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Do Exchange Rate Volatilities Shock Oil Price Fluctuations: Evidence from Top Four Oil Importing Countries in Asia – China, India, Japan and South Korea

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Do oil price returns impact exchange rates fluctuations; Evidence from the top four oil importing countries in Asia – China, India, Japan and South Korea.

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Abstract

Using daily data obtained from Federal Reserve Bank of St. Louis database, we convert oil price and exchange rates to first difference logarithm to examine the link between oil price and exchange rates. We apply Johansen Cointegration models to examine relationship between the series, and our results indicate the variables are not cointegrated. Augmented Dicky Fuller test indicates that the series are nonstationary at level, but stationary at first difference. Impulse response analysis based on unrestricted vector autoregressive (VAR) yields varying results for the relationship between oil price and exchange rates across the currencies of the four countries considered. Thus, we suggest that decision making regarding oil price and exchange rate dynamics must be considered based on a country's unique features rather than on a universal platform.

Keywords**:** oil price fluctuations, exchange rate performance, top oil importing countries in Asia, cointegration, Granger causality, impulse response function.

1. Introduction

Crude oil price fluctuations and exchange rate performances are major macroeconomic parameters in business decisions. Domestic and multinational entities are affected by variations in these variables either directly or indirectly, and individual countries respond differently to the shocks. Moreover, statistical studies indicate that about 70 percent of the world's economic activities are crude oil driven. Thus, the nexus of oil price surge and exchange rate movements are a major risk facing government, corporate bodies and households. And given the inelastic nature of crude oil use, the effort to mitigate the burden of an oil price surge has resulted in hedge contracts. Similarly, globalization of economic activities is the product of exchange rates and the related hedge contracts. Contracts are executed in the major trading currencies with the U.S. dollar as the leading trading currency. Endowment of crude oil varies among countries, whereas, some countries have in abundance, others do not. Demand and supply for crude oil involve currency settlement usually denominated in the US dollar. Therefore, it is prudent to analyze the movements of oil price and exchange rates for internal and external shocks.

For these reasons, over the past three decades, oil inventory, oil price and exchange rate relationships have become a crucial area of study. For instance, Amano and Norden (1998) explain why real oil price captures exogenous terms-of-trade shocks and why such shocks could be the most important factor determining real exchange rates in the long run. Oil price and exchange rate movements have also been noted by, inter alia, Krugman (1983a). Krugman stress that when we speak of the effect of the price of oil on the exchange rate, it is not the dollar rate, but the dollar-mark or dollar-yen rate that we have in mind. Also, Bernanke, Gertler, and Watson (1997) indicate that finding a measure of oil price shocks that "works" in a VAR contest is not a straightforward. This suggests that there is more room for study in this area since earlier findings are tentative. While most of the papers look at cross-country data, there is significant benefit to study a different group of countries and time series to capture structural changes with respect to time and region. Amano and Norden (1998) examine the relationship between real domestic price of oil and real effective exchange rates for Germany, Japan and United States with a concluding remark that their research can be extended for additional currencies.

We realized that much studies have been done in the analysis of oil price and exchange rates in the top oil exporting countries. But on the importing countries side, exhaustive work has not been done. Thus, we decide to focus on the top oil importing countries in Asia. The countries considered are China, India, Japan and South Korea. World's Top Oil Exports reports that global purchases of oil totaled US$1.182 trillion in 2018. Among the continents, Asian countries accounted for the highest dollar worth of imported crude oil during 2018, with purchasing costing $628.2 billion (53.2%) of the global total. China is the highest world importer of crude oil; US$239.2 billion (20.2%) followed by the USA. India is third $114.5 billion (9.7%), Japan fourth $80.6 billion (6.8%) and South Korea fifth $80.4 billion (6.8%).

Our empirical findings indicate that oil price and exchange rates are not cointegrated, reflecting a short run relationship for vector autoregressive model (VAR) application, rather than the adoption of vector error correction model (VECM). Contrary to our finding on cointegration, Amano and Norden (1993) indicate that the U.S. real exchange rate appears to be cointegrated with the real oil price. Similarly, Rautava (2004) examines the impact of international oil prices and real exchange rate on Russia's economy and conclude that long run relationship exists between oil price and real exchange rates. To validate our findings for cointegration we realized that Mamun and Nath (2005) examine quarterly data from 1976:1 to 2003:3 and show evidence of a long run equilibrium relationship between exports and outputs in Bangladesh.

Our empirical finding is based on daily data, while related findings cited above are based on monthly and quarterly data. We justify that differences in data frequency and period of coverage may result in varying degree of findings.[1] Estimating daily returns for oil prices and exchange rates provide in-depth information about market microstructural issues. Such real-time market dynamics may be lost to data compiled on monthly, quarterly and annual basis.

Moreover, our data analysis is based on nominal oil price and nominal exchange rates, while the earlier researchers adopt real variables; conversion of data from nominal to real has inherent limitations and may skew the results. Converting data from nominal to real involves adjusting the nominal data with inflation. The process involves choosing a base year and then using price index to convert the nominal data to real data. The entire process is arbitrarily and subject to manipulation. For instance, Lizardo and Mollick (2010) converted monthly data from nominal to real to study oil price and exchange rates relationships from 1970's to 2008 and concluded that increases in real oil prices lead to significant depreciation of the USD against net oil exporter currencies. They moved further that currencies of oil importers, such as Japan and Demark suffer a depreciation relative to USD when the real prices of oil go up. Contrary to their finding, we use nominal daily data to study the top four oil importing countries in Asia and find that China, India and South Korea currencies depreciate when oil prices increase, but the Japanese yen appreciates when oil price rises. Thus, we conclude that it cannot be generalized that an increase in oil price automatically leads to depreciation of importing countries currencies. One must consider macroeconomic factors pertaining to the countries concern. We justify our finding that inflation rate varies among the countries and such factors are likely to influence exchange rates outcome.

Granger causality test results show a non-causal relationship in both direction between oil price and exchange rates for India and South Korea. However, results for China and Japan show unidirectional causality between oil price and exchange rate for Brent and WTI respectively. In

[1] Andersen, 2000 states that it is evident that access to intraday observations from liquid financial markets such as the foreign-exchange, bond, or equity index market index afford vastly improved ex post volatility measurement and forecast evaluation.

related literature, Amano and Norden (1998) report that causality runs from oil price to exchange rate and not vice versa. Brahmasrene, Huang and Sissoko (2014) indicate that exchange rates Granger-caused crude oil price in the short run, while crude oil price Granger-caused exchange rate in the long run. Amano and Norden (1998) report that causality runs from oil price to exchange rate and not vice versa. Akram (2004) finds a non-linear negative relationship between the value of the Norwegian krone and the crude oil price. The strength of correlation between exchange rate and oil price varies with the level and trend in oil prices. For instance, a change in oil price has a stronger impact on exchange rate when the level of oil price is below 14 dollars, than at higher levels. The strength of the relationship increases when oil prices display a falling trend. The reported nonlinear oil price effects are only significant in the short run. In the long run oil prices are found to have no effect on exchange rates.

Our study is different from the earlier publications in varying ways; first, most of the previous literatures focused on the oil exporting countries; we concentrated on the top oil importing countries. Second most of the papers model their findings from monthly and quarterly data; we utilized a high daily frequency data to check the robustness and validity of our findings. Third, we avoid the challenges associated with conversion of oil price and exchange rate data to real by using unadjusted nominal data.

The rest of the paper is organized as follows; section two presents data and methodology, section three focus on empirical results, while section four deals with discussions of significant findings, and section five summarizes the paper

2. Data and Methodology

2.1 Data

The data set comprised daily data for crude oil spot price (U.S dollar per barrel) and exchange rates (U.S dollar as the base currency) from 1987-05-20 to 2020-02-21. Spot oil price data for West Texas Intermediate (WTI) and Brent are obtained from the U.S. Energy Information Administration database.[2] WTI - Cushing, Oklahoma daily crude oil prices are available from January 2, 1986, while Brent – Europe daily crude oil prices are available from May 20, 1987. To ensure equity comparison for WTI and Brent we ran all data from May 20, 1987. Nominal exchange rates are obtained from the Board of Governors of the Federal Reserve Systems (US) database, retrieved from FRED, Federal Reserve Bank of Saint Louis.[3] Oil price and exchange rate series are converted to first difference logarithms for econometric analysis of relationships.

[Insert figure 1]

Figure 1 shows a graphical presentation of the series converted to first difference logarithms. Exchange rates series are stationary in first difference logarithms; however, the extent of variations differs among the four currencies considered. The Chinese yuan and South Korean won are more stable, depicting insignificant variations overtime. However, the Indian rupee and the Japanese yen show evidence of significant derailment in their stationarity. We conclude that there are substantial variations across exchange rate variables. In the early 1990s, we notice a significant drift in exchange rates in all the four currencies, but the pattern of drift varies in magnitude. The countries' exchange rates platforms were hit in different magnitudes following the crises of the European Monetary System in the early 1990s.

[2] We examine the WTI and Brent, because China, Japan, and South Korea import bulk of crude oil from WTI, while, India trades much with Brent market.

[3] Oil price and exchange rate data are not seasonally adjusted and are daily frequency.

The plots for Brent and WTI oil prices depict marginal variation, indicating a similar direction of price movements. The two graphs are evidence that oil prices (Brent and WTI) are stationary in first difference logarithm. However, there is significant price trajectory between late 1990 and early 1991 (Gulf War era), and 2008 (financial crises era).

All the variables have kurtosis less than 3 (platykurtic), therefore the data set has a lighter tail than normal distribution. Thus, the extreme events are less likely to occur than would be the case for normality. The distribution produces fewer and less extreme outliers than does the normal distribution.[4] Except for the South Korean won exchange rate for Chinese yen, the Indian rupee and Japanese yen are negatively skewed.[5] Crude oil prices for WTI and Brent are, however, skewed to the right, displaying positive skewness. Oil price and exchange rate data are nonsymmetrical.

2.2 Methodology

This section uses econometric frameworks to analyze the relationships between oil price and exchange rates. Since the sample period runs from May 20, 1987 to February 21, 2020 due care is adopted in the analysis and interpretation of our findings. To ensure statistical accuracy and avoidance of deceptive results, we employ multiple techniques in the analysis of relationships between the variables.

2.2.1 Unit root test

Most often econometrics and financial data are usually non-stationary and may yield spurious regression at levels. We perform the unit root test to determine the order of integration for the

[4] More risk-averse investors might prefer assets and markets with platykurtic distributions because those assets are less likely to produce extreme results.
[5] Negatively skewed (also known as left-skewed) is a distribution which has more values concentrated to the right side (tail) of the distribution graph, while the left tail of the distribution is longer. Positive skewed distribution is the opposite of negative skewed distribution.

series use in the study. The null hypothesis is defined as the presence of unit root[6], while the alternative is that the series are stationary.[7] Augmented Dickey Fuller (ADF) is a known test for large samples. We perform on the order of test equation specifications; intercept, trend and intercept, and none. We find trend and intercept as the ideal specification for each series and that;

$$\Delta y_t = \delta_0 + \delta_1 t + \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta \, \Delta y_{t-1} + \mu_t$$

Where δ_0 is intercept term, β is coefficient of time trend, t is deterministic time trend, Δy_{t-1} is the augmented term, $\rho - 1$ is the lag order of the autoregression and μ is an independent error term with zero mean and fixed variance σ^2. We depend on automatic selection of maximum lags for the optimal lag structure.[8] We base the lag length selection on Schwartz information criterion and Akaike information criterion and arrive on similar results, so we report our results on Akaike information criterion.[9] The estimation is based on finding an intercept and a trend with either one or both to be statistically significant at 5%.[10] If we do not find the desired level of significance, we drop the insignificant term and re-estimate the test statistics. At level for all our estimations we find out that the series have a unit root. We estimate the series on first difference and second difference and find no unit root, so we report findings on first difference.

The ADF has been criticized of low statistical power in distinguishing between the true unit root processes ($\gamma = 0$) and near unit root processes (γ is close to zero), see Schwert 1987 and Dejong et al. 1992. Several authors have raised concerns that ADF test tends to reject non-stationarity hypothesis when the series have long run average of integration. Uncertainty exists in the selection of optimal lag order, ρ, thus, we stick to lag length automatic selection with 35

[6] We refer the presence of unit root $I\ (1)$ as non-stationary and no unit root $I\ (0)$ as stationary series.
[7] Stationarity of series imply that its mean, variance and covariance are constant over time (that is the series are time invariant).
[8] No general rule exists in the selection of maximum lags selection.
[9] The measure of information criterion is to provide a measure of information that strikes a balance between the measure of goodness of fit and parsimonious specification of the model.
[10] In the context of unit root testing, Maddala and Kim (1998, p. 128) question the appropriateness of using a conventional significance level.

maximum lags for our daily frequency. What test to include in equation is uncertain, therefore, we follow Phillip's and Perron's (1988) recommendation that one needs to estimate first order autoregression with a constant and possibly a time trend in order to calculate the appropriate transformed Z statistic[11].

In order to overcome the challenges associated with ADF test, we utilize the Phillips-Perron test to corroborate our results. The Phillips-Perron approach is nonparametric with respect to nuisance parameters and there by allows for a wide variety of class time series models in which there is a unit root. This method offers a promising alternative to Dickey-Fuller in terms of practical application where the presence of nonzero drift is common. Although, we do not tabulate the statistical findings of the PP test, we conclude that ADF and PP tests have similar limiting distributions and lead to homogeneous qualitative results. Our data are nominal for both WTI, Brent oil prices and exchange rates and they all have unit root at level.[12]

2.2.2. Cointegration test

We perform the cointegration test to analyze the order of integration between oil price and exchange rates.[13] Since oil price and exchange rates are $I(1)$ at level, we say that oil price and exchange rates are cointegrated if there exists a linear combination of these variables that is $I(0)$. If both series are driven by the same trend, then one would expect that the log of oil price minus the log of exchange rate is fluctuating about a constant mean.[14] Thus, there is a long run equilibrium relationship. Applying the concept to higher orders of integration, the vector in k-dimension process y_t are cointegrated if the components are $I(d)$ with a linear combination $Z_t = \beta' y_t$, where $\beta = (\beta_1, \ldots, \beta_x)' \neq 0$ and that z_t is $I(d^*)$ with $d^* > d$. We refer to Vector β as the

[11] The Z score tests statistical significance help in deciding whether to reject null hypothesis.
[12] Pascalau 2010 concludes that in general, it appears that real variables are stationary while nominal ones have a unit root.
[13] If two integrated variables share a common stochastic trend such that a linear combination of these variables is stationary, then they are cointegrated, Kilian and Lutkepohl 2017 pp75.
[14] Mean reverting and appears stationary.

cointegration vector. Thus, we assume that if $Z_t = p_t - p_t^* \sim I(0)$, then $p_t \sim I(0)$ denotes the log of oil price and $p_t^* \sim I(1)$ also denotes the log of exchange rate expressed in domestic currency values per U.S. dollar as the base currency. Therefore $\beta = (1, -1)'$ is the expressed cointegrating vector. Note that this definition is slightly different from the one given by Engel and Granger (1987).[15] The definition covers the case when the components of y_t have no common trend, Kilian and Lutkepohl 2017, pp 77.

Our daily data have asymptotic properties (larger sample size), therefore, we use the Johansen test of cointegration that allows for more cointegration relationship; a better model than the use of Auto Regressive Distribution Lags (ARDL). We use the bivariate model to perform Johansen Cointegration test for oil price and exchange rates. The Johansen test involves estimation of the equation shown below;

$$\Delta x_t = \sum_{i=1}^{p-1} \pi_i \Delta x_{t-1} + \pi x_{t-p} + \varepsilon_t$$

Thus, x_t is the vector variable of the series for oil price and exchange rates. Cointegration test involves the rank of matrix π[16]. And the rank of the matrix is equal to the number of the characteristics roots that deviate from zero. We identify p as the lags in determining the lap length for the vector equation. Results interpretation is based on the trace statistic and maximum Eigenvalue statistic.

2.2.3 The Vector Autoregressive and Optimal lag length

[15] If each element of a vector time series x_t is stationary only after differencing, but a linear combination $\alpha' x_t$ need not to be differenced, the time series x_t have been defined to be integrated of order (1, 1) with co-integrating vector α. Interpreting $\alpha' x_t = 0$ as long run equilibrium, co-integration implies that the equilibrium holds except for a stationary, finite variance disturbance even though the series themselves are non-stationary and have finite variance.

[16] For example, $m\ x\ n$ matrix; m rows are horizontal and the n columns are vertical. Each element of a matrix often denoted by a variable with subscripts such as a_1, 1 representing the elements of the first row and first column of the matrix.

The unrestricted VAR is used as a multivariate linear representation to analyze the interventions between oil price and exchange rates. We aim at explaining how unobservable random variables correspond to changes in oil price and exchange rates in a short run transmission through regression analysis. The unrestricted VAR helps us to explain the volatile nature of the observables in terms of their lag effects as endogenous to their own lags. The order of integration is non-stationary at level I(0), but stationary at first difference I(d). At first difference all the roots lie inside the unit circle, and the VAR satisfies the stability condition. We assume the variables to be endogenous and represented by k over the sample period (t = 1, 2…, T), and then express them as a linear function of their past values. We presented the variables in a k vector matrix, where, k-vector ((k x y) matrix))y_t, which has the i^{th} element, $y_{i,t}$, the observation at "t" of the i^{th} variable. Hence, if the i^{th} variable is oil price, then $y_{i,t}$ is the value of oil price at time t. The p^{-th} order of VAR is termed a VAR with ρ lags. We considered eight lags as the optimal lag structure by focusing on the Akaike information criterion. We present the VAR model as y_t = c + $A_1 y_{t-1}$ + $A_1 y_{-2}$ + … + $A_\rho y_{t-p}$ + ε_t, where the observations y_{t-1} is known as the i^{th} lag of y, c is a k-vector of constants, A_i is time invariant (k x k) matrix and ε_t is a k-vector of the error term.

2.2.4 Pairwise Granger causality test

According to Granger, (1969) in some occasions' difficulty exist in deciding the direction of causality between two related variables and the re-occurrence of feedback. The paper employs Granger's two variable model to help forecast the relationship between oil price and exchange rates in relation to the four major Asian oil importing countries' domestic currencies. Here we do not infer cause-effect relationship, rather using the model to predict or forecast statistical association in terms of time pattern relationship between the series. We use Pairwise Granger causality tests to determine the direction of causality, where; H_0: no Granger causality, whereas, H_1: rejection of the null hypothesis (implies there is Granger causality). H_0 is rejected if the probability value of F-statistic ≤ 0.05. The number of lags chosen for the causality test are based on the specification of the AIC deemed as the optimal lag for the VAR analysis.

2.2.5 Generalized Impulse Response Functions and Vector Autoregressive Model

We perform impulse response function to analyze the short-term innovations on the reaction of oil prices and exchange rates. The series are not cointegrated, therefore, we perform the short-run vector autoregressive model (S-VAR) to analyze the dynamic impact of random disturbances of the system variables. The VAR model bypasses the need for structural modelling by considering all the series as endogenous in the model as a function of the lagged values for all endogenous variables in the system. We aim at extrapolating the interrelationships among the series rather than determining the estimated parameters. We include the variables in their level with the choice of lag intervals for the endogenous 8 lags, consistent with the optimal lag for the AIC. The individual coefficients in the estimated VAR models are often difficult to interpret; thus, we estimate the impulse response function. The impulse response helps to trace the effect of the present and the future values of the endogenous variables of one standard deviation shock to one of the innovations. This helps to explain the degree at which the changes in the variables are passed to other variables at different stages either directly or indirectly. We employ a multivariate model to present the VAR in the algebraic representation below:

$$\ln(y_t) = \alpha + \sum_{i=1}^{\rho} \beta_i \ ln(y)_{t-1} + \sum_{j=1}^{\rho} \emptyset_j \ ln(v)_{t-j} + \mu_1$$

$$\ln(v_t) = \delta + \sum_{i=1}^{\rho} \beta_i \ ln(y)_{t-1} + \sum_{j=1}^{\rho} \emptyset_j \ ln(v)_{t-j} + \mu_2$$

The variables are defined as follows; $y \ and \ v$ are the series of interest; $\alpha \ and \ \delta$ are intercepts; β_i and $\emptyset_j$ are short-run dynamic coefficients of the models dynamic adjustment long-run equilibrium; μ_1 and μ_2 are residuals in the equation. Here ρ is the appropriate lag length for the variables in the VAR using the AIC. Suppose μ_1 increases by a value of one standard deviation; such a shock will change the current value of $\ln(y_t)$ in the current as well as future periods. Since $\ln(y_t)$ appears in the entire regression model, the change in μ_1 will have an indirect impact on all series in the model. Similarly, a change of one standard deviation in μ_2 of the $\ln(v_t)$ will have an impact on the entire regression model because of the “pass-through” effect.

Cholesky dof adjusted decomposition is used to ordering and analyzing the relationship between exchange rate and oil price. It assists us to trace the effects on the present and the future values on the endogenous variables of one standard deviation shock to one of the innovations. This helps in explaining the “pass through” concepts as a measure of the degree to which the changes in oil prices are passed to the exchange rates values at different stages either directly or indirectly. Given oil price (oilp) and exchange rate (ex), we employ two model variables to demonstrate the algebraic representation as shown below:

$$oilp_t = \beta_1 + \beta_2(ex_{t-i}) + \beta_3\,(oilp_{t-i}) + \varepsilon_1$$

$$ex_t = \beta_4 + \beta_5\,(oilp_{t-i}) + \beta_5\,(ex_{t-i}) + \varepsilon_2$$

ε_1 and ε_2 are the impulse, innovations, shocks or error terms.

Accordingly, we put a shock to the innovation or the residual of the above model to see how it affects the whole VAR model. A change in ε_1 and ε_2 will bring a change in oil price and exchange rate during the next ten-day period. We aim at identifying how oil price and exchange rates react to each other when shocks are applied to the error term.

3. Empirical Results

3.1 Unit Root Results

It is always feasible to perform econometric and financial models on stationary data to avoid spurious correlation. We perform tests to analyze the presence of unit root on the variables of interest for the bivariate and multivariate analysis. Table 2 presents the summary of Augmented Dickey-Fuller test for unit root analysis.

[insert table 1]

The results show all series are $I(1)$ at level. However, at first and second differences, all the series results are $I(0)$, we present results for first difference only.

3.2 Cointegration Results

We performed two separate Johansen cointegration tests to analyze the relationship between the series. We first run the model to examine the relationship between WTI-oil price and exchange rates and later perform similar model for Brent-oil price and exchange rates and find equivalent results. Initial analysis involves ensuring that all the series are $I(0)$ at level, but stationary at first difference. Correlogram tests reveal that all the series have a unit root at level but are stationary at first difference. Thus, one of the preconditions for Vector auto-regressive (VAR) analysis is met. Selection of optimal lag as a precondition to run Johansen cointegration test and VAR requires utmost care; too many lags lose degrees of freedom, create a statistically insignificant coefficient, and has multicollinearity, while too few lags may lead to specification errors. We choose 4 lags for the Akaike information criterion because all the lag order selection criteria depict lag 4 except for Schwarz information criterion. We perform a bivariate cointegration equation for oil price and exchange rates, and oil price is considered as the target variable.

[insert table 2]

Table 2 presents the summary of all the five sets of assumptions of cointegration test specification. We report the number of cointegrating equations according to the trace statistics and the max-eigenvalue statistics. Based on the number of cointegrating equation from the table, we conclude that oil price and exchange rates are not cointegrated. The trace and max statistics indicate that there is no cointegrating relationships between Won and oil price for Brent and WTI. Similar findings are obtained for Yen and Yuan, except for Rupee, where the trace indicates no cointegrating equation between oil price for Brent and WTI models. But, the max-eigen gives a conflicting result that there is at most one cointegrating equation between Rupee and oil price for both Brent and WTI. Following Serletis and King (1997), we decided to adopt the trace and concluded no cointegrating relationship between the series[17].

3.3 Pairwise Granger causality results

Having noticed evidence of no cointegration, we performed pairwise Granger causality tests to determine the direction of short-term causality between the variables of interest in their order of integration. We realized that the period lags have impact on the causality results, thus, we perform the analysis on several lags ranging from lag 1, 2, 5, 10 and 20.

[insert table 3]

Using the Pairwise Granger Causality Tests, we find that Yuan Granger cause Brent oil price. Lags 1, 2, 5 and 10 are statistically significant, with p-values < 0.05. However, we realize that Brent oil price does not Granger Yuan. This is consistent with Brahmasrene T., et.al. 2014 empirical results that exchange rates Granger-caused oil prices in the short run. We extended the same model to analyze the causal relationship between WTI oil price and Yuan, but we find no causality in either direction.

We find that Rupee does not Granger cause Brent oil price in all the lags. The reverse shows that Brent oil price does not Granger cause Rupee, therefore, we conclude that Rupee and Brent oil price have an independent relationship. Findings for causal relationship between Rupee and WTI oil price is not different than what was found for the Brent.

[17] Serletis and King (1997) suggest that the trace test tends to have more power than the maximum eigenvalue when the eigenvalues are evenly distributed.

Yen does not Granger cause Brent oil price, and the reverse finds similar results. However, we find that Yen Granger cause WTI oil price for lags 5, 10, and 20. This implies a unidirectional causality, because WTI does not Granger-cause Yen.

Won is independent with both Brent and WTI oil prices. Won does not Granger cause Brent oil price and vice versa. Results for causal interactions between Won and WTI oil price is the same as seen with Brent. Our findings are heterogenous across countries and oil markets. Yuan does Granger-cause Brent, but Brent does not Granger-cause Yuan. Similarly, Yen Granger-cause WTI oil price, but WTI oil price does not Granger-cause Yen. We conclude unidirectional causality in the short run for Yen and WTI.

3.4 Impulse Response Analysis

We use impulse response in Unrestricted VAR model to examine the relationship between oil price and exchange rates. As noted above, the individual coefficients in the estimated VAR models are often difficult to interpret, so we use the impulse response function to explain the reaction of an endogenous variable to one of the shocks. All variables are considered as endogenous for the unrestricted VAR with 4 lag intervals consistent with the optimal lag length of the AIC. We choose the Cholesky-dof[18] adjusted decomposition method for our impulse definition with ten-day period unaccumulated responses. We perform the asymptotic responses of standard errors with exchange rates impulses and oil price responses and vice versa. We aim to analyze the contemporaneous response from the shocks to the series in either directions.

[insert figure 2a]

[18] One possible identification restriction is to use Choleski decomposition such that exchange rate at time (t) does not have a contemporaneous effect on oil price at time (t). Here the changes in the error term of the ex_t equation in the structural equation has no direct effect on $oilp_t$. But the lagged value of exchange rate (ex_{t-1}) affect the current value of oil price $(oilp_t)$, hence there is indirect effect of ex_t on $oilp_t$.

Figure (2a) shows the impulse response of changes in first difference logs of Brent oil price and exchange rates. The Yuan, Rupee, and Won respond inversely to one-standard deviation shocks in Brent oil prices. However, we find the response of Brent oil price to exchange rates for Yuan, Rupee and Won are imperceptible. The Yen is positive to one-standard deviation shocks in Brent oil price. This finding is unusual and gives room for further investigation into why the Yen strengthened against the U.S dollar when oil price rises and vice versa. Similarly, we notice that the response of Brent oil price to Yen is unobserved.

[insert figure 2b]

Figure (2b) shows the response of changes in first difference logs of WTI oil price and exchange rates for China, India, Japan and South Korea. The results are like the Brent and exchange rates relationship. However, we observe that relationships are more pronounced in Brent than WTI. In short, with a one-day lag, we conclude instantaneous response of exchange rates to oil price innovations and not vice versa.

4. Discussion

The results demonstrate that heterogeneity exists between oil price movements and currency performance in the foreign exchange markets. Hence, there is no uniform policy in managing oil price fluctuations and exchange rate performance relationships. It is vital for policy makers to consider unique features of these economies before the implementation of strategic policies.

Differences and similarities can be seen from our results and earlier research findings published in this field of study. Using the Pairwise Granger Causality Tests, we report that Yuan Granger cause Brent oil price, while Yen Granger cause WTI oil price and not vice versa. This is consistent with Brahmasrene, et al. 2014 results that exchange rates Granger caused oil prices in the short run. Similarly, Amano and Norden 1998 report that causality runs from oil prices to the exchange rate and not vice versa. Rupee and Won have independent causal relationship with oil price. Our results identified unidirectional causality and independent causality between exchange rates and oil prices.

Analyzing the results of impulse response, we report that the Yen, Rupee and Won respond negatively to oil price shocks. An increase in oil price is associated with depreciation of Chinese, India, and South Korean currencies. On the other side, an increase in oil price is associated with the appreciation of the U.S. dollar. Similarly, Orlowski and Sywak 2019 detect pronounced and rather instantaneous inverse responses of exchange rates to changes in commodity futures prices.

Contrary, we find a rather opposite situation for Japanese yen. The yen responds positively to a shock in oil price, but the reverse is not the case. This implies that an increase in oil price corresponds with appreciation of the yen. An in-depth study reveals that Japan has a long-standing net trading surplus with U.S., so any time the US dollar appreciates it exhibits a positive influence on the Yen.

Several factors account for the heterogenous findings for the relationship between oil price returns and exchange rate movements. For instance, the nominal data are affected by inflation, and the levels of inflation differ among the countries considered.

[Insert figure 4]

Results from table 4 indicate that the direction and magnitude at which exchange rates respond to oil price returns are influence by the level of inflation. India has the highest rate of inflation of 7.55%, followed by China, South Korea, and Japan at declining of 5.04%, 3.68% and 0.52% respectively. The Rupee, Yuan and Won respond negative to oil price returns and the magnitude of their respective responsiveness (in terms of conspicuousness) matches the pattern of inflation rates. Japan has unnoticeable inflation rate of 0.52%, thus, we observe that the yen respond positive to oil price returns.

These countries have different improvement profiles, as well as different structural policies for advancement, thus, the likelihood of finding different results. To understand the intricacies of our results, we suggest the need to monitor and analyze the peculiar features of these economies. We propose to dig into those features more carefully as extension of this paper in the future.

5. Summary

We apply bivariate time series models to analyze the relationship between oil prices and exchange rates in four top oil importing countries in Asia. Johansen test of cointegration result indicates a short run relationship between nominal oil price and nominal exchange rates, therefore, our equation is based on the unrestricted VAR. Impulse response analysis based on VAR equation suggest heterogeneous findings. Yuan, Won and Rupee respond inversely to oil price shocks for both Brent and WTI, but not vice versa. Uniquely, the Yen responds positively to innovations applied to oil prices.

Our results indicate that no uniform policy can be implemented to manage exchange rate performance and oil price fluctuations. Future studies will examine in detail the specific macroeconomic fundamentals of these countries to substantiate our findings.

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Table 1. Augmented Dickey-Fuller Test at level with trend and intercept

		Coefficient	t-statisitic	Critical value @ 5%	P-value	Findings
Brent oil price	level	-0.001115	-2.066539	-3.410346	0.5639	$I(1)$
	1st diff	-0.974387	-88.63637		0.0001	$I(0)$
WTI oil price	level	-0.001516	-2.364148	-3.410346	0.3985	$I(1)$
	1st diff	-1.045524	-95.19281		0.0001	$I(0)$
Rupee/USD	level	-0.002724	-2.686803	-3.410346	0.2421	$I(1)$
	1st diff	-1.817078	-68.99775		0.0000	$I(0)$
Won/USD	level	-0.002385	-3.58822	-3.410348	0.0571	$I(1)$
	1st diff	-1.552368	-30.77868		0.0000	$I(0)$
Yen/USD	level	-0.000796	-2.479517	-3.410346	0.3384	$I(1)$
	1st diff	-0.983225	-89.44655		0.0001	$I(0)$
Yuan/USD	level	-0.000557	-1.956507	-3.410346	0.6243	$I(0)$
	1st diff	-1.010633	-91.93384		0.0001	$I(0)$

Table 2. Summary of Johansen's cointegration results: selected (0.05 level*) Number of cointegrating Relations by Model

	Oil price Brent		Oil price WTI	
Currency	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}
Rupee/USD	0	1	0	1
Won/USD	0	0	0	0
Yen/USD	0	0	0	0
Yuan/USD	0	0	0	0

Note: The tests assume a linear deterministic trend in data and intercept in cointegrating equation. Lags interval: 1 to 4

Table 3. Granger Causality Tests

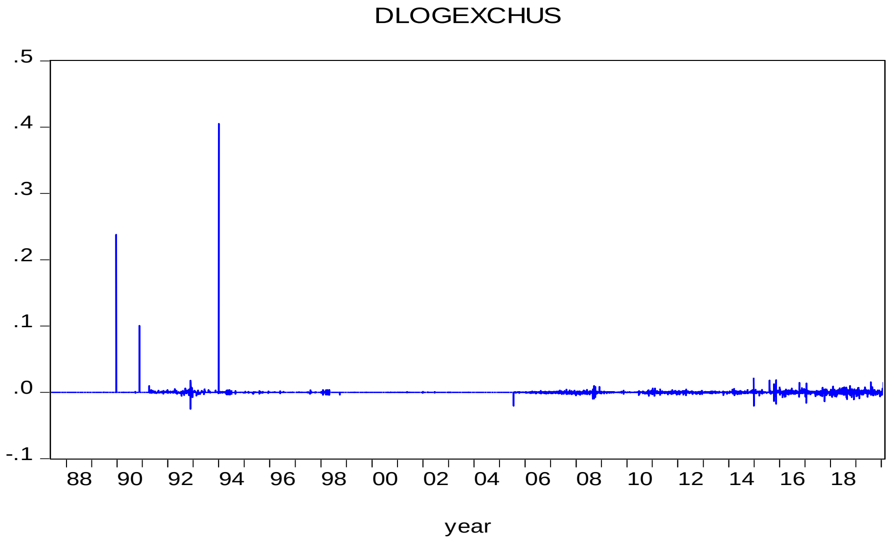
Hypothesis	Yuan does not Granger cause Brent Price	Brent does not Granger cause Yuan	Yuan does not Granger cause WTI	WTI does not Granger cause Yuan
Number of Lags				
1	10.81 (0.00)***	0.21 (0.64)	0.30 (0.58)	0.18 (0.67)
2	6.34 (0.00)***	0.12 (0.89)	0.60 (0.55)	0.41 (0.66)
5	3.62 (0.00)***	0.40 (0.85)	0.42 (0.83)	0.18 (0.97)
10	2.30 (0.01)***	0.40 (0.95)	0.76 (0.66)	0.22 (1.00)
20	1.43 (0.09)*	0.99 (0.46)	0.94 (0.53)	0.81 (0.70)
Hypothesis	Rupee does not Granger cause Brent	Brent does not Granger cause Rupee	Rupee does not Granger cause WTI	WTI does not Granger cause Rupee
Number of Lags				
1	0.35 (0.56)	0.07 (0.79)	0.03 (0.87)	0.01 (0.94)
2	0.33 (0.72)	0.34 (0.71)	0.24 (0.79)	0.37 (0.69)
5	0.28 (0.92)	0.17 (0.98)	0.19 (0.96)	0.44 (0.82)
10	0.39 (0.95)	0.30 (0.98)	0.15 (1.00)	0.76 (0.67)
20	0.80 (0.71)	0.50 (0.97)	1.30 (0.16)	1.08 (0.35)
Hypothesis	Yen does not Granger cause Brent	Brent does not Granger cause Yen	Yen does not Granger cause WTI	WTI does not Granger cause Yen
Number of Lags				
1	0.29 (0.59)	0.78 (0.38)	1.81 (0.18)	1.18 (0.28)
2	0.41 (0.66)	0.40 (0.67)	2.21 (0.11)	0.65 (0.52)
5	0.37 (0.87)	1.57 (0.17)	2.44 (0.03)**	0.87 (0.50)
10	0.75 (0.68)	1.49 (0.14)	2.87 (0.00)***	1.27 (0.24)
20	0.66 (0.87)	1.44 (0.09)*	1.64 (0.04)**	1.21 (0.24)
Hypothesis	Won does not Granger cause Brent	Brent does not Granger cause Won	Won does not Granger cause WTI	WTI does not Granger cause Won
Number of Lags				
1	0.19 (0.66)	0.29 (0.59)	0.23 (0.63)	0.06 (0.81)
2	0.18 (0.84)	1.08 (0.34)	0.43 (0.65)	0.62 (0.54)
5	1.00 (0.42)	2.09 (0.06)*	1.39 (0.22)	1.84 (0.10)*
10	1.13 (0.33)	1.63 (0.10)*	1.21 (0.28)	1.26 (0.25)
20	0.85 (0.65)	1.06 (0.38)	0.80 (0.72)	0.79 (0.73)

*Note: *** 1% significant, **5% significant, *10% significant*

Table 4: Summary of Annual Inflation statistics

	China	India	Japan	South Korea
Mean	5.044244	7.554002	0.524157	3.685385
Median	2.786468	7.164252	0.249355	3.049659
Maximum	24.25698	13.87025	3.251438	9.333361
Minimum	-1.401474	2.490887	-1.352837	-1.352837
Std. Dev.	6.340551	3.042577	1.139944	2.310435
Skewness	1.635418	0.282208	0.851437	0.714452
Kurtosis	4.730497	2.095142	2.095142	2.095142
Jarque-Bera	18.82786	1.563832	4.010166	2.853390
Probability	0.000082	0.457528	0.134649	0.240101

Figure 1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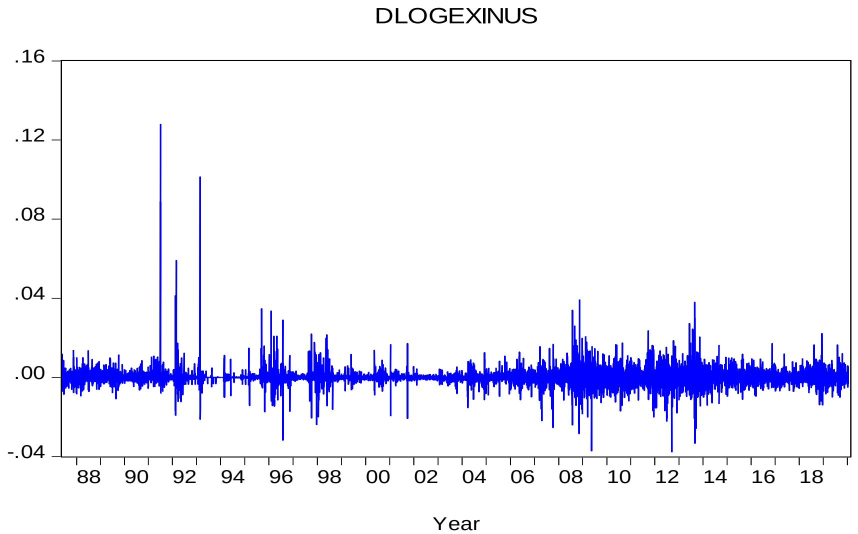
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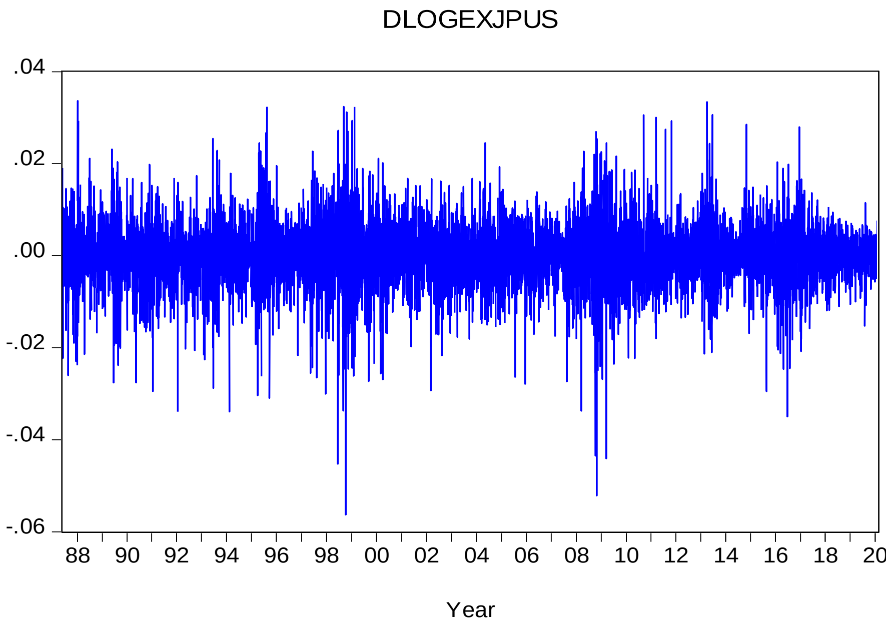
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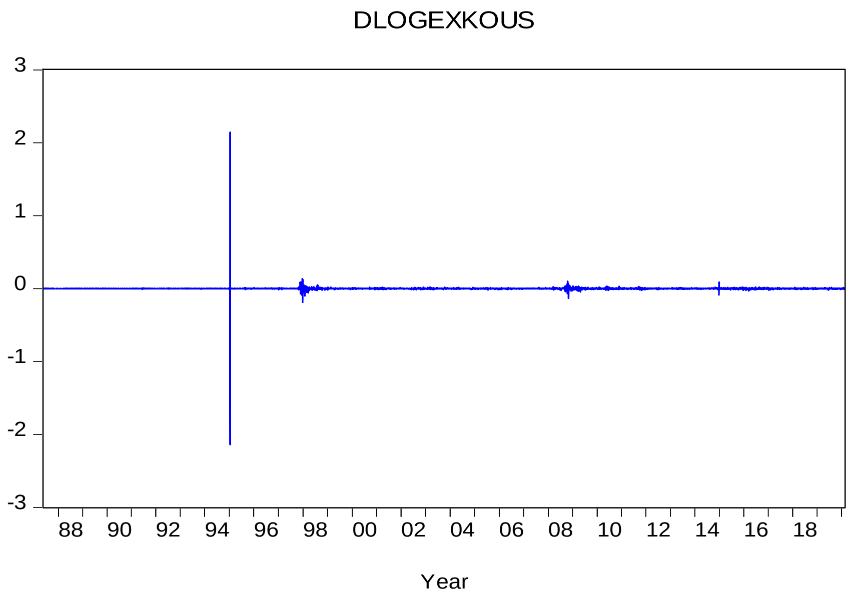
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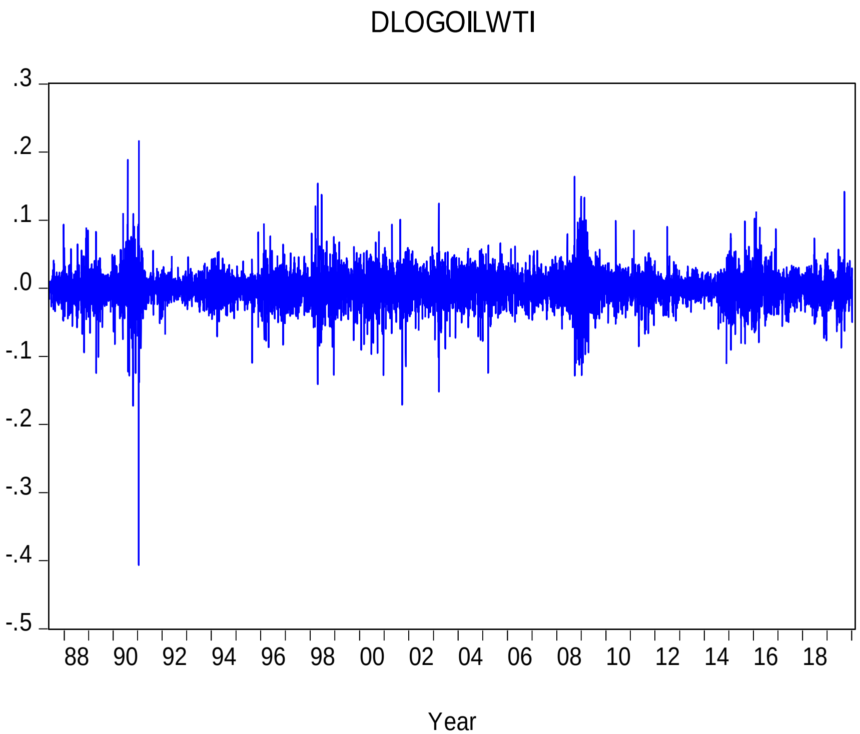
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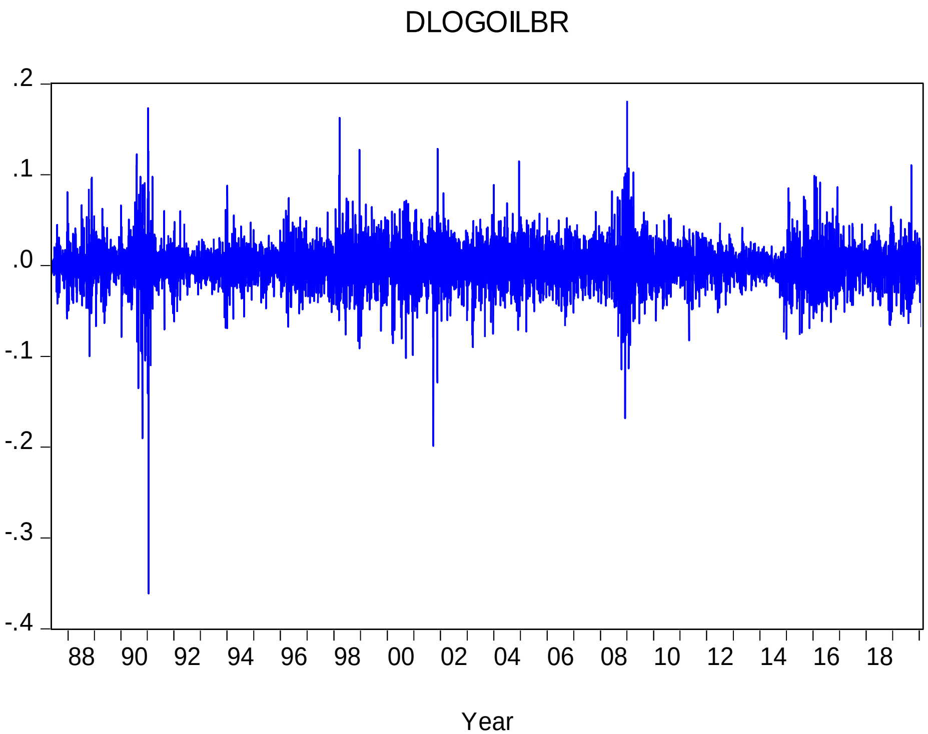
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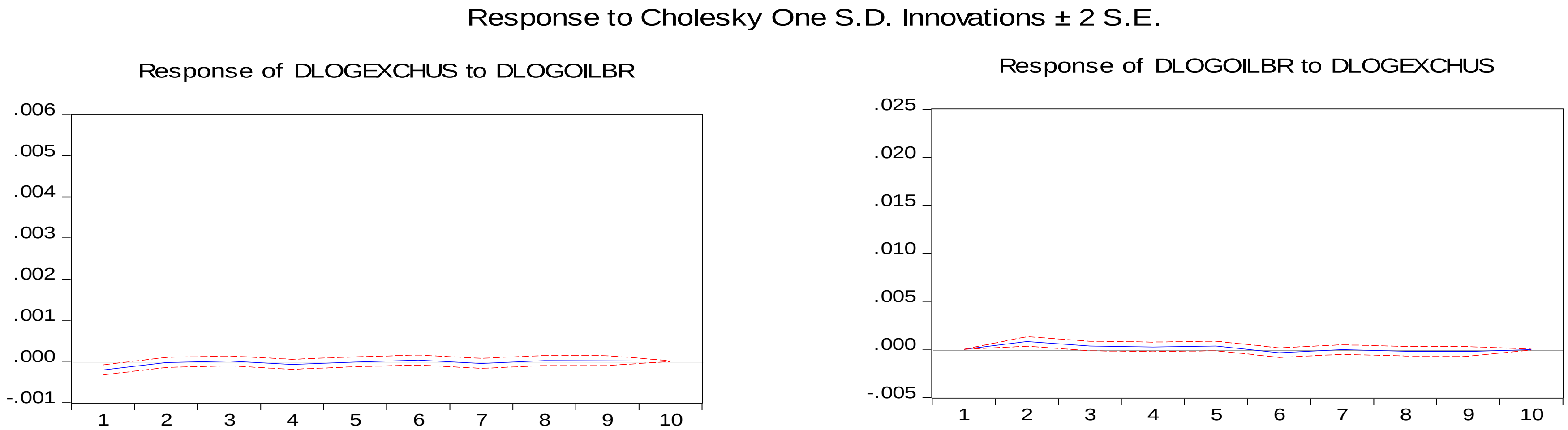
Figure 2a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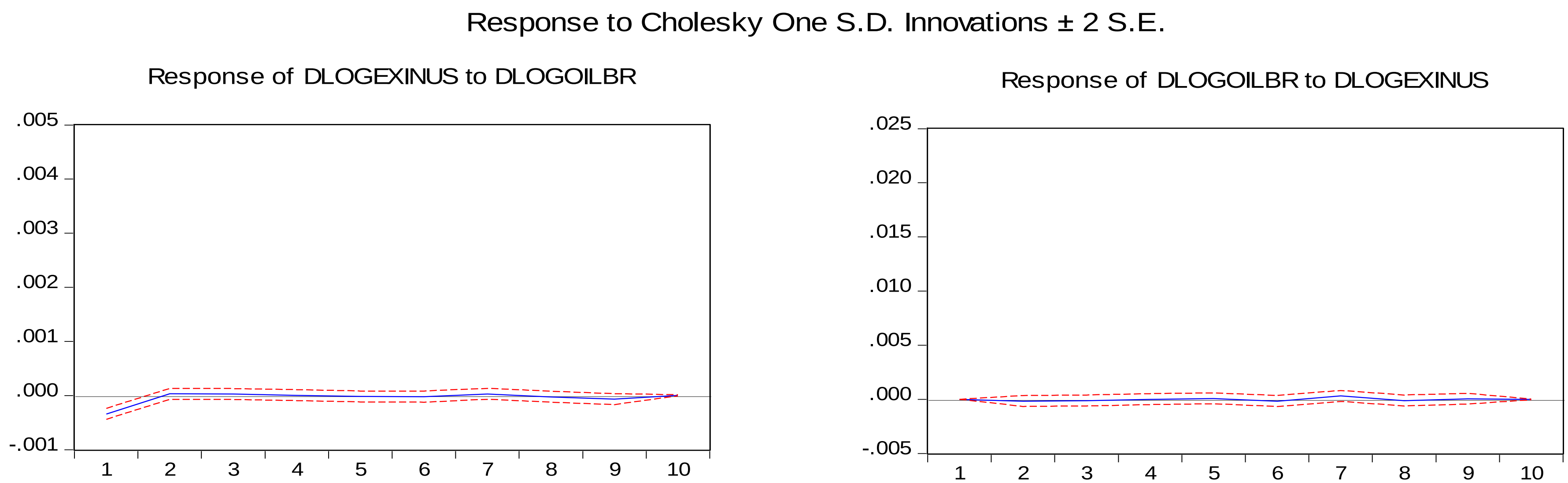
Response of DLOGOILBR to DLOGEXCHUS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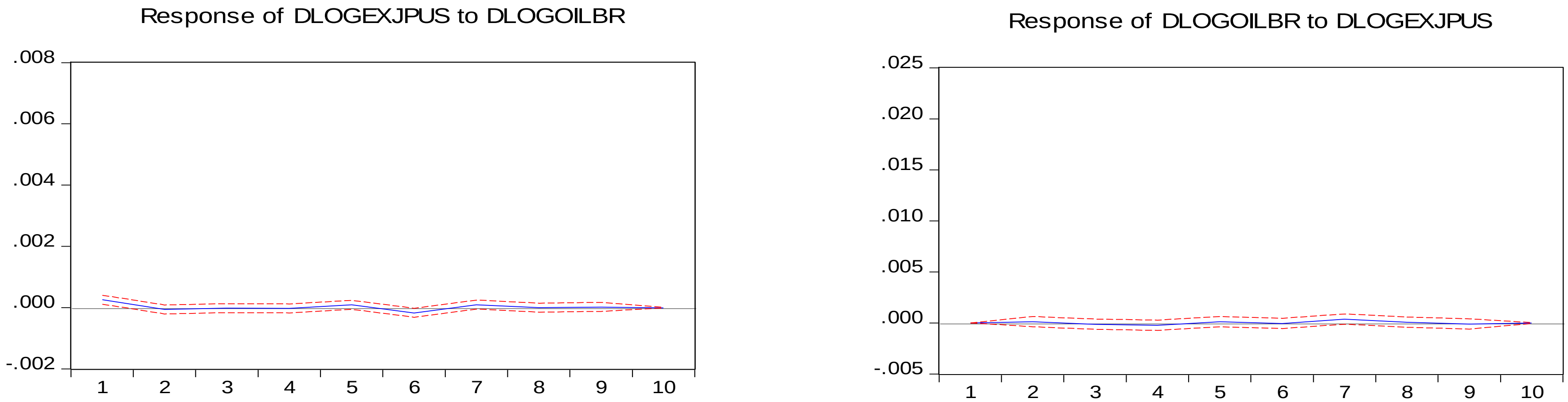
Response to Cholesky One S.D. Innovations ± 2 S.E.



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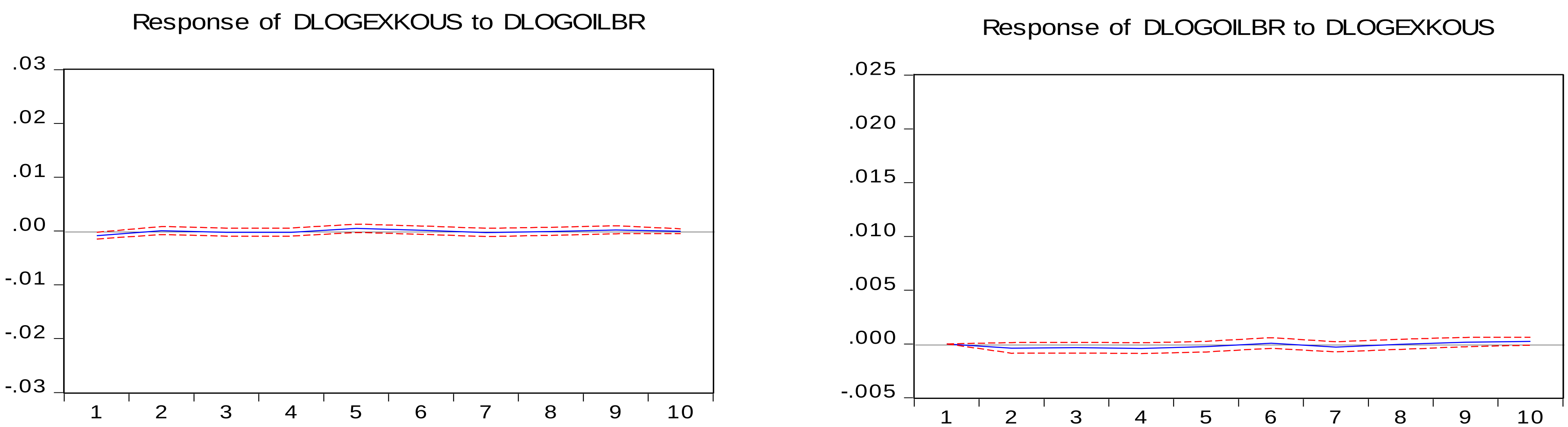
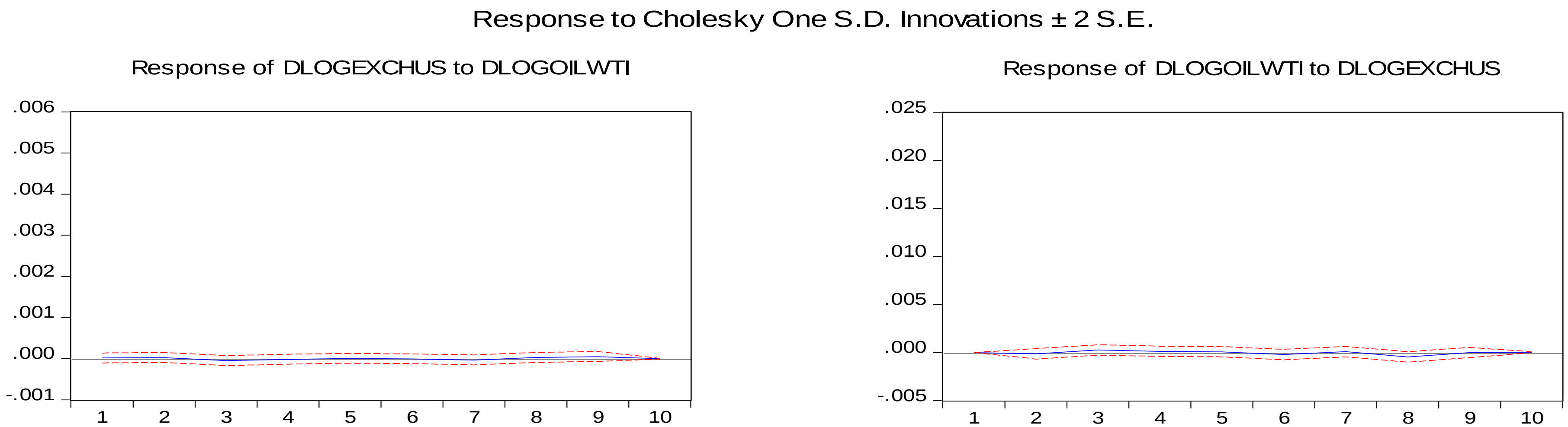


Figure 2b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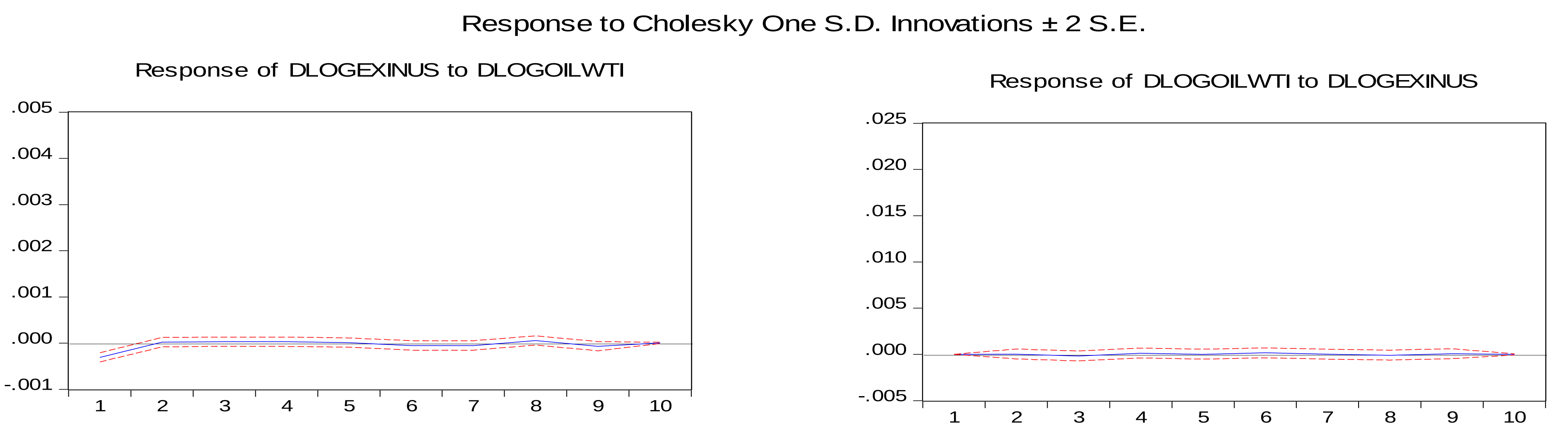
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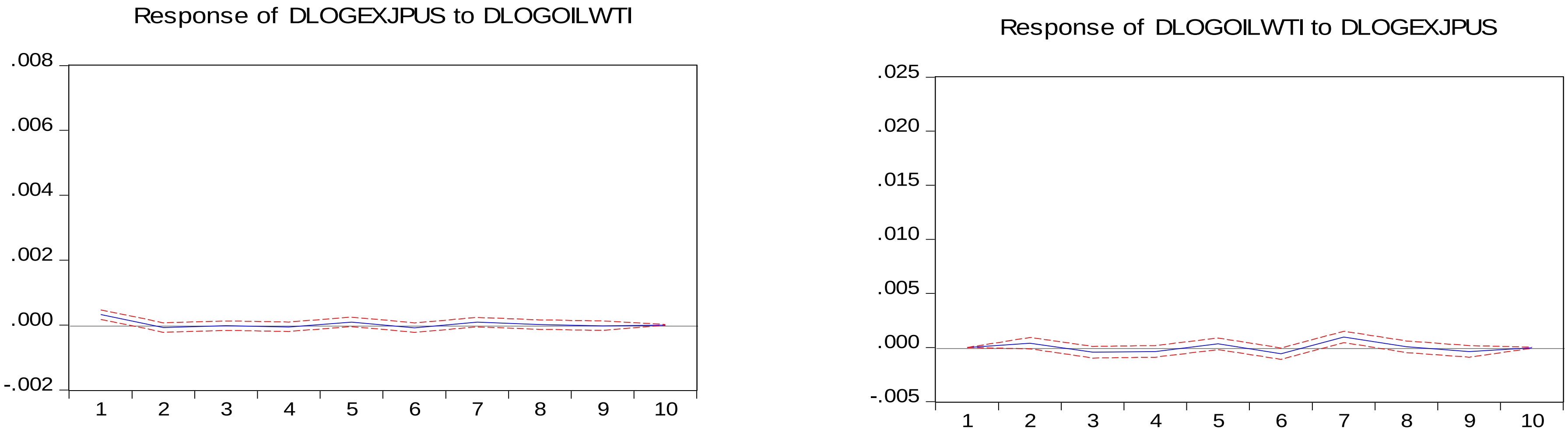
Response to Cholesky One S.D. Innovations ± 2 S.E.



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