Topics in Middle Eastern and African Economies Vol. 18, Issue No. 2, September 2016

Crude oil price changes: Common trend and common cycle features

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Abstract

The purpose of the paper is to assess the impact of OPEC and US crude oil production adjustments on global crude oil price changes. Results in the paper indicate there is a common long term trend between change in OPEC production and crude oil price, but there is no evidence of common trend between change in crude oil price and US oil production. Our finding also indicate there is no evidence of common cycle feature between change in OPEC production and crude oil price, but there is strong evidence of common cyclical association between change in US production and crude oil price. These results imply change in OPEC production adjust crude oil price trend in the long term, but the short term cyclical change of crude oil price is influenced by change in US crude oil production .

Keywords: OPEC; Oil price; Common trend; Cyclical feature

JEL Classification: F32, F21, F17

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1- Introduction:

The sharp decline in oil prices from above $100 per barrel in late 2014 to less than $30 per barrel in early 2016 came amid over supply of crude oil at a time when global demand for crude oil stagnated. Financial concerns in China, US oil production expansion, and the outcome of the talks on Iran’s nuclear program, have all contributed to the current crude oil price decline. Furthermore, the slowdown of the economic growth in the two major crude oil consuming nations, US and China, as well as stronger US dollar created downward pressure on demand for crude oil. Oil price fall was not alone, it was a commodity-wide collapse, with all major commodity prices hitting their lowest level since 2003, wiped out almost all the gains of the decade-long commodities’ "super-cycle", fueled by China.

On supply side, the period (2010 -2014) have witnessed a remarkable increase in oil supply due to the shale technology revolution which increased US domestic production by around 3.5 million b/d since the start of 2009, which regarded as a record increase for an individual country during the whole history of oil industry. Beside the increased supply of oil in US, the increased refinery capacity in US during the last four years accommodated excess supply of oil, which may have adverse effect on crude oil price, as refinery capacity expansion can mitigate excess supply constraints, and thus unleash flow of excess production to oil markets[2].

Production losses due to political unrest in a number of oil producing countries (OPEC members) in Middle East and North Africa (MENA) may not have significant effect on global oil prices because excess supply of oil gained by Shale technology revolution match exactly the loss of oil production in MENA region[3].

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[2] Refineries are designed to operate efficiently using specific crudes such that prices of crude oil rises or falls based on the availability of specific types of crude relative to existing refining capacity. Currently much of the world’s refining capacity is set up to use light sweet crudes, heavy sour crudes represent much of the unused production capacity in OPEC.

[3] The Chinese also adopted the fracking technology and thus, an increase in Chinese oil production through “fracking” can augment the excess supply of crude oil in global energy markets in the future, given that no offsetting events will occur in oil producing countries. Furthermore, an excess supply of oil can also be materialized if Russia decide to increase its production to compensate revenue loss caused by crude oil price drop.

The political factors that influence crude oil prices takes different shapes, including unpredictable political events in oil producing MENA countries, and oligopolistic strategies adopted by OPEC cartel. More specifically, some analyst attribute Saudi Arabia's reluctance to cut production in the face of the recent oil price fall to strategy of trapping the high operating cost Shale producers to shutdown condition.

The remaining parts of the paper include the following. Section two highlights literature review, section three and four discusses data analysis and the methodology of the research. Section five include empirical analysis, and the final section concludes the research finding.

2- Literature review

Since 1970s oil market models offered analytical framework of oil shocks and their impact on the global economy. The focus of most of these models is to produce projection of future prices or to assess the determinants of oil shocks. MacAvoy (1982) is one of the first models that combines supply and demand with the purpose of determining an equilibrium price that clears oil market. Amano (1988) uses small scale econometric model to forecast oil prices for the years (1986 – 1991). Kaufmann et al (2004), Dees et al (2007), and Kaufmann et al (2009) analyze short-run determinants of oil prices. Dees et al (2007) determine demand for oil in OECD and non-OECD countries as a function of income, exchange rates, and technological progress. On the supply side, non-OPEC production is estimated as a function of geological forecast (based on logistic curve) and oil price effects. OPEC production fills the difference between total demand and total non-OPEC supply. Kaufmann et al (2008) show there is a non-linear association between oil prices and refinery capacity utilization levels. De Santis (2003) built a general equilibrium model to understand Saudi government decision making and its influence, as a major producer of oil, on OPEC oil price behavior. Huppmann and Holz (2009) employ an optimization model which uses production cost taken from Aguilera et al (2009) to show that when Saudi Arabia is assumed to be a dominant player in OPEC cartel, it receives oligopolistic profit while the rest of OPEC producers gain competitive profit. The current paper contributes to existing literature by investigating common trend and cyclical association between crude oil prices and change in production of the two major producers, US and OPEC cartel.

3- Data analysis

Data employed in this study collected from Statistical Review of World Energy and Index Mundi database[4]. Variables underlying our research include Brent oil price, OPEC production and US crude oil production. The sample period covers annual series from 1965 to 2014. Summary statistics for each of these variables presented in table (1). As can be indicated by the mean and the min/max statistics, the three variables in the table, show high volatility during the sample period. Positive skewness and high values of excess kurtosis coefficients indicate the distribution of variables characterized by positive skewness and peakness relative to a normal distribution. The positive (negative) skewness results imply a higher probability for increase (decrease) above (below) its mean values during the sample period. The Jarque-Bera (JB) test statistic provides evidence to reject the null-hypothesis of normality for all variables. Phillip-Perron (PP) test indicate, while there is evidence of random walk behavior for all variables at levels, but there is evidence of stationarity of all variables at the first difference. Thus, to capture the random walk behavior of each variable, residuals from AR(p) process for each variable (at the level) need to be estimated.

Table 1: Summary statistics

	Oil price US$/b	OPEC production (000 b/d)	US production (000 b/d)
Mean	48.39	26668	9129
Min/ Max	10.7 115	13922 37427	6783 11297
Skewness:	1.04	-0.92	1.12
Ex.Kurtosis:	3.44	0.62	1.45
JB test p-value	26.5 0.000	6.76 0.03	12.29 0.002

[4] The BP statistical review can be accessed at http:www.bp.com/statistical review.

PP test (level)	-6.1	-5.4	4.9
PP test (1st difference)	-51.3*	-40.9*	47.6*

*significant at 5% error level.

4- Methodology

To assess the long-term association between oil price change and OPEC and US crude oil production changes, we employed the Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al (2001). To examine cyclical association of crude oil price change with change in OPEC production and US crude oil production we used the serial correlation common feature approach developed by Engle and Kozicki (1993). According to Engle and Kozicki (1993), the concept of serial correlation common feature refers to a situation where a linear combination of elements of stationary series reduce into innovations (or low order moving average representation). In this case a linear combination of stationary variables eliminates all correlation with the past and is completely unpredictable with respect to the past information. Following Engle and Kozicki (1993) to test for serial correlation common feature in this paper we test for presence of serial correlation feature in the first differenced stationary series, and then we test if there exist a linear combination of these variables that eliminates the serial correlation feature. Elimination of the serial correlation feature is indication that the feature is common across the stationary variables and that means they are generated by similar stochastic process. The concept of cointegration arises from comovement among non-stationary variables and implies that variables share common stochastic trends, but the serial correlation common feature among stationary series imply a common cycle representation.

4-1: Common trend:

To explain the common feature testing procedure developed by Engle and Kozicki(1993), Vahid and Engle (1993), we decompose each variable into a trend (d) , a cycle (c_t), and stochastic error term (e_t), so that:

$$y_t = \beta_1 d + \delta_1 c_t + e_{1t} \qquad (1)$$
$$x_t = \beta_2 d + \delta_2 c_t + e_{2t} \qquad (2)$$

where (y_t) stand for crude oil production (OPEC or US crude production) and (x_t) is the crude oil price, and β_i *and* δ_i $(i = 1,2)$ are the corresponding coefficients. Assuming there is a common trend among the two series, then a linear combination of crude oil production and the price can be expressed as:

$$y_t - x_t = (\beta_1 - \beta_2\theta)d + (\delta_1 - \theta\delta_2)c_t + (e_{1t} - \theta e_{2t}) \qquad (3)$$

If there exist a parameter θ, such that $\beta_1 - \beta_2\theta = 0$, then d is not a component of the linear combination. In this case d is called a common feature. Thus, to test for a common trend between y_t *and* x_t in the equations (1) and (2) we test for cointegration (ie., the null of no common trend against the alternative of a significant trend) using the parametric bound test of Pesaran et al (2001)[5].

4-2: Common cycle analysis:

The test for common cycle follows similar approach as that of the common trend. Given that y_t *and* x_t are non-stationary processes of order one (I(1)), then each series can be reduced to stationary process, I(0), by detrending equations (1) and (2) so that:

$$\Delta y_t = \alpha_1 c_{1t} + \varepsilon_{1t} \qquad (4)$$
$$\Delta x_t = \alpha_2 c_{2t} + \varepsilon_{2t} \qquad (5)$$

where Δ is the first difference, $\alpha_i (i = 1,2)$ are the coefficients corresponding to cyclical components and ε_{it} are stationary error terms.

[5] Cointegration imply, although many events can cause permanent effect on a variable, there is long-run equilibrium relation tying the individual components together, represented by the linear combination $y_t - \lambda x_t$.

The common cycle feature test constitutes a common serial correlation test which extend the notion of common trend test described above. Thus, to test whether there is a common cyclical association between the two series we investigate if there is a linear combination such that:

$$u_t = \Delta y_t - \delta \Delta x_t \qquad (6)$$

which does not have the cyclical component. Thus, the common cyclical feature test includes minimization of equation (6) with respect to δ, or more formally:

$$s(\hat{u}_t) = \min_{\delta} \ s(\Delta y_t - \delta \Delta x_t) \qquad (7)$$

Engle and Kozicki (1993), show that equation (7) can be reduced to[6]:

$$s(\hat{u}_t) = \min_{\delta} \ \hat{u}' M_x \Delta x_t (\Delta x_t' M_x \Delta x_t)^{-1} \Delta x' M_x \hat{u} / \hat{\sigma}_h^2 \qquad (8)$$

where M_x is a projection matrix, such that $M_x = [I - \Delta x (\Delta x' \Delta x)^{-1} \Delta x]$ and

$$\hat{\sigma}_h^2 = \hat{u}' M_x \hat{u}' / N$$

For N is the number of observations.

Since minimization of equation (8) requires nonlinear procedure because the parameter δ appears in the denominator and the numerator of the equation (8), then the estimation procedure can be carried out using nonlinear estimation approach of Limited Information Maximum Likelihood (LIML) method. However, more simpler and asymptotically equivalent estimator (Engle and Kozicki , 1993) can be obtained by minimizing only the numerator of equation (8), which is equivalent to estimation of equation (6) using Two Stage Least Square (2SLS) after augmenting it with instrumental variables and then testing for legitimacy of the instrumental variables[7]. Such a process involves two steps. First we employ 2SLS in the following:

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[6] See Engle and Kozicki (1993), pages 370-371, for verification of equation (8).

[7] Use of 2SLS requires the assumption $E(\Delta x_t u_t) \neq 0$ in equation (9).

$$\Delta y_t = \delta_0 + \delta_1 \Delta z_t + \delta_2 \Delta x_t + \mu_t \qquad (9)$$

Where ($z_t = x_{t-1}, y_{t-1}$) stand for instrumental variables[8]. Then using the estimated residuals from equation (9) (that is $\hat{\mu}_t$) we use the OLS to conduct LM test statistic:

$$\hat{\mu}_t = w_0 + \lambda_1 \Delta y_{t-1} + \lambda_2 \Delta x_{t-1} + \varepsilon_+ \qquad (10)$$

With the LM statistic distributed as Chi-square with two degrees of freedom, i.e., the number of instrumental variables minus the number of endogenous variables. So, the test of the LM statistic in (10) is a test for the legitimacy of the IV variables used in 2SLS estimates.

The test for a serial correlation can be computed using the LM test, which is NR^2, where R^2 is the coefficient of determination and N is the sample size, so that NR^2 is distributed as chi-square with degrees of freedom equal to the number of lagged variables coefficients in equation (10).

5- Results

To investigate long term association of crude oil price with OPEC and US crude oil production in this paper we adopted the bound (or ARDL) test procedure developed by Pesaran et al (2001)[9]. An important merit of the bound test, unlike other multivariate conintegration tests, such as that of Johansen and Juselius (1990), it does not require the pre-testing of the variables for unit roots. It is applicable regardless of whether the independent variables are stationary, (I(0), or random walk, I(1)[10]. The cointegration result of crude oil price with OPEC production estimated as 7.61, reject the null of no cointegration. However, the result of cointegration of crude oil price with the US production is 3.85, fail to reject the null hypothesis. These results imply while there is a long term association between OPEC production and crude oil price, there is no evidence of common trend between crude oil price and US oil production[11].

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[8] Engle and Kozicki (1993) show, the test statistic for a common feature serial correlation is asymptotically equivalent to the test statistic for the legitimacy of the instrumental variables.

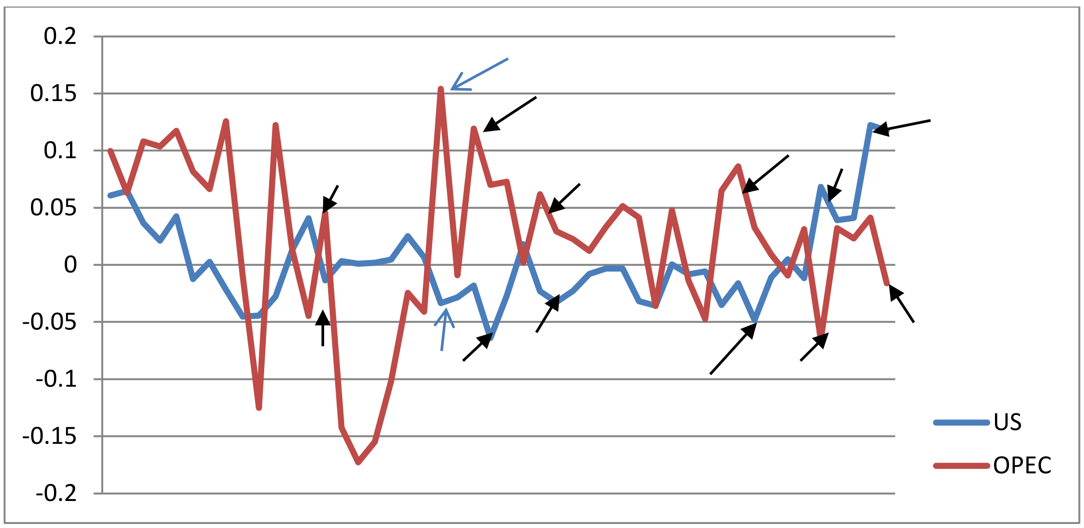
[9] Since both tests are well documented in the literature we decided not to detail further their methodology. For more details about these two tests we advise readers to refer to the original articles by the two authors.

[10] But inconclusive if the order of integration of the variables of order two, or more.

[11] The lower and upper bound values provided in Pesaran et al (2001, table CI(v)) are (6,56/7,30). The lower values assume regressors are I(0), and the upper values assume I(1). When the F-statistics is above the upper critical values we reject the null-hypothesis of no cointegration, and when it is below the lower critical values the null-

The LM test results of common cyclical feature between the crude oil price and OPEC production is 7.15, reject the null hypothesis of common serial correlation feature at the 5% significance level. However, the LM test for a common serial correlation between US production and crude oil price is 0.38 which fails to reject the common cycle feature. These results imply OPEC cartel manage its production to smooth the cyclical change in oil price that arise from US oil production swings as can also be deduced from Figure 1.

Figure 1: Change in OPEC production versus US crude oil production



Source: Statistical Review of World Energy and Index Mundi database

6-Concluding remarks:

To investigate long term association of crude oil price change with change in OPEC production and US crude oil production we adopted the bound (or ARDL) test procedure developed by Pesaran et al (2001)[12]. To test common cycle feature between oil price change and crude oil production of OPEC producers and U.S production we employed common serial correlation test developed by Engle and Kozicki (1993).

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hypothesis is not rejected. If the F-statistic fall between the lower and the upper critical values, the result is inconclusive. The lag order underlying ARDL specification is determined using AIC identification.

[12] Since the bound test is well documented in the literature we decide not to detail further its methodology. For more details about this test we advise readers to refer to the original article.

The ARDL test result of cointegration of crude oil price with OPEC production reject the null of no cointegration. However, the result of the bound test of crude oil price and the US production fail to reject the null hypothesis. These results imply while there is a long term association between OPEC production and crude oil price, there is no evidence of common trend between crude oil price and US oil production[13].

The LM test results of common cyclical feature between the crude oil price and OPEC production reject the null hypothesis of common serial correlation feature at the 5% significance level. However, the LM test result of common serial correlation between US production and crude oil price fail to reject the common cycle feature.

These results imply change in OPEC production adjust crude oil price change in the long terms, but the short term cyclical change of crude oil prices is influenced only by change in US crude oil production. These results are consistent with the view that OPEC policy priority in the past four decades was price stabilization rather than oligopolistic policy manipulation. However, trading of crude oil in the future commodity markets may be generated common cyclical association between U.S production and change in crude oil prices.

[13] Critical values for the the bound test provided in Pesaran et al (2001, table CI(v)) are (6,56/7,30) which are the (lower/upper) bound values. The lower values assume regressors are I(0), and the upper values assume I(1). When the F-statistics is above the upper critical values we reject the null-hypothesis of no cointegration, and when it is below the lower critical values the null-hypothesis is not rejected. If the F-statistic fall between the lower and the upper critical values, the result is inconclusive. The lag order underlying ARDL specification is determined using AIC identification.

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