be negative and significant, then we can say that there is long-term causality between the variables. However, the short-run coefficients α_i & b_i measure short-term causality. The VECM can be represented by equation (9)

$$\Delta y_t = \alpha + \beta ECT_{t-1} + \textstyle\sum_{t=1}^{k} \alpha_i \Delta Y_{t-i} + \sum_{t=1}^{k} b_i \Delta X_{t-i} + \varepsilon_t \qquad (9)$$

Where, (ECT) stands for error correction term. It represents the speed of correction or adjustment towards long-run equilibrium. For long-run causality to exist, ECT should be negative and significant. The results of VECM presented in Table 7 indicate the absence of long-run causality in the models of the three variables in the pre-oil price shock at a 10% level of significance. However, Brent oil and $S\&P_{500}$ models are found to exhibit long-run causality in the shock period at a 10% level of significance. That means that there is an error correction mechanism existing in Brent oil and $S\&P_{500}$ that allows for correction of disequilibrium caused in the previous period. However, in some cases, short-run causality is indicated in results. For instance, FX is consistently influenced by its lags and the lags of the $S\&P_{500}$

market across the shock periods. So, the $S\&P_{500}$ and Brent oil show dynamic behavior across the shock periods, and there is short-run causality between Brent oil and the stock market.

TABLE 7
RESULTS OF VECM FOR PRE AND DURING THE OIL PRICE SHOCK

	Pre- Oil Price Shock			During- Oil Price Shock		
	OIL	**FX**	**S&P500**	**OIL**	**FX**	**S&P500**
ECT	-0.006	0.001	0.000	0.0111*	0.000	0.006*
	(0.17)	(0.00)	(0.09)	0.00	(0.01)	0.00
				(0.01)	(0.00)	(0.03)
OIL(-I)	-0.010 (0.00)	-0.002 (0.24)	-0.023 (0.3101)	0.0001* 0.00	0.010 (0.08)	-0.013 (0.03)
OIL(-2)	0.000	-0.008	-0.026	-0.018	0.001	-0.005
	(0.06)	(0.09)	(0.04)	(0.63)	(0.16)	(0.19)
OIL(-3)				0.002	0.005	0.000
				(0.25)	(0.03)	(0.09)
FX(-1)	0.032	0.000	-0.027	-0.165	0.0589*	0.0025*
	(0.10)	(0.27)	(0.38)	(0.41)	0.00	(0.00)
FX(-2)	0.051	0.0456*	0.000	0.013	-0.016	0.0066*
	(0.06)	(0.00)	(0.84)	(0.13)	(0.07)	(0.01)
FX(-3)				0.289	0.020	0.0075*
				(0.16)	(0.46)	0.00
S&P500 (-1)	0.015	0.0248*	0.016	0.035	0.0175*	0.023
	(0.08)	0.00	(0.07)	(0.02)	0.00	(0.35)
S&P500 (-2)	0.017	-0.011	0.011	-0.071	-0.005	0.0089*
	(0.20)	(0.04)	(0.33)	(0.09)	(0.03)	0.00
S&P500 (-3)				0.0311*	0.0000*	-0.031
				(0.03)	(0.02)	(0.08)

Table 7 showed the results for pre and during the shock period. Because Table 6 showed no cointegrating relationship in the post-shock periods, so we used the VAR model instead of the VECM model to investigate if there is a long-run causality between the variables in the post-shock period. A bivariate VAR model with k lags of both the variables can be represented, as shown in Equations (10) and (11).

$$y_t = \beta_{10} + \sum_{i=1}^{k} \beta_{1i} Y_{t-i} + \sum_{i=1}^{k} \alpha_{1i} X_{t-i} + \varepsilon_{1t} \tag{10}$$

$$X_t = \beta_{20} + \sum_{i=1}^{k} \beta_{2i} X_{t-i} + \sum_{i=1}^{k} \alpha_{2i} Y_{t-i} + \varepsilon_{2t} \tag{11}$$

Table 8 shows that Brent oil is affected by its lags (2) as well as the two lags of FX and $S\&P_{500}$. Similarly, FX is influenced by the two lags of the $S\&P_{500}$ and its lags, while the $S\&P_{500}$ is affected by its own lags only. Brent oil shows the most dynamic behavior among all.

TABLE 8
RESULTS OF VAR FOR THE POST-OIL PRICE SHOCK

	OIL		FX		S&P500	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
OIL(-I)	0.153	0.000*	0.003	0.07	0.008	0.06
OIL(-2)	0.033	0.001*	-0.002	0.16	-0.002	0.06
FX(-I)	0.445	0.000*	0.530	0.000*	-0.025	0.06
FX(-2)	-0.758	0.000*	0.012	0.000*	0.028	0.40
S&P500 (-I)	0.341	0.005*	-0.020	0.000*	0.724	0.0268*
S&P500 (-2)	-0.265	0.000*	0.103	0.000*	-0.043	0.0561*

To study the lead-lag effect, we conduct the Granger causality test, which also gives the direction of causality. There are two ways in which we can employ the Granger causality test. The first way occurs if the series are not cointegrated. Since the given series are cointegrated before and during the shock period, whereas no cointegration is present after the shock period. So, we apply the VEC Granger causality/Wald test for the pre-crisis and during the crisis periods, while Granger test (Granger, 1969) is used for the post-shock period.

Table 9 depicts the results of the VEC Granger causality/block homogeneity Wald test for the pre-crisis and during the crisis periods for the short-run causality. The consistent short-run causality relationship is reported for the $S\&P_{500}$ and Brent oil returns. Other variables influence each of these two variables. However, FX and $S\&P_{500}$ are only related during the shock period and not in the pre-shock period.

TABLE 9
VEC GRANGER CAUSALITY/BLOCK EXOGENEITY WAFX TEST RESULTS

Model	Dependent Variab	Independent Variable (Differenced Series)	Pre-Shock		During Shock	
			x^2 value	Prob.	x^2 value	Prob.
1	**OIL**	**FX and S&P**	12.6372	0.1847	34.9155	0.001*
3	**FX**	**OIL and S&P**	54.1194	0.0145*	120.1161	0.0016*
4	**S&P**	**FX and OIL**	27.4020	0.0278*	46.0196	0.0045*

Since in the post-shock period, there is no cointegration present, so in the post-shock period, we apply the Granger test (Granger, 1969). A bivariate k^{th} order VAR to conduct the Granger causality test has been shown in Equations (12) and (13). However, in this study, we have three variables, and hence, there will be a set of 9 equations or nine null hypotheses to be tested. For the sake of convenience, we have shown only two VAR equations.

$$Y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i Y_{t-i} + \sum_{j=1}^{k} \beta_j X_{t-j} + \varepsilon_t \tag{12}$$

$$X_t = \gamma_0 + \sum_{i=1}^{k} \gamma_i X_{t-i} + \sum_{j=1}^{k} \delta_j Y_{t-j} \epsilon_t' \tag{13}$$

In Table 10, the Granger test results show unidirectional causality from $S\&P_{500}$ to FX and from Brent oil to FX. The results are like the results of VAR. Thus, we can say that our results are robust.

TABLE 10
GRANGER CAUSALITY TEST RESULTS

Null Hypothesis	Post-Shock F-statistic	Prob.
FX does not Granger-cause OIL	26.4858	0.3456
OIL does not Granger-cause FX	1.86944	0.0001*
S&P500 does not Granger-cause OIL	7.29423	0.000*
OIL does not Granger-cause S&P500	3.72616	0.0120*
S&P500 does not Granger-cause FX	57.7754	0.000*
FX does not Granger-cause S&P500	0.87274	0.1965

Asymmetric Information

Finally, we explicitly test the following relationships:

H0. *There is a negative relationship between Brent oil prices and the US dollar exchange rate.*

H1. *There is a positive relationship between Brent oil prices and stock market prices.*

H2. *There is a negative bidirectional relation between stock market prices and the US dollar exchange rate.*

To investigate these hypotheses, we used a system of simultaneous equations that allow us to adequately investigate the multipart interactions among Brent oil prices, FX, and $S\&P_{500}$. The simultaneous equation estimation allows examining both direct and indirect relationships. The direct effects of each variable can be observed through its associated coefficient, while indirect effects can be decomposed into more than one component. The following are the simultaneous equations system:

$$S\&P_{\ t} = \alpha_0 + \alpha_1 Oil_t + \alpha_2 FX_t + \alpha_3 X_{1t}^{s} \tag{14}$$

$$Oil_t = \beta_0 + +\beta_1 FX_t + \beta_2 S\&P_t + \beta_3 X_{2t}^{0} \tag{15}$$

$$FX_t = \gamma_0 + \gamma_1 Oil_t + \gamma_2 S\&P_t + \gamma_3 X_{3t}^{d} \tag{16}$$

$$\frac{\partial\, S\&P}{\partial\, FX} = \alpha_1 \frac{\partial\, Oil}{\partial\, FX} = \alpha_1 \beta_1 \tag{17}$$

$$\frac{\partial\, S\&P}{\partial\, FX} = \alpha_2 + \alpha_1 \frac{\partial\, Oil}{\partial\, FX} + \alpha_1 \frac{\partial\, X_2^{Oil}}{\partial\, FX} \tag{18}$$

which is equal to $\alpha_3 + \alpha_1\beta_1 + \alpha_1\beta_3 = \alpha_3 + \alpha_1(\beta_1 + \beta_3)$.

Table 11 reports the estimation results of the simultaneous equation system. We rely here on the relative contribution of direct and indirect effects and then emphasize the total effect. Equation (14) shows that the $S\&P_{500}$ is positively and significantly affected by Brent oil prices and the FX. Equation (15) points out that Brent oil price is positively affected by $S\&P_{500}$ and FX. Equation (16) points out that the FX exchange rate is negatively and significantly affected by Brent oil and the $S\&P_{500}$. (See Table 11 below)

TABLE 11
SIMULTANEOUS EQUATIONS DIRECT, INDIRECT AND TOTAL EFFECT RESULTS

Table 11 : Simultaneous Equations Direct , Indirect and Total Effect Results						
Variables	**Direct Effects Coef**	(SD)	**Indirect effects Coef**	(SD)	**Total Effects Coef. (SD)**	(SD)
Oil	-	0	0.0467	0.013304***	0.0371	0.02598***
FX	0.1564	-0.126486***	0.1599	0.06912***	0.2698	-0.0698208***
S&P	0.0033	0.0021069***	0.0059	0.0026339**	0.0072	0.00384094***
Const	-35.4000	-7.9444	-	-	-	-
FX	-	-	-1.2005	-0.161656***	-1.1926	-0.196289**
Oil	-0.2069	-0.05845***	-0.4321	-0.073758**	-0.6882	-0.044197***
S&P	-0.0418	-0.012422***	0.0603	-0.0067064***	-0.0065	-0.00594412***
Const	-26.6965	-22.0447***	-	-	-	-
S&P	-	0.0000	0.7168	0.08936887***	0.8113	0.0134256***
Oil	7.7825	0.0156***	6.3294	0.955545***	1.1908	0.001184***
FX	-49.3632	-4.5293	-26.1155	0.5533	20.1994	0.2867
Const	-1152.8654		-	-	-	-
Log-likelihood	-330.7578		-	-	-	-
2	515.5792		-	-	-	-

Having confirmed the bidirectional nonlinear relation between Brent oil-FX, we next turn to examine the asymmetric impact of Brent oil prices on FX. In the short-run and long-run asymmetric tests for Brent oil, the FX could be detected by using a Wald test, and the results are shown in Table 12. The results show that the previous month's shock in the FX has a significant and positive impact on the future FX. For the Brent oil price-FX equation, the results indicate that the previous month's positive and negative shocks in Brent oil prices have a significant negative impact on the FX; however, the positive shock has a more pronounced effect than adverse shocks. Such a finding indicates that FX reacts to movements in Brent oil prices, and much of the interaction occurs in the short run, a result also reported by Basher et al. (2012).

The Wald statistic (WSR) suggests the rejection of the null hypothesis of weak-form symmetric adjustment like Bildirici and Turkmen (2015). For the long-run relation between oil price and exchange rate, L_{+OIL} and L_{-OIL} are negative. However, only L_{+OIL} is statistically significant, which highlights the speed of adjustment to equilibrium after a shock. The Wald statistic suggests the rejection of long-run symmetry of positive and negative changes in Brent oil prices. It is noticeable that the relation between the Brent oil prices-FX is asymmetric, suggesting that market participants are willing to increase the prices of dollar for an increase in Brent oil prices. However, they are less sensitive to the decline in Brent oil prices

TABLE 12
ASYMMETRIC RELATIONSHIP BETWEEN OIL PRICES AND FX

Variable	Coefficient	t-stat
Constant	0.5122***	2.8369
Yt_{-1}	0.4612***	3.5696
Oil_{+t-1}	0.8255***	4.2127
Oil_{-t-1}	0.3415***	1.5826
ΔYt-1	0.1156***	3.968
ΔOil_{+t-1}	0.4378***	3.5469
ΔOil_{-t-1}	0.2105***	1.2654
L_{+Oil}	1.659***	
L_{-Oil}	0.0245	
WL_R	9.12521	
WS_R	15.1265	
AdjR^2	0.6104	

CONCLUSION

This article investigates the inter-relationships between three different markets – the stock market, the Brent oil market, and the foreign exchange market (FX), during Brent oil price shock periods. According to the descriptive statistics, oil prices are highly negatively correlated with the foreign exchange rate and positively associated with the $S\&P_{500}$ index.

The paper investigated if Brent oil prices follow a random walk. We rejected the null hypotheses of unit root and concluded that Brent oil prices are mean-reverting and that they do not follow a random walk, and thus arbitrage opportunities are present. Then we investigated the volatility relationships between the three markets using the constant conditional correlations (CCC) model, the dynamic conditional correlations (DCC), and the time-varying conditional correlations (VCC), and we found evidence that there are volatility relationships between the three markets.

The results of the VAR system show that the coefficient of regressing Brent oil prices on the $S\&P_{500}$ price index (with lag two levels) is positive and significant. Also, the results show that the relation between Brent oil prices and FX prices is negative and significant. All that means that Brent oil price shocks remain mostly positive shocks that then translates into higher returns on the stock markets while negative returns on the FX markets.

The IRF parameter estimates of testing the relationship between the prices of Brent oil, $S\&P_{500}$ index, and the FX of the trade-weighted US dollar index during the shock periods shows that the long-run responses of Brent oil prices to an impulse in $S\&P_{500}$ are significant. Also, the long-run responses of FX to an impulse in Brent oil prices are negative and insignificant. Conversely, the short-run responses of FX to an impulse in Brent oil prices are negative and significant.

We also investigated the long-run equilibrium between three markets, and we concluded that there is a long-run equilibrium between Brent oil, FX, and $S\&P_{500}$ before and during the shock period, but not after the shock period, which shows a dynamic relationship between all these variables. Therefore, we used VECM and VEC Granger Causality/Wald test for the pre-shock and during the shock periods while using VAR and Granger analysis for the post-shock period. The Granger test results show unidirectional causality from $S\&P_{500}$ to FX and from Brent oil to FX. The results are like the results of VAR. Thus, we can say that our results are robust.

Further, Wald tests show that there is a nonlinear bidirectional relationship between Brent oil prices and FX and they both grangers cause each other and that there is an asymmetric response of FX to Brent oil prices shock, as such the positive oil shock and negative oil shock, both have a significant impact on FX in the short run, but in the long term, only positive oil shock has an impact on the FX

Finally, implications for future research are to develop trading strategies that can benefit from the interrelationship that were discovered in this article and to examine if the same relationship will exist if we include developing and emerging markets in the analyses.

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