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Oil Price Volatility and Industrial Production Nexus in OPEC +Countries

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Conference paper for:

Int'l Conference on Pollution Control and Sustainable Environment to be held in Kollam, India

Article Info
Volume 83
Page Number: 10253 - 10266
Publication Issue:
May - June 2020

Abstract:

This study documents the control of oil price volatility on industrial production of emerging oil exporting countries of Mexico, Brazil and the world using ARMA-GARCH(1,1)-cDCCmodel. The Corrected Dynamic Conditional Correlation (cDCC-GARCH)was employed using monthly data of 1990:01-2019:09.The model is opted for due to its greater flexibilities and for allowing the conditional variance-covariance of returns which vary over time. Findings from DCC and cDCC parameters reveal that the dynamic linkages between oil price movement and economic activities in Brazil and Mexico will persist and otherwise forthe world. The study, therefore, recommends the duo of Brazil and Mexico to diversify their oil-economies and heavily venture into non-oil exports for alternate revenues. The study also report that the corrective cDCC-GARCH trulyendorse DCC parameters.

Article History
***Article Received**: 19 November 2019*
***Revised**: 27 January 2020*
***Accepted**: 24 February 2020*
***Publication**: 18 May 2020*

***Keywords**: Oil Prices; Oil Price Shocks;Uncertainties; Returns; Industrial production index, ARMA-GARCH (1,1)-cDCC model.*

1. Introduction

In emerging economies, industrial infrastructures are prune to oil price shocks which hinder industrial development and eco-growth (Shahbaz et al, 2017;Sarwar et al, 2019).On the same line, we examine the problem-statement of how the fluctuations in crude oil market affect the industrial production of emerging but high oil-exporting nations of Mexico, Brazil and the total of OECD countries (henceforth, the World). This study, therefore, provides symptom of volatility transmission between oil prices and the economic activities of oil exporters.van Eyden, et al (2019) analyze the effect of oil price volatility on the growth for 17 countries of the Organisation for Economic Co-operation and Development for 1870-2013and found that oil price volatility has a negative and significant impact on growth of the OECD. Unlike Bollerslev (1990)Constant Conditional Correlation CCC-GARCH, which restricts the correlation coefficients to be constant over time, the flexible DCC-GARCH allows time-varying correlations. In methodological extension, Engle (2002)therefore came up with multivariate DCCmodel allowing for time varying correlations.

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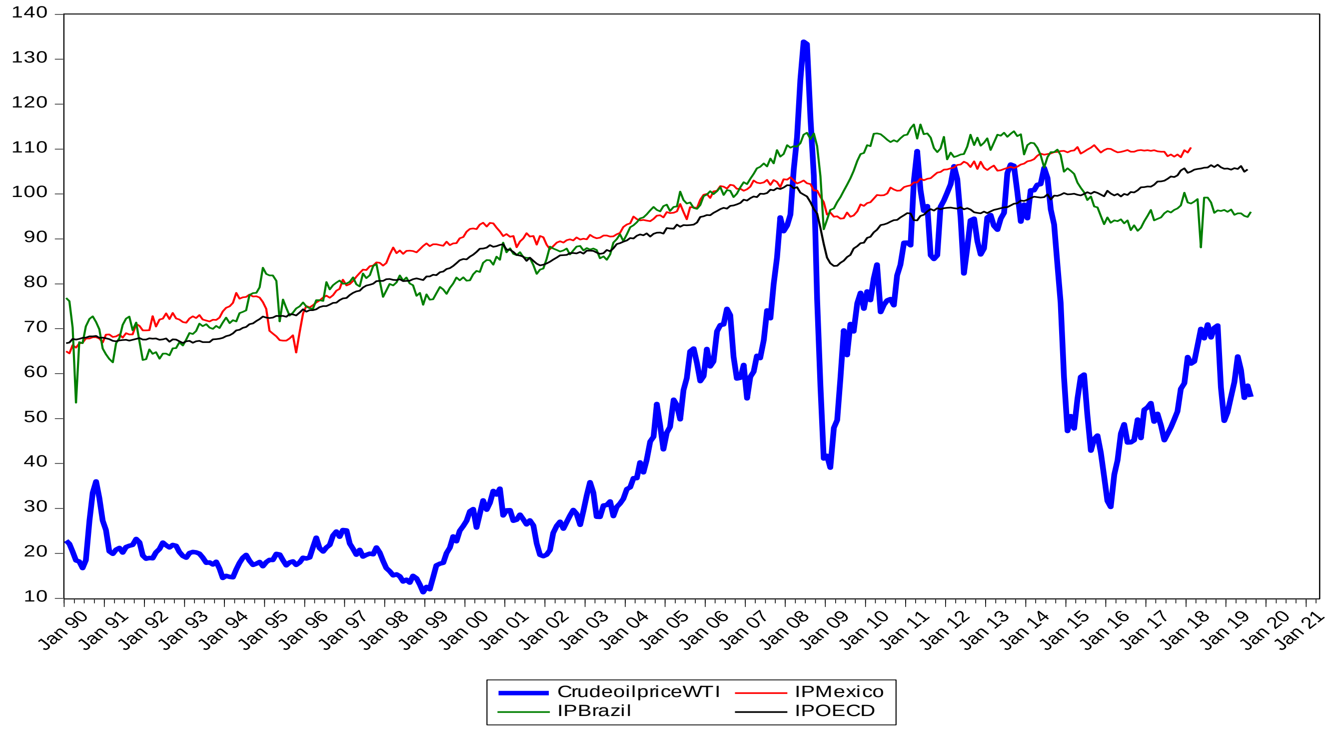

Figure 1 Monthly oil prices, industrial production indexes of Mexico, Brazil and the world.

The study, therefore, reinvestigates the timevarying correlation between oil prices and industrial production index(IPI) for twonet oil exportersnamely, Brazil, Mexico, and the world.Figure 1 above depicts original monthly oil prices, industrial production indexes of Mexico, Brazil and the world. The study uses oil price (WTI) which is measured in USD from the U.S. Energy Information Administration (EIA).IPI is a combined indicator and expressed in the form of an index number. It refers to industrial output and covers sectors such as mining, manufacturing and construction. Put different, it measures the short term variations in the production volume of a basket of industrial goods during a time and is measured in the samebase time (2015=100).IPI is computed as Fisher indexes with weight-based on annual estimates of value-added. Then we therefore use generalized autoregressive conditional heteroskedasticity (GARCH)linked to Engle (2002)'sdeveloped DCC.This study tackles these inquiry: (i) HowBrazil and Mexico oil-exporting countries industrial production indexes (IPI) respond to disturbances on oil prices? (ii) How is fluctuation in the oil-exporting countries IPI linked to oil price shocks? (iii) Did the

cDCC-GARCH model of Aielli (2013) endorse DCC-GARCH?The rest of the paper is structured as follows: Section two is about the literature. Section three provides methodology with the introduction ofcDCC-GARCH model. Section four documents the nature and sources of data. Section five elaborates empirical results while section six presents concluding remarks.

2. Literature

Concerning the origin of oil price shocks, this study considers Hamilton (1983; 2009), Mork et al (1994)and Kilian (2009).It is noted that uncertainties in the oil price are often considered vital for understanding uncertaities in the business cycle. Therefore there is no accord about the relation between real oil price changes, economic activities of net oil exporters and market for crude oil among energy economists. Thiem (2018) also reports Hamilton (1983) as an icon whofirst pointed out that the majority of US post-war recessions occasioned through strong oil price shocks and noted that the

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role of oil price shocks in US economic activities has had effect on a study on the macroeconomic effect of oil price fluctuations. Filis, et al (2011) asserts that neo-classics, opposing the Keynesian economists, maintains that impact on output is highly reduced and thus price shocks should have minimal effect on the economy. Cavalcanti and Jalles (2013) documents theinfluence of oil price uncertainties on the Brazilian and American inflation rate and found that the oil-import dependence rate has peaked sharply in US but otherwise in Brazil. In BRICS study, Boubaker and Raza (2017) investigates theeffects of volatility between oil prices and the BRICS stock markets usingARMA(1,1)-GARCH(1,1)-cDCC model. The study provides evidence of time varying volatility in all markets under study. Benavides and Herrera (2019) inquire whether the uncertainty of international oil prices affected Mexico's economic activity during 1983:2-2017:4 and found that uncertainty has a negative influence on Mexico's economic activity. Further, they reveal the presence of asymmetric effects, as the output growth rate increases (decreases) after a negative (positive) oil price shock.Katirciolu, et al (2015) further documents the relation of oil prices and macroeconomic variablesfor OECD using second-generation panel data analysis.As oil price account for the input cost of production, its increase would also affect the total cost of production (Brown and Yucel, 2002).Like our study, the study uses the growth rate in industrial production andchanges in oil prices among other variables. They find the variables under study to be higher for the US than for Japan. In the same parlance,Papaetrou (2001)investigatesthe link between oil price and employment in Greece using industrial production as alternative measures of economic activity. Jimenez-Rodriguez and Sanchez (2005) empirically assess the effects of oil price shocks on production of industrialized countries. The study uncovers that oil price increases are found to have effect on growth than that of oil price cut.From the literature, it is obvious that most studies focus on influence of oil price volatility on economic stocks of developed countries. We, therefore, contribute to the literature by reinvestigating the emerging oil exporting economies under study.Many scholarly studies were done targeting the effect of oil price fluctuations on stocks cum other macroeconomic variables using the varied explicated methods in the literature. However, at this point (of departure) and of our knowledge, no literature is traced to usingcDCC-GARCH in modeling the relation between oil prices and industrial production indices of emerging oil exporting economies and so filling this gap form basis of our grand novelty.

3. Methodology

3.1 CorrectedDCC-GARCH model

cDCC-GARCH model of Aielli (2008) and Aielli (2013) are employed. The main merit ofcDCC model is that it recognizes likelycrude oil volatilities and endorses DCC parameters with high consistency.To start volatility modeling, this study commences with four estimation procedures:

a. Testing for ARCH effects to know if the series is volatile.
b. Estimation with the ARCH-type models, ARMA-GARCH model. This is imperative only if the series - industrial production indices for Mexico, Brazil, and the world are volatile.
c. Post-estimation test: This is done to verify the validity of ARCH effects to know if (b) above has captured the ARCH effects in the series and
d. Obtaining Dynamic Conditional Correlation coefficients.

3.2ARCH effects

Testing for ARCH effect follows the procedure of the ARCH LM test proposed by Engle (1982) to determine the existence of ARCH effects in the residuals and autocorrelation of squared residuals of an estimation. It begins with the estimation of the AR model as presented in equation 1:

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$$r_t = \alpha_0 + \alpha_i r_{t-i} + \varepsilon_{t;}\ \varepsilon_t \sim IID\ (0, \sigma_t^2) \quad (1)$$

where r_t is the rate of returns of the series, and ε_t is constant variableand residual term respectively. The squared of the estimated residual in equation (1) can be regressed on its lag to test for ARCH as follows:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^2 + v_t \quad (2)$$

H_0: $\gamma_0 = 0$, while H_1:$\gamma_1 \neq 0$

Where v_t is an error term

The test is on H_0 that the lags of the squared residuals have coefficients that are not significantly differ from zero.If the critical value (c.v.)is less than test statistic, then reject the null hypothesis and vice versa. The $H_0$of no ARCH effects is rejected if the probability (p) values of these tests are less than c.v. at 10%, 5% and 1% significant levels while the rejection of H_0implies the existence of ARCH effects in the series. The series can be volatile if and only if ARCH effects are present and therefore the estimated parameters should be significantly different from zero and vice versa if the returns is not volatile.

3.3 Estimating ARMA-GARCH (1,1)-cDCC model

The study make use ofARMA (p,q) form for mean model:

$$r_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \quad (3)$$

$$\varepsilon_t = \sigma_t^{1/2} v_t \quad (4)$$

where r_t is the returns, p and q are values of AR(p) and MA(q) while ε_t and care the residual term and constant variable respectively. Inequation (4), v_t and σ_t are standardized residuals and conditional variance term.respectively. For the GARCH model, the conditional variance of the model can be shown as:

$$\sigma_t^2 = \varphi + \delta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \quad (5)$$

In Engle (2002), the DCC model is defined in equation 6.

$$H_t = D_t R_t D_t \quad (6)$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$

Re-writing equation (6), we have

$$R = D_t^{-1} H_t D_t^{-1} = E_{t-1}(\varepsilon_t \varepsilon'_t) \quad since\ \varepsilon_t = D_t^{-1} r_t \quad (7)$$

h is referred to as uni-GARCH model but these model could certainly incorporate functions of other variables in the system as a predetermined while R is the unconditional correlation matrix.Regarding R in equation (7), unlike D, its parameterizations similar to H except that the conditional variances must be unity therefore R remains the correlation matrix. For the correlation matrix in its simplest way, the specification is the exponential smoother as it was expressed by Engle (2002):

$$\rho_{i,j,t} = \frac{\sum_{t=1}^{t-1} \gamma \varepsilon_{i,t-s}\ \varepsilon_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \gamma^s \varepsilon_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} \gamma^s \varepsilon_{j,t-s}^2\right)}} = [R_{t,}]i,j \quad (8)$$

From equation 8, the process is followed by integration of the q's:

$$q_{i,j,t} = (1-\gamma)(\varepsilon_{i,t-1}\varepsilon_{j,t-1}) + \gamma(q_{i,j,t-1}) \quad (9)$$

Then we can obtain dynamic conditional correlation (DCC) coefficient/ correlation estimator which will

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be positive definite as the covariance matrix, $Q_t$as shown as:

$$\rho_{IPI,oil,t} = \frac{q_{IPI,oil,t}}{\sqrt{q_{IPI,IPI,t}\, q_{oil,oil,t}}} \qquad (10)$$

and

$$Q_t = k + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \qquad (11)$$

where$k = (1-\alpha-\beta)\bar{Q}; \bar{Q} = E(\varepsilon_t\varepsilon_t^{'})$ is $n \times n$unconditional variance matrix of ε_t (the standardized residuals) and it meets α +β <1 and α +β> 0conditions to buttress DCC model mean-reverting.The parameters α and β are nonnegative scalar parameters.Substituting k in equation 11, we obtain the DCC(1,1) model:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \qquad (12)$$

Where Q_t is a symmetric positive definite matrix.In the DCC model, there are always two steps, according to Engle (2002), for parameter estimation. In the first step, the study estimate the uni-GARCH for each variable returnswhile in the second step, the correlations are estimated. Using this model (12), we follow up the pioneering Engle (2002),Filis, et al (2011) and Jiang, et al (2019) methodology.For endorsement of DCC-GARCH by cDCC, Aielli (2013) formulated the correctedmodel, by recasting the specification of the correlation Qtdefined in the DCC-GARCH of Engle (2002). The specification of the corrective cDCC-GARCH model is the same as the specification of the DCC-GARCH. However, the recastedAielli (2013) in equation (14) targets the improvement on equation (12).

$$Q_t = (1-a-b)\bar{Q} + a\varepsilon_{t-1}^{*}\varepsilon_{t-1}^{*'} + bQ_{t-1} \qquad (13)$$

Similar to equation (12), the*a, b* are non-negative coefficients with a total of less than one(a + b < 1). Similarly to model (12), model (13) also mimics and closely follows Aydogan, et al (2017) and Sarwar, et al (2019).

3. Data

The study uses monthly data from1990:01 to 2019:09in oil-exporting countries of Brazil, Mexico and the total of OECD countries. We employ West Texas Intermediate (WTI) oil price andthe industrial production indices(IPI) of the countries stated countries. Country selection is justified based on the fact that Mexico, an emerging economy is a top 14 oil-exporter in 2018 with exports of $26,482,792,000, 2.3% of total crude oil exports, while Brazil, top 16 oil-exporter record oil exports of $25,130,987,000, 2.2% of total world imports(InternationalTrade Centre, 2018).The WTI oil price is measured in US dollars from the U.S. Energy Information Administration (2019) sourced from FRED, Federal Reserve Bank of St. Lous.We also use IPI-OECD to proxy global economic activities or real GDP of the world which sourced from OECD's website. To capture global economic activities, we use the IPI of the world. For data transformation, we take a log difference in oil price and the IPI to obtain returns of the variables. The rate of returns (growth) is computed using continuously compounded growth rate formula is given below for each of the series:

$$Returns = log\left(\frac{s_t}{s_{t-1}}\right)$$

Where s_t represents the series. The used variables include: GROILPrice, GRIPMex, GRIPBrz, and GRIPOECD and represent their returns on oil price, returns on industrial production index of Mexico, Brazil and the world respectively.

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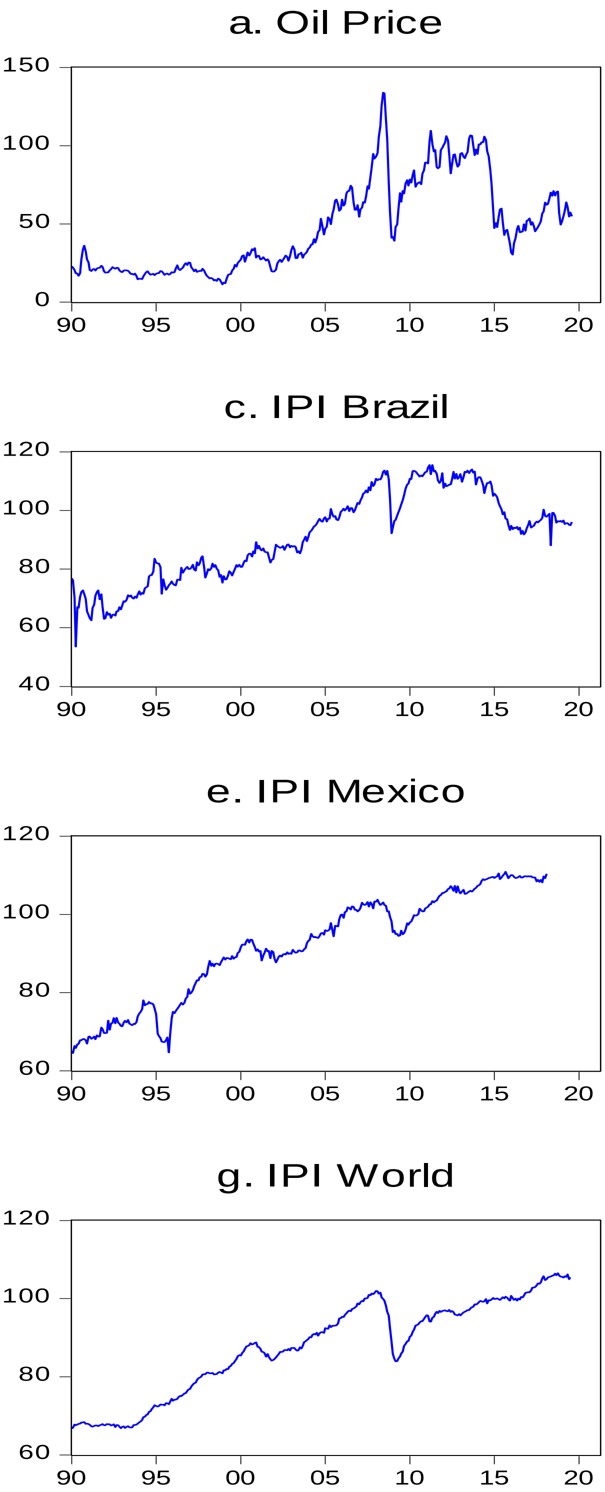

Figure 2: Oil Price, Industrial Production Indexes (IPI)(2015=100) and their Returns (1990:01-2019:09)

Table 1: Definition of variables

Variables	Meaning	Source
Oil	Oil Price	U.S. Energy Information Administration, FRED Louis (2019)
Braz	Industrial Prod. Index (IPI) of Brazil	OECD Website
Mex	Industrial Prod. Index (IPI) of Mexico	”
World	IPI of the world (total OECD Countries)	”
lnoil	Log of Oil Price	Log Transformation
lnbraz	Log of IPI Brazil	”
lnMex	Log of IPI Mexico	”
lnWorld	Log of the World	”
Roil	Returns of Oil Price	”
Rbraz	Returns of IPI Brazil	”
Rmex	Returns of IPI Mexico	”
Rworld	Returns of IPI World	”

Source: Author's computation

The descriptive statistics of returnsare shown in Table 2. The table reports mean and median values all close to zero, oil price have the highest SD, the skewness of all the series are negative while positive values of kurtosis of the returns show similar leptokurtic shape.

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Table 2. Summary statisticsof returns

	Roil	Rworld	Rbraz	Rmex
Mean	0.002456	0.001283	0.00062591	0.0014867
Max	0.392189	0.016492	0.2244	0.069469
Min	-0.331981	-0.038475	-0.27115	-0.067886
Std. Dev.	0.084848	0.006074	0.028911	0.011369
Skewness	-0.336768	-2.173341	-1.4990	0.038952
Excess Kurtosis	2.1065	14.13042	33.140	10.444
Jarque-Bera	72.54925	2117.900	16424	1618.2
ADF	-13.85***	-5.848***	-22.7843	-19.8779
Q (5)	5.62711 (0.228781)	40.3772 (0.00000)**	9.65884 (0.0465838)*	133.021 (0.0000000)**
Q(10)	9.10932 (0.427245)	45.8437 (0.0000006)**	13.7919 (0.1299221)	146.889 (0.0000000)**
Q^2 (5)	26.6357 (0.000067)**	113.025 (0.0000000)**	49.3726 (0.000000)**	34.6377 (0.0000018)**
Q^2(10)	30.6048 (0.00068)**	117.834 (0.000000)**	50.1038 (0.0000003)**	47.4212 (0.0000008)**
ARCH (5)	3.6519 (0.0031)**	24.395 (0.0000)**	5.2740 (0.0001)**	7.2780 (0.0000)**
ARCH (10)	3.8114 (0.0001)**	12.649 (0.0000)**	3.0464 (0.0010)**	4.3857 (0.0000)**
Observation	356	356	356	356

Note: ADF: stationarity of returns.Q/LB:autocorrelation; Q(5), Q(10) and Q^2(5), Q^2(10) up to 5 and 10 lags. ARCH (5) and ARCH (10) denotes the Engle (2002) to check the presence of ARCH effects up to 10 lags. ***p < 0.01

In pre-estimation, the ARCH (5) and ARCH (10) test estimates in table 2 indicates the existence of ARCH effect in the growth of all the returns series at .01 significant level.The test p-values shown in table 2 are all zero to three and four places, resoundingly rejecting the "no ARCH" hypothesis denoting that the returns are volatile.

Table 3: Correlation of returnseries

Correlation	Unconditional Correlation	Conditional Correlation	Conditional Correlation
rho		DCC (Engle)	cDCC (Aielli)
Rmex-Roil	0.085837 (1.620994)	0.111217** (0.0217)	0.109850** (0.0248)
Rbraz-Roil	0.022265 (0.419009)	0.109150** (0.0524)	0.106870** (0.0603)
Rworld-Roil	0.231179 (4.470715)	0.054292 (0.4368)	0.051943* (0.4603)
Rbraz- Rmex	-0.054006 (-1.017606)	0.009776 (0.8757)	0.007092* (0.9105)
Rworld- Rmex	0.263108 (5.131144)	0.210149*** (0.0001)	0.208916*** (0.0002)

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Rworld- Rbraz	-0.022334 (-0.420320)	0.186389*** (0.0088)	0.184913*** (0.0096)

Note: The p-values are in parentheses, *** p< 0.01

The table further shows, as expected, that all series are stationary and depict evidence of autocorrelations through Q and Q^2 tests in residuals and squared residualsrespectively and finally, the test revealspresence of ARCH effects in the series. With strong ARCH effects, we then proceed to GARCH analysis. Table 3 shows unconditional correlationresults of the series which depicts positive and significantcorrelation but series Rbraz's correlation with Rmex and Rworld-Rbrazwhich shows negative and significant correlation.It is evident from p-values of cDCCthat DCC results were endorsed and confirmed.

4. Empirical Results

For mean equation panel (A), we first of all model ARMA (2,2) for Roil, Rmex (1,1)Rbraz (2,1) and Rworld (2,2)based on BIC rules followed by estimating GARCH model resultsof which tabled in 4. With a correctly specified model, the symptomatic tests evidenced of no autocorrelation(henceno ARCH). In the (post) estimation, the ARCH (5) and ARCH (10) estimates in table 4 reflect no ARCH effect in the growth of the returns series at .01 significant level. The test p-values shown in table 4 resoundingly telling us that we cannot reject the "no ARCH" hypothesis.Consequently, the model can obtain the residuals at the accepted level while the ARCH effect is adequately and sufficiently captured by the model. In panel A,all coefficients are statistically significant at 0.01 S.L.As usual, ARCH and GARCH coefficients aresignificant throughout the period implying that the current volatilities (of returns) are easily affected by the information available in the previous periods.

Table 4: ARMA-GARCH Parameters

	Roil	**Rmez**	**Rbraz**	**Rworld**
A: Mean Equation				
(p,q)	(2,2)	(1,1)	(2,1)	(2,2)
Constant (M)	0.004736 (0.1181)	0.001228* (0.0116)	0.001539 (0.1696)	0.001616*** (0.0004)
AR(1)	1.202211*** (0.00000)	-0.708761*** (0.00000)	-0.787267*** (0.00000)	1.005504*** (0.0000)
AR (2)	-0.293713 (0.1841)		0.006984 (0.9257)	-0.203881 (0.1526)
MA(1)	-0.981316*** (0.00000)	0.559163*** (0.00000)	0.744694*** (0.00000)	-1.111543*** (0.0000)
MA (2)	0.043775 (0.8506)			0.473619*** (0.0000)
B: Variance Equation parameters GARCH (1,1)				
Constant (φ)	0.001519** (0.0822)	0.015019 (0.3479)	3.101492*** (0.0001)	6.699761*** (0.0005)
ARCH (1)δ	0.196239** (0.0441)	0.347926*** (0.0080)	0.505056** (0.0125)	0.23138*** (0.0071)
GARCH (1)γ	0.574108***	0.718008***	0.017026	0.507488***

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	(0.0024)	(0.00000)	(0.3860)	(0.0000)
C: Diagnostic Tests				
Q (5)	1.16790 [0.27983]	14.6342 [0.0021575]**	9.78419 [0.0075057]**	3.44441 [0.06346]
Q (10)	2.30024 [0.89011]	16.4355 [0.0365540]*	13.1432 [0.0686951]	10.4032 [0.10866]
Q^2 (5)	2.91939 [0.40422]	1.85358 [0.6033448]	5.07082 [0.1666840]	1.21069 [0.7504]
Q^2(10)	4.78722 [0.78005]	15.9156 [0.0436036]*	6.44215 [0.5978310]	5.22010 [0.73381]
ARCH (1-5)	0.55669 [0.7332]	0.36244 [0.8741]	0.41404 [0.8390]	0.24942 [0.9400]
ARCH (1-10)	0.64825 [0.7719]	1.3622 [0.1965]	0.41682 [0.9383]	0.48850 [0.8973]

Notes: The s.e. in ( ), p-values in [ ], Q/LB –autocorrelation;Q (5) and Q^2 (10) up to 5 and 10 lags.ARCH (5) and ARCH (10) for presence of ARCH up 5 and 10 lags ***p<0.01, **p<0.05, *p<.10

Based on the condition of (a +b < 1), we conclude from Table 5 that the two models DCC-GARCH and cDCC-GARCH are effective and appropriate and connotes thatthe oil pricevolatility has a vital impactonindustrial production in the countries. TheDCC estimates further show thatvalues of a+b(Roil-Rmex and Roil-Rbraz) are close to 1 indicating that the impact of oil price on industrial production inMexico and Brazil will persist and continue for a long time as the value close to unity and otherwise for the World.Further, as the mean revert condition of (a +b < 1) is sustained, any shock in Roil-Rworld is fast mean-reverting and their shock is temporal while that of Mexico and Brazil is a slow mean-reverting denoting a persistent effect on shock. We also note that if (a +b > 1) condition holds, then non-mean reverting occurs meaning that, whenever there is a shock in the series, the shock will be permanent and will not return to its long-run equilibrium mean.Table 5(B) is a confirmation of DCC results in 5(A) asit endorses the 5(A) results with high robustness.

Table 5: DCC and cDCCparameters

	Oil-Exporters		**The World**
A. DCC	**Roil-Rmex**	**Roil-Rbraz**	**Roil-Rworld**
a	0.0000002 (1.000000)	0.072454 (0.2053)	0.099346 (0.067173)
b	0.853244 (0.2057)	0.672784 (0.0468)	0.218766 (0.28116)
a + b	0.8532442	0.745238	0.318112
B. cDCC	**Roil-Rmex**	**Roil-Rbraz**	**Roil-Rworld**
a	0.0000003 (1.000000)	0.082930 (0.1954)	0.086884*** (0.0602)
b	0.862421	0.595556	0.213911

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	(0.2881)	(0.0629)	(0.4665)
a + b	0.8624213	0.678486	0.300795

Notes: The s.e. in parentheses, ***p<0.01, **<0.05, *p<0.1

From 5(B)'scDCC confirmation and endorsement, Mexico and Brazil should diversify their oil-economies and heavily venture into non-oil exports for alternate non-oil revenues. The vital advice is due to the effect of high volatilities of oil prices on their economic activities.

Evolutionof oil price volatility

Evidence of dynamic linkages between oil pricevolatilities/uncertainties and industrial productionare shown in figures 3 and 4. The former shows series volatilities while the latter depicts bivariate volatilities. Figure 3a depicts strong fluctuations of about five easily distinguishable high spikes. The firstcan be traced to the 1990 gulf war during the Iraq invasion of Kuwait when the 1990 spike reveals conditional covariance at the highest level in September 1990 immediately after the invasion. The next is the 1998 spike which was not as high as that of 1990. The 1998 spike associated with January 1998 Asian economic crises and OPEC's cut in quota at various meetings. A year after, March 1999 OPEC further cut quotas and also in March 2000 OPEC oil ministers increase oil production all constitute the second spike. The second heightened spike associated with the 2008 financial crisis, showed obvious volatilities. The year 2008 spikes depict in Januarythat there were high and lowdemand and spare capacity respectively while in May, President Bush enacted a temporal stopof adding oil to Strategic Petroleum Reserve. Also in September and December 2008, the conditional variance was at peak due to Hurricane Gustav strikes and OPEC decision to cut production respectively.

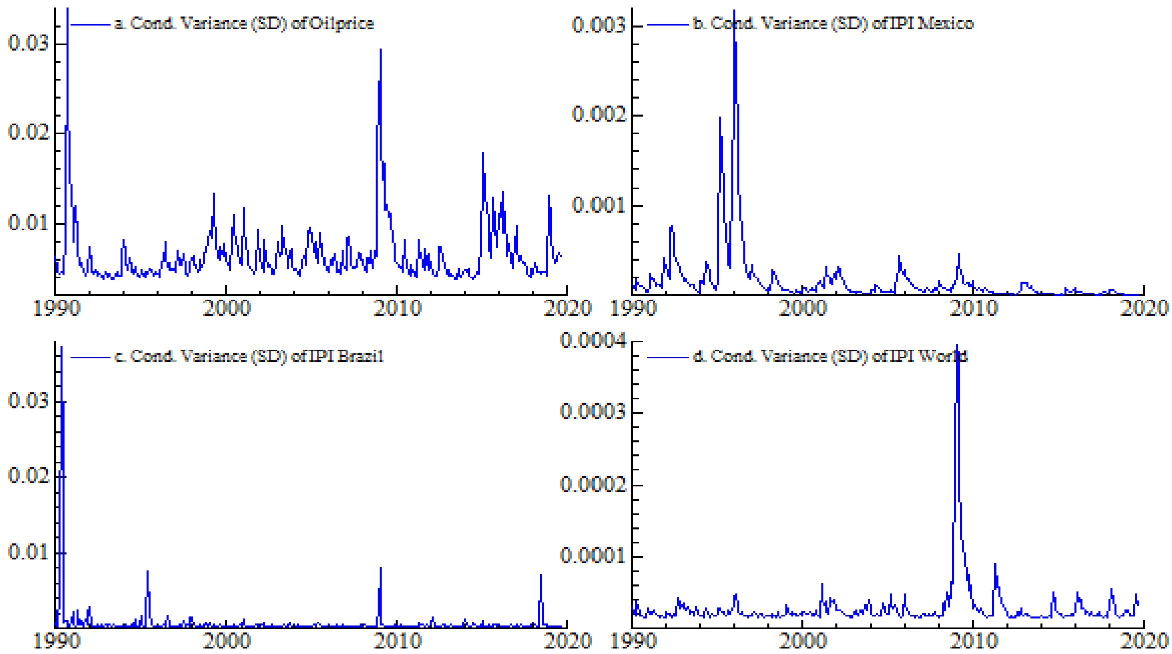

Figure 3: Volatility Series

The global economic meltdown owing to the 2008 Asian financial crisis attractedhuge fluctuations in the oil market and industrial productions leading to low productions in Brazil with greater hindrance in Mexico as a result of violent volatilities as shown in figure 3b and c. In 3b, there are violent volatilities in

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Mexico observable in three main spikes in1993-1997 and henceforth moderately lowered up to 2019. There are four spikes in Brazil volatilities obviously in 1990 while others record low spikes in 1995, 2008, and 2019 as shown in figure 3c while d depicts only one visible spike during the 2008 financial crises.

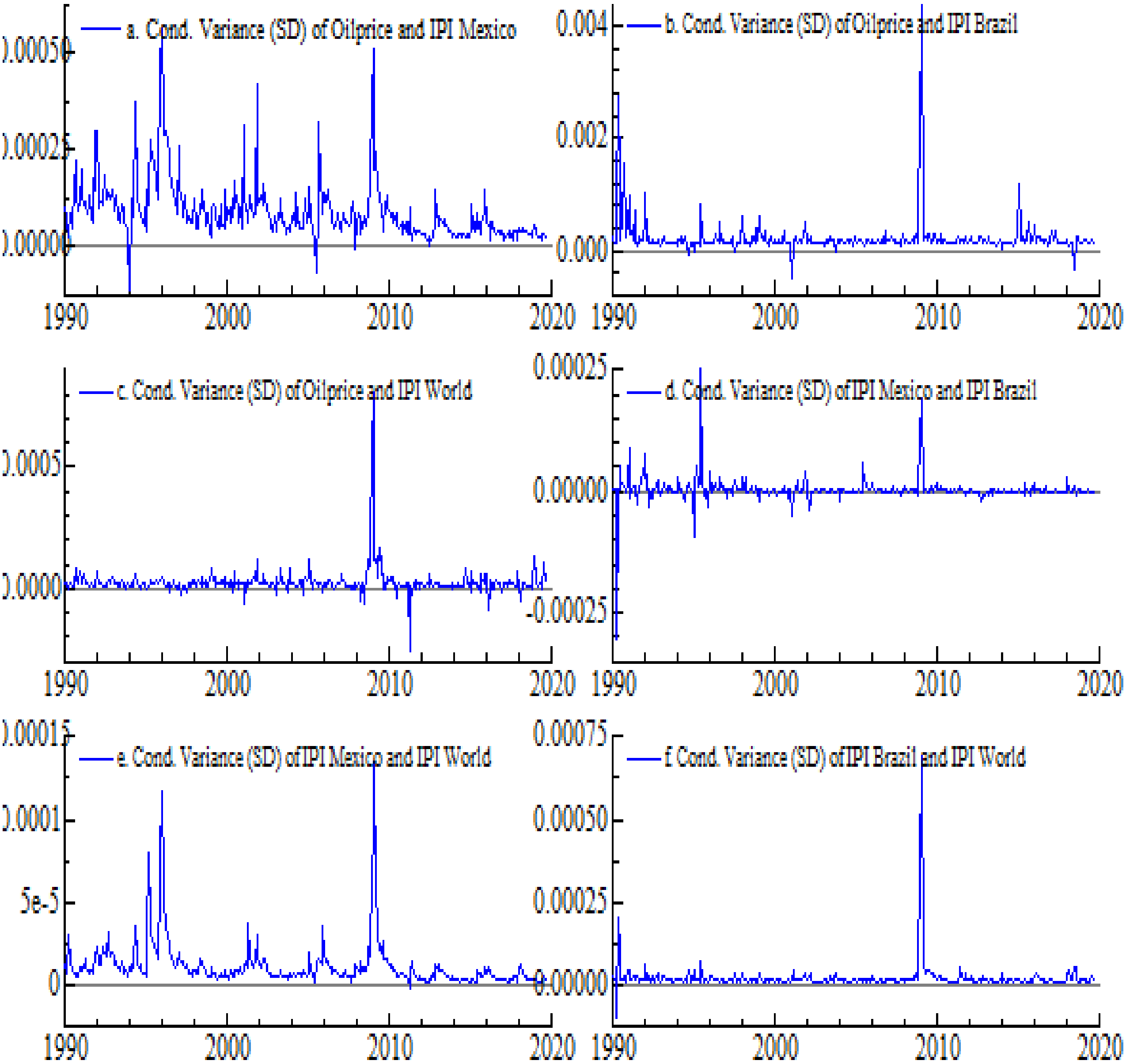

Figure 4: Bivariate Volatility Series

Therefore, the policymakers across the globe should work out modalities to forestall future occurrence of the financial crisis. Shortly after financial crises in 2008, oil prices spike up because of tensions in Gaza Strip. In 2017, demand was high and OPEC cuts and rising political logjam were the reasons Libya and the North Sea caused reduction in production by OPEC and Russia. In the same parlance, the bivariate relationship of oil price with IPIsin Figure

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4 depicts DCC between oil prices and industrial productions of Brazil, Mexico, and the world. The bivariate figure also shows that all correlations fluctuated during the Iraq-Kuwait Gulf wars in 1990 and 2003 and the 2008 Asian financial crisis with their returns portraying evidence of volatility in the series.

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5. Conclusion

The aim of thestudy is to furnish the literature with oil price movements and industrial production.The study analyse the oil price shocks and volatilities on IPI of Brazil, Mexico and the world using the monthly dataset from 1990:01 to 2019:09. The econometric methodology is based on Engle (2002)'s DCC and cDCC-GARCH developed by Aielli (2008, 2013).The research confirms that oil price volatility plays a significant role in the determination of industrial production volatility. The study documents the effect of oil-price volatility on industrial productions in the emerging economies of Mexico, Brazil, and the world.

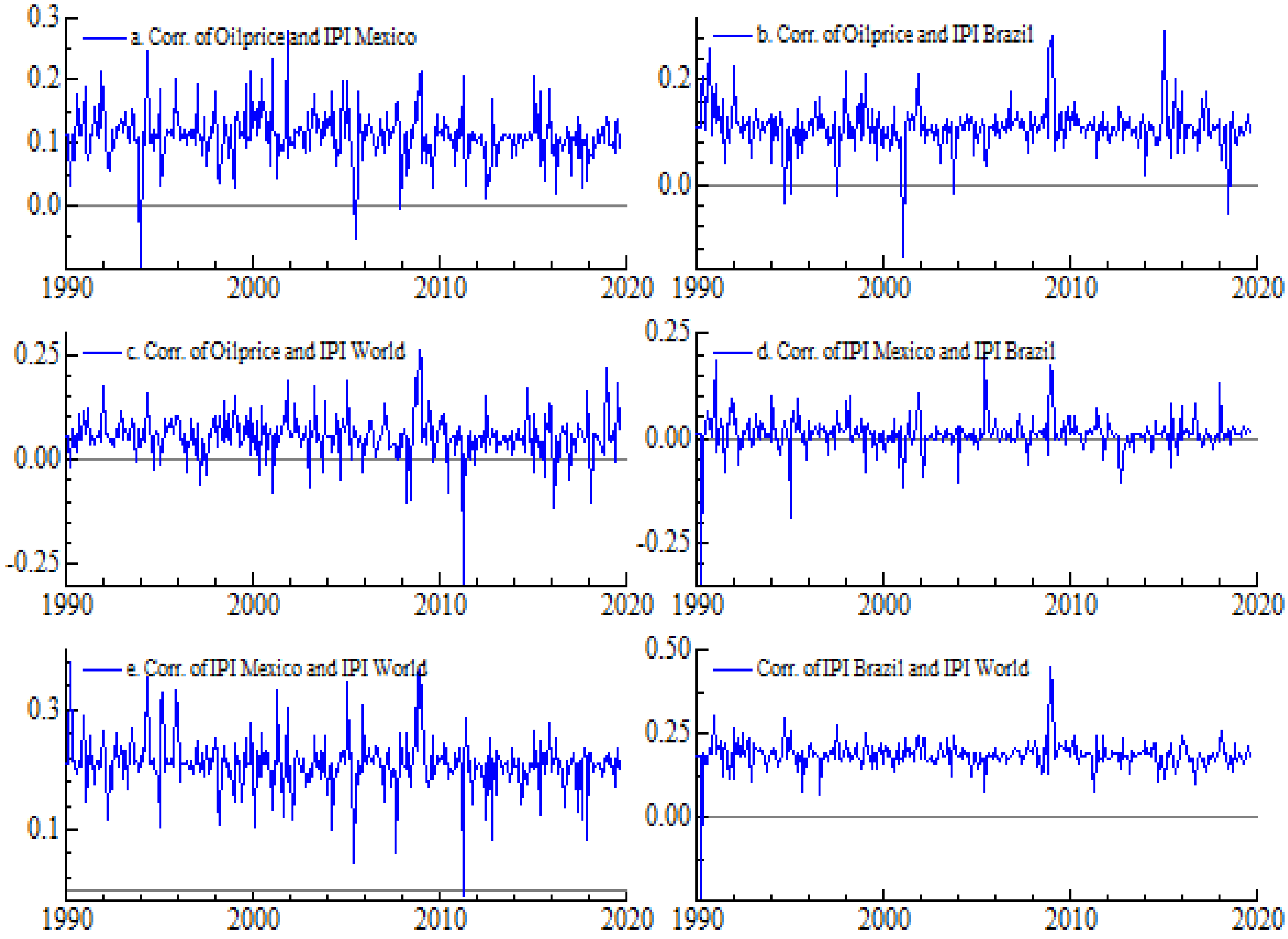

Figure 5: The estimated DCC between oil price oil (USD) industrial production indexes (2015=100) of crude oil-exporting countries.

Findings from dynamic conditional correlation (DCC) estimates revealthat the volatility of return series on production has significant influence on the relationship between oil and industrial productions of countries under study. The research also noted that the dynamic linkages between oil price and industrial production in Mexico and Brazil will persist for a long time and otherwise for the world.

The result also uncovers some vital features of oil shocks and IPI returnseries at varied times especially

when the world financial crises had vital impact on the interdependencies of oil price uncertainties and IPI returnseries. The study further recommends the duo of Brazil and Mexico to diversify their oil-economies and thoroughly revamp their non-oil exports for alternate revenues. Finally, the studynotices that the corrective cDCC is consistent and truly endorse DCC parameters.

References

1. Aielli, G. P. (2008). Consistent estimation of large scale dynamic conditional correlations (Working Paper No. 47). Messina, Italy: Department of Economics, Statistics, Mathematics, and Sociology, University of Messina.
2. Aielli, G. P. (2013). Dynamic conditional correlation: on properties and estimation. Journal of Business & Economic Statistics, 31(3), 282-299.
3. Aydoğan, B., Tunç, G., &Yelkenci, T. (2017). The impact of oil price volatility on net-oil exporter and importer countries’ stock markets. Eurasian Economic Review, 7(2), 231-253.
4. Benavides, D., & Herrera, F. (2019). effects of oil price uncertainty on mexico's economic growth.InvestigacionEconomica, 78(309), 80-106. doi:10.22201/fe.01851667p.2019.309.70120
5. Bjørnland, H. C. (2009). Oil price shocks and stock market booms in an oil-exporting country. Scottish Journal of Political Economy, 56(2), 232-254.
6. Blanchard, O. J., &Gali, J. (2007). The Macroeconomic Effects of Oil Shocks: Why are the 2000s so different from the 1970s? (No. w13368). National bureau of economic research.
7. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31(3), 307-327.
8. Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. Review of Economics and Statistics, 72(3), 498-505.
9. Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. Journal of Political Economy, 96(1), 116-131.
10. Boubaker, H., & Raza, S. A. (2017). A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. Energy Economics, 64, 105-117.
11. Brown, S. P., &Yücel, M. K. (2002). Energy prices and aggregate economic activity: an interpretative survey. The Quarterly Review of Economics and Finance, 42(2), 193-208.
12. Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial econometrics, 4(4), 537-572.
13. Cavalcanti, T., &Jalles, J. T. (2013). Macroeconomic effects of oil price shocks in Brazil and in the United States. Applied Energy, 104, 475-486.
14. Engle R. (2002). Dynamic conditional correlation. J. Bus. Econ. Stat, 20(3):339e50
15. Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4):987e1007
16. Filis, G., Degiannakis, S., &Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis, 20(3), 152-164.
17. Greene, D. L., Jones, D. W., &Leiby, P. N. (1998). The outlook for US oil dependence. Energy Policy, 26(1), 55-69.
18. Guesmi, K., &Fattoum, S. (2014). Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. Economic Modelling, 38, 305-310.
19. Guesmi, K., Saadi, S., Abid, I., &Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. International Review of Financial Analysis, 63, 431-437.

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20. Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. Journal of political economy, 91(2), 228-248.
21. Hamilton, J. D. (2009). Understanding crude oil prices. The Energy Journal, 30(2).
22. Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. Energy, 166, 577-586.
23. Jiménez-Rodríguez*, R., & Sánchez, M. (2005). Oil price shocks and real GDP growth: empirical evidence for some OECD countries. Applied Economics, 37(2), 201-228.
24. Kaneko, T., & Lee, B. S. (1995). Relative importance of economic factors in the US and Japanese stock markets.
25. Katircioglu, S. T., Sertoglu, K., Candemir, M., &Mercan, M. (2015). Oil price movements and macroeconomic performance: Evidence from twenty-six OECD countries. Renewable and Sustainable Energy Reviews, 44, 257-270.
26. Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-69.
27. Mork, K. A., Olsen, Ø.,&Mysen, H. T. (1994). Macroeconomic responses to oil price increases and decreases in seven OECD countries. The Energy Journal, 19-35.
28. Nasir, M. A., Naidoo, L., Shahbaz, M., &Amoo, N. (2018). Implications of oil prices shocks for the major emerging economies: A comparative analysis of BRICS. Energy Economics, 76, 76-88.
29. Nordhaus, W. D. (2007). Who's afraid of a big bad oil shock?.Brookings Papers on Economic Activity, 2007(2), 219-238.
30. Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. Energy Economics, 23(5), 511-532.
31. Rafiq, S., Salim, R., & Bloch, H. (2009). Impact of crude oil price volatility on economic activities: An empirical investigation in the Thai economy. Resources Policy, 34(3), 121-132.
32. Sarwar, S., Chen, W., &Waheed, R. (2017). Electricity consumption, oil price, and economic growth: Global perspective. Renewable and Sustainable Energy Reviews, 76, 9-18.
33. Sarwar, S., Khalfaoui, R., Waheed, R., &Dastgerdi, H. G. (2019). Volatility spillovers and hedging: Evidence from Asian oil-importing countries. Resources Policy, 61, 479-488.
34. Shahbaz, M., Sarwar, S., Chen, W., & Malik, M. N. (2017). Dynamics of electricity consumption, oil price, and economic growth: Global perspective. Energy Policy, 108, 256-270.
35. Singhal, S., & Ghosh, S. (2016). Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. Resources Policy, 50, 276-288.
36. Thiem, C. (2018). Oil price uncertainty and the business cycle: Accounting for the influences of global supply and demand within a VAR GARCH-in-mean framework. Applied Economics, 50(34-35), 3735-3751.
37. Van Eyden, R., Difeto, M., Gupta, R., &Wohar, M. E. (2019). Oil price volatility and economic growth: Evidence from advanced economies using more than a century’s data. Applied energy, 233, 612-621.
38. Youngho, C., &Joonfong, W. (2003). Oil price fluctuations and Singapore economy. Energy Policy, 31(11), 1151-1165.