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IMPACT OF OIL PRICE VOLATILITY ON THE VOLATILITY OF THE TRADING VOLUME OF THE NIGERIAN CAPITAL MARKET

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Abstract

This study examines the effect of oil price volatility on the volatility of the trading volume in the Nigerian capitalmarket usingmonthly frequency data that cover the period from January,1997 to December 2016. It employs the EGARCH [1,1] methodology for data analysis .Average monthly exhange rates and inflation rates are introduced as control variables The results of the the empirical analysis show that an asymmetric behavior is present and that there is volatility persistenceThey.suggest that oil price volatility has a negative and significant impact on the volatility of the trading volume in the Nigerian capital market. The results of the study suggest that market participants in Nigeria should target oil price fluctuations as an important means for predicting the volatility of Nigeria#s stock market performance.

Keywords: Ngeria, crude oil price, volatility, trading volume.

1.0 Introduction

Energy, particularly crude oil, is one of the most essential production inputs.Oil has often been identified by many as a commodity that plays an important role in the world economy(see Heo, Yoo & Kwak, 2010; Difiglio, 2014; Le & Chang, 2015; cited in Yoshino,Rasoulinezhad & Chang,2019). .According to researchers such as Yoshino,Rasoulinezhad and Chang(2019),one of the main reasons of political tensions between nations was the economic advantages of crude oil as an essential production input in post-industrial era or its application in transport and electricity generation sectors. Notwithstanding the observable attention being paid to alternative renewable natural sources of energy like wind, water, nuclear, and solar power, the part played by crude oil in macroeconomic movements is still significant. Oil prices have been highly variable—twice as variable as those of other goods.

In the recent times, the sharp decrease in oil prices that started in mid-2014 which reduced global crude oil prices to less than half attracted attention to the role of oil prices on the macro-economy and the factors responsible for oil price shocks.According to Yoshino,Rasoulinezhad & Chang (2019),oil prices dropped from above US$100 per barrel in June 2014 to less than US$30 per barrel in February 2016 and since early April 2016, oil prices have started to increase oncemore because of an increase in demand.. The authors blam several reasons for the sharp drop in the global oil price to several reasons notunconnected to supply and demand and expectations in the oil market.

Literature provides evidence that since the 1970s, oscillations in global oil prices have continued to attract a lot of attention, become a subject of debate as well as a considerable issue for many countries, such as the oil-exporting ones where the governmental budget is tied to oil incomes and economic growth in them can be hit by these changes directly and

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indirectly, and oil-importing nations in which oil is the raw material for producing goods and transportation fuels.

Shortly after the tremendous oil price shocks of the 1970s, a large body of literature began to grow in the quest to identity the effect of oil price changes on the real economic activity. Hamilton (1983), which was among the early studies that probed the oil price and aggregate economy nexus, found that ten out of the eleven post-war recessions in the United States up to 1983 were preceded and caused by oil price shocks. This discovery motivated several scholars to carry out additional investigations on the causal relationship between the two variables. Examples of such studies include Bernanke, Getter and Watson (1997), Bohi (1989), Brown and Yucel (2001), Burbidge and Harrison (1984), and Gisser and Goodwin (1986).

Theinquiries concerning the connection between oil price and the stock market are relatively recent . Peter and De-Mello (2011) cited in Soyemi, Akingunola and Ogebe (2017)attribute this situation to the difficult nature of evaluating stock market activities which did not trend until the late 1990s. Some of those past studies fail to observe any relationship between them. (see Degiannakis, Filis & Arora,2017) whilemany othersfind reasonable evidence of relationship between them.

Concerning the effect of oil price shocks on stock market volatility, Malik and Ewing (2009) observe significant transmission of volatility between oil price and some sectors in the US stock market. According to Vo (2011), there is inter-market dependence in volatility between U.S. stock and the oil markets. For Arouri and Rault (2011), there is volatility transmission from oil to European stock markets.After carrying out a related study,Degiannakis, Filis and Kizys (2014)observe that an upward movement in the price of oil relqated to increased aggregate demand significantly increases stock market volatility in Europe, and that supply-side shocks and oil specific demand shocks have no effect on volatility.

The importance of trading volume as one of the funadamental building blocks of the theories of stock market interventions and in modeling asset markets is highly appreciated in literature. However, although a lot of models of asset market have channeled their attention on the way that returns behave, such as how they can be predicted, how they can change and their information content, their implications for trading volume appear not to have received much attention (see Lo & Wang,2000).

In Nigeria particularly, the studies that have examined the relationship between oil price shocks and stock return are relatively scanty. That apart , the results of those studies also fail to agree..For instance , while some studies such as Omisakin, Adeniji and Omojolabi (2009), Mordi, Michael and Adebiyi (2010), Abbas and Terfa (2010), Adebiyi, Adenuga, Abeng and Omanukwue(2010), Akomolafe and Danladi (2014), Akinlo (2014), Iheanacho (2016), Lawal, Somoye and Babajide (2016), Soyemi et al. (2017),Ojikutu,Onolemhemhen and Isehunwa (2017) and Obi, Oluseyi and Olaniyi (2018), others find oil price shock as having a positive effect on stock price.For instance, both Adaramola (2012) and Effiong (2014) report a negative rlationship between oilprice shock and stock return. For Okany (2014),however, no cointegration exists between the two variables. Both Babatunde, Adenikunji and Adenikunji (2013) and Effiong(2014) adopt a completely different position as they claim thatthe effect of oil price shock on stock price in Nigeria is insignificant. This conflict of results has left much gap in literature.We intend to contribute to this debate by examining the nexus between oil price volatility and the volatility of one of the stock market performance indicators in Nigeria. Precisely,the main objective of this paper is to ascertain the impact of oil price volatility on the volatility of the trading volume of the Nigerian capital market

The choice of Nigeria in this study is motivated by the fact thatNigeria is qualified among all the African countries to be used as proxy . Nigeria is an emerging economy which is not

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only the sixth largest member of OPEC and the largest net-exporter of oil in Africa but also a highly promising economy for internationalportfolio diversification(see Akinlo,2012).
The significance of this study, which covers the period from January 1st 1997 to December 31st 2016, lies on its envisaged ability to generate results that will improve stock returns forecasting accuracy, provide relevant information for investors and policy makers, make available reference materials for researchers and the academia, as well as assist firms in constructing diversified portfolios and determining risk management strategies.
This study extends the existing literature in two distinct ways. Firstly, the study provides, to the best of our knowledge, the first empirical inquiry on the impact of Brent oil price volatility on stock market activities in Nigeria, with emphases on the trading volume in the Nigerian capital market. Secondly,it is one of the few recent studies on the oil/stock relationshipin Nigeria using monthly instead of quarterly or annual data, with the intention of reducing averaging biases and capturing more data points. Thirdly, this empirical study has its scope extended to December 2016. By so doing,we have incorporatedsome of the months when Nigeria entered,and had the full impact of, a five- quarter economic recession that ended in the beginning of the first quarter of 2017.The results of the study would enhance the outcome of those previous and related studies that failed to take the previous recession into consideration.
The remaining part of this paper is arranged as follows. In the next section, we present a brief literature review. The third section describes our empirical model, while the fourth section presents the estimation results . The last section concerns the conclusions.

2.0 Review of the related literat6ure

2.1 Theory

Many researchers understand oil as representing information flow. For an oil-importing country, an increase in oil price will have a positive impact (see Hooker 1999). An oil price increase will bring about an increase in production costs, as oil is regarded as the most important production input (see Arouri & Nguyen,2010).According to Hamilton (1988a, 1988b), and Barro (1984) cited in Youssef and Mokni (2019), the escalating cost of crude oil will affect consumer's behavior, which will, in turn, decrease their demand and spending as a result of higher consumer prices. When the consumption of crude oil is reduced, there will arise a cut down in production and, in return, an increase unemployment (see Brown & Yücel, 2001; Davis & Haltiwanger, 2001 in Youssef & Mokni,2019). In addition, oil price changes affect stock markets as a result of the uncertainty they create for the financial sector, depending on the forces that push up oil prices (demand-side or supply).According to Degiannakis, Filis and Arora (2017), some transmission channels exist between oil and stock market return, namely, stock valuation channel, monetary channel, output channel, fiscal channel and uncertainty channel.
Market Volume or Volume of trade is the total quantity of shares or contracts traded in a stock market for a given security. Volume of trade is measured on share options, contracts, futures contract and other types of commodities. Every stock exchange takes stock of its trading volume and provides the data. This is reported almost on hourly basis throughout the current trading day. Trade[or trading] volume informs investors about the stock market's activity and liquidity. When the trading volume is high for a specified security, the implication is that it has high liquidity , there is better order execution and an active market for bringing buyers and sellers together.Trading volume is usually higher when the price of a security is changing. The news concerning a company's financial status, products, or plans whether it is positive or negative, will usually bring about a temporary movement in the trade volume of its shareA nexus exists between trading activity in individual stocks and market –

wide volume. According toWang (2015),technical traders employ different types of stock trading rules to forecast the prices of stocks ,viz:-

(a) Moving average rules. These are the trading rules most commonly used by technical traders.They are based on price moving averages of different lengths anchored on the philosophy that the price may be on a trend if a shorter moving average is crossing a longer moving average.

(b)Support and resistance rules .These refer tothe important reference points of past prices which the technical traders look at when they make their buy or sell decisions.

(c)Trend line rules. Trend lines are the lines which connect the peaks or troughs and extend into the future.These includeuptrend line and downtrend line.

(d)Big buyer, big seller and manipulator rules.These are institutional traders who manage huge sums of money and usually desire to purchase or sell a large amount of stocks. Since the amount of stocks offered or asked around the trading price is usually not big, the large buy or sell order has to be sliced into small pieces and implemented incrementally over a long period (see Bouchaud, Farmer & Lillo, 2008; Aldridge, 2013 cited in Wang,2015).

(e)Band and stop rules The bands are envelopes around a moving average which have variable sizes. The most widely used band is the Bollinger Band which adds and subtracts the moving estimate of two standard deviations of returns to a moving average(see Bollinger, 2002 cited in Wang,2015).

(f)Volume and strength rules.These refer tothe trading rules that use not only their own past prices but also other information such as volume and the prices of other stocks in the market.

Several studies have employed varying measures for trading volume. For instance, the total number of shares traded was used as a measure of trading volume in the studies of Eppe and Epps (1976), Gallant, Rossi and Tauden (199),Hiemstra and Jones (1994) and Ying(1966) cited in Lo and Wang (2000). A group of studies use aggregate turnover – the total number of shares traded divided by the total number of shares outstanding (see Campell, Grossman & Wang 1999;,LeBaon,1992; Smidt,1990; the 1996 NYSC Fact Book cited in Lo and Wang (2000).Yet a different group of authors use individual share volume in anlyzing price/volatility and volatility/volume nexus (see Andersen,1996; Epps and Epps,1976 as well as Lamoureux & Lastrapes, 1990,1994 in Lo and Wang (2000). Other measures of trading volume include individual turnover, individual dolar volume normalized by aggregate market dollar volume, and number of trading days per year (Lo & Wang,2000).This study is anchored on the model that measures trading volume as the total number of shares traded.We anchore our paper on this measure of trading volume for the purpose of simplicity.

Volatility has been defined in literatureas upward and downward drifts of the prices of crude oil universally. It is considered as the most common risk measure in finance and the risk associated with the upward and downward movements in the value of an asset.Volatility has also been defined as the conditional standard deviation of the underlying assets return and denoted by σ. It refers to a characterization of price changes over time. It has to do with consecutive positive and negative price shocks. When the market prices of crude oil tend to change significantly over a relatively short period, the market is said to be having high volatility.In contrast, the crude oil market is said to be having low volatility when the prices are stable over time. The three main volatility estimates in the literature include conditional-volatility, realized-volatility, and implied-volatility (Degiannakis, Filis and Kizys ,2014).Conditional volatilityis the conditional standard deviation of the asset returns given the most recently available information. The conditional variance process of Y_t can be defined as $V(Yt/I_{t-1})$ which is equivalent to σ_t^2 ,for I_{t-1}.This denotes the information set that investors know when they make their investment decisions at time t. The daily conditional-volatility is the conditional variance of daily returns which is generated by the GARCH (1,1) model. It is generally used and based on the assumption that investors know the most recently available information when they make their decisions to invest in securities.The implied-volatility is a Chicago Board of Options Exchange volatility index which is viewed as an essential instument for measuring the sentiments of investors which are inferred from option prices. This forward-looking implied-volatility represents a measure of the expectation of stock market volatility over the next 30 - day period. Implied volatilityis the instantaneous standard deviation of the return on the underlying asset, which would have to be input into a theoretical pricing model in order to yeld a theoretical value identical to the price of the option in the marketplace, assuming all other inputs are known.

Realized volatilityis based on the idea of employing high frequency data to compute measures of volatility at a lower frequency. An example is using hourly log-returns to generate a measure of daily volatility. By the term monthly realized volatility we denote the daily estimate of monthly variance. According to Kang, Ratti and Yoon (2015),the realized-volatility is based on the methodology of Merton (1980) which assumes that stock returns are generated by a diffusion process.

Both the conditional-volatility and realized-volatility measures are current-looking volatility in the sense that both of them estimate the stock market volatility at the current time. After forecasting monthly variance with past daily squared returns, Ghysels.Santa-Clara & Valkanov (2005) report that the forecast variance process is highly correlated with both the GARCH and the rolling windows estimates (see French,Schwert & Stambaugh, 1987).

2.2 Empirical Review

Karpoff (1986) developed a theory of trading volume based on assumptions that market agents frequently revise their demand prices and meet potential trading partners randomly. The author created a model that describes two distinct ways that informational events affect trading volume, namely, (a) investor disagreement leads to increased trading. and(b) volume can increase even if investors interpret the information identically.

Wang(2015) employed the fuzzy systems theory to convert the technical trading rules commonly used by stock practitioners into excess demand functions that were subsequently used to drive the price dynamics. The technical trading rules were recorded in natural languages where fuzzy words and vague expressions abound.The author demonstrated the details of how to transform the technical trading heuristics into nonlinear dynamic equations.

The study by Tkac (1999) provided a theoretical rebalancing benchmark for trading volume which delivered a connection between trading activity in individual stocks and market-wide volume. While supporting the empirical use of an adjustment for market-wide trading activity when filtering out normal trading volume, the study employed data on a sample of large NYSE/AMEX firms. The findings show that while 20% of the sample firms exhibited trading behavior which is in agreement with the cross-sectional prediction of therebalancing benchmark, systematic deviations existed. The author find that average excess turnover vs. the benchmark has a positive correlation with option availability and institutional ownership but is negatively related to firm size. In addition,the study finds that the sample data did not yield a uniform conclusion on the effect of S&P 500 inclusion. S&P 500 inclusion did not significantly increase the trading of firms which were already trading above the benchmark levels; however, it resulted in additional trading for firms that undertrade the benchmark before their inclusion.

In the recent times, several papers have examined the potential asymmetric relationships between the crude oil market and other asset prices, such as stock prices or stock returns. For instance, Bittlingmayer (2005) observes that oil price fluctuations arising from war risks, and those related to other causes, display asymmetric effects on stock price dynamics. Cheikh,Naceur,Kanaan and Rault (2018) contend that ignoring non-linearity can lead to

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problematic results, just as Balcilar et al. (2015) argue that using a linear framework would result in mixed results.

3.0 Methodology

3.1 Data

This study examines the asymmetrical effects of oil price fluctuations on the Nigerian value of shares traded. We choose monthly data spanning the period of January 1997–December 2016. Monthly frequency data are employed(see appendixA) as many empirical studies have shown preference for high-frequency data when investigating oil-stock-prices correlation(see Cheikh et al.,2018). In order to check for robustness, another crude oil benchmark such as West Texas Intermediate (WTI) has beencompared with the Brent crude price. . We find that using the WTI price type does not significantly alter the results of our benchmark specifications. Oil prices are denominated in US dollars and available from the US Energy Information Administration (EIA).Inthe crude oil market, there are various types and qualities of oil for difference purposes. The price of oil highly depends seriously on in its grade, factors such as specific gravity, its content as well as location. 160 different blends of oil have been identified. However, the three primary benchmarks are WTI, Brent and Dubai. Prices are quoted in different markets all over the univere. In allignment with Alikhanov and Nguyen (2011), we select Europe Brent for the oil exporting country that we intend to investigate.

After examining the three main volatility estimates in the literature, we anchor this study on the conditional volatility model in aligment with Kang et al.(2015) that employed it while esitimating the impact of oil ptire on the stockmarket return and volatility relationship in the US stock market. We first compute the ratio of the first difference of daily returns to the square root of the number of trading-days intervening . The daily stock volatility is the square of the ratio, that denotes daily contribution to monthly stock volatility (see Baum. Caglayan & Talavera,2008).In a relted study,after forecasting monthly variance with past daily squared returns, Ghysels et al. (2005) report that the forecast variance process is highly correlated with both the GARCH and the rolling windows estimates (see French et al., 1987).

The daily data for trading volume are obtained from the Nigerian Stock Exchange's data stream of the relevant period. The average monthly data on Nigeria's official exchange rate and inflation rate are retrieved from the CBN publications of the relevant years. The variables of the study include the historical prices of Brent spot crude oil(OP) used as independent variable and market value of shares traded (MVAL) employed as the dependent variable. The Nigerian official exchange rates (OER) which are the Nigerian naira exchange rates against the US$ and inflation rates (INF) are employed as control variables.Literature recognizes inflation rates and exchange rates as part of those macroeconomic variables that affect stock market significantly(see Fama,1963). In addition, according to Ahkhanov and Nguyen (2011), exchange rate has a significant effect on stock return for exporting country just as industrial production has significant effect on a country engaged in production. Other studies such as Chen, Roll and Ross (1986),Wongbangpo and Sharma (2002) cited in Alikhanov and Nguyen(2011)emerged with results that suggest a negative relationship between exchange rate and stock market performance.

3.1.1 Descriptive statistics

Table 1 summarizes the statistics of the data series. The average monthly series for all the variablesare positive. OER has the highest average monthly data (131.3484), while MVOL has the lowest average monthly data (**4.03E+09**). The size of the standard deviation indicates the risk of the data series. OER has the highest standard deviation(52.08417),while

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MVOL has the lowest standard deviation (**1.30E+10**). MVOL has the highest positive skewness (**13.96910**) and positive kurtosis (**2909)**

Table 1 : Descriptive Statistics

	MVOL	OER	OP	INF
Mean	4.03E+09	131.3484	57.48429	11.47804
Median	1.61E+09	130.3400	50.31000	11.38500
Maximum	1.98E+11	321.5451	133.9000	24.10000
Minimum	33671122	21.88610	9.800000	0.900000
Std. Dev.	1.30E+10	52.08417	34.55795	4.202081
Skewness	13.96910	0.285226	0.458444	0.248519
Kurtosis	208.9909	5.911730	1.911314	3.143751
Jarque-Bera	432128.0	88.03586	20.25920	2.677119
Probability	0.000000	0.000000	0.000040	0.262223
Sum	9.66E+11	31523.63	13796.23	2754.730
Sum Sq. Dev.	4.04E+22	648349.7	285426.2	4220.139
Observations	240	240	240	240

We use the Jarque Bera statistic to determine the normality of the data series. The statisticmeasures the difference between the skewness and kurtosis of the series with those of the normal distribution.The null hypotheses of the Jarque Bera test is that the distribution is normal .Consequently, a probability-value greater than 0.05 indicates that the distribution is normally distributed.We find that the Jarque Bera statistic for MVOL is 432128.0 .It has a p-value of 0.00000; This means that MVOL is not normally distributed since the p-value is less than 0.05.We eqully observe thatthe Jarque Bera statistic for INF is 2.677119.With a p-value of 0.262223; the implication is that INF is not normally distributed since itsp-value is less than 0.05.Further,the Jarque Bera statistic for OER is found to be88.03586. It has a p-value of 0.00000; This means that OER is not normally distributed since itsp-value is less than 0.05.In addition,the Jarque Bera statistic for OP is 20.25920. It has a p-value of 0.000040; This means that OP is not normally distributed since the p-value is less than 0.05

3.1.2 Unit Root Tests

By conducting unit root tests,we examine the properties of our key variables,particularly their stationarity. We test for the presence of unit roots in their levels(I,0) and first differences of oil prices(DOP) and trading volume(DMVOL). Since our study'sscope covers periods of high fluctuations in oil and stock markets,especiallly between 2007 and 2016, it is expected that structural changes would occur in the oil price and market value series.

The summary results of these statistical tests(Tables 2 &3) for both oil price and trading volume series show that the null hypothesis of a unit root cannot be rejected for some of the variables across levels. The non-stationarity of some of the seies at their levels [I,0] implies that the application of Ordinary Least Squares technique will invariably produce a spurious regression whose estimates will be both unreliable and misleading. According to Asaolu and Ilo (2012),modern econometric techniques have demonrated that a linear combination of two variables that are each I(1) and which contain stochastic trends can be achieved through appropriate methods such that their residuals become I(0) or stationary.As long as they are not cointegrated if a and b are I(1), then the residuals from the regression of those series would be I(0) (see Adam,1992 in Asaolu & Ilo,2012). Hence, we difference the series in order to find out if the series are stationary at first differences. We observe that for the variables in first log differences, all unit root tests suggest that we should reject the null hypothesis of non-stationarity.

Since the Augmented Dickey Fuller test in table 2 shows a significant result (p-value is 0.0000),we reject the null hypothesis. This means that DOP does not have a unit root [it is stationary]. Also, since the Augmented Dickey Fuller test in table 3 shows a significant result (p-value is 0.0000),we reject the null hypothesis. This means that MVOL is stationary.

Table 2 : Unit Root test for DOP

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.620566	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(DOP)

Method: Least Squares

Date: 06/04/19 Time: 14:35

Sample (adjusted): 4 240

Included observations: 237 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DOP(-1)	-0.742573	0.086140	-8.620566	0.0000
D(DOP(-1))	-0.166106	0.064700	-2.567305	0.0109
C	0.118816	0.397821	0.298666	0.7655

R-squared	0.458697	Mean dependent var	0.039030
Adjusted R-squared	0.454070	S.D. dependent var	8.286513
S.E. of regression	6.122662	Akaike info criterion	6.474448
Sum squared resid	8771.955	Schwarz criterion	6.518348
Log likelihood	-764.2221	Hannan-Quinn criter.	6.492143
F-statistic	99.14494	Durbin-Watson stat	2.001256
Prob(F-statistic)	0.000000		

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Table 3 : Unit Root test for MVOL

Null Hypothesis: DMVOL has a unit root

Exogenous: Constant

Lag Length: 4 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.68711	0.0000
Test critical values:	1% level	-3.458225	
	5% level	-2.873701	
	10% level	-2.573327	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(DMVOL)

Method: Least Squares

Date: 06/04/19 Time: 15:47

Sample (adjusted): 6 239

Included observations: 234 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DMVOL(-1)	-3.498800	0.299373	-11.68711	0.0000
D(DMVOL(-1))	1.667359	0.261181	6.383929	0.0000
D(DMVOL(-2))	1.000142	0.202224	4.945713	0.0000
D(DMVOL(-3))	0.497300	0.133783	3.717206	0.0003
D(DMVOL(-4))	0.163381	0.065345	2.500284	0.0131
C	83195668	9.39E+08	0.088589	0.9295

R-squared	0.804803	Mean dependent var	-2329814.
Adjusted R-squared	0.800522	S.D. dependent var	3.22E+10
S.E. of regression	1.44E+10	Akaike info criterion	49.63935
Sum squared resid	4.71E+22	Schwarz criterion	49.72795
Log likelihood	-5801.804	Hannan-Quinn criter.	49.67507
F-statistic	188.0097	Durbin-Watson stat	2.046086
Prob(F-statistic)	0.000000		

Source : Researcher's Computation

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3.1.3 Johansen Cointegration Test for MVOL, OP, INF and OER

From the trace test output(Table 4a),the null hypothesis is thar there is no cointegration among the variables.,meaning that none of the variables are co integrated. This is rejected since p-value is 0.0000 (less than 0.05). In table 4b, the hypothesis is that there is at most 1 ointegrating equation. This is rejected as the p-value is =0.0248. The third hypothesis that there is at most 2 cointegrating equation. This is accepted as the p-value is 0.3954.Further, the trace test indicates 2 cointegrating eqn(s) at the 0.05 level.The implication of the findings above is that the variables will be cointegrated or there is long run association between the variables in the long run.

Tablt 4a : Trace Test

Date: 06/23/19 Time: 17:13
Sample (adjusted): 6 240
Included observations: 235 after adjustments
Trend assumption: Linear deterministic trend
Series: MVOL OP OER INF
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.212363	88.45404	47.85613	0.0000
At most 1 *	0.095818	32.35533	29.79707	0.0248
At most 2	0.035750	8.685107	15.49471	0.3953
At most 3	0.000553	0.130021	3.841466	0.7184

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 4b : Maximum Eigenvalue Test

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.212363	56.09871	27.58434	0.0000
At most 1 *	0.095818	23.67022	21.13162	0.0215
At most 2	0.035750	8.555087	14.26460	0.3250
At most 3	0.000553	0.130021	3.841466	0.7184

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

3.1.4 Stability Test for the model for DMVOL as the dependent variable (DMVOL,DOP,DOER,DINF)

The classical Chow (1960) structural stability test was carried out to spot out evidence of potential structural break (see Zivot.& Andrews, 1992).. Though most of the residuals are within their confidence interval limits or bounds, the CUSUM squared result rejected the hypothesis of coefficient stability at five per cent significance. This suggests the presence of structural change in the model. structural breaks potentially occured in the model at 2008M12 and lasted through 2011M07 during which point the residuals drifted upward. This break point period coincided with the global financial crisis, which though noticed in 2007 only had impact on the Nigerian economy from end-2008.

3.1.5 Test for Serial Correlation

The absence of serial correlation in the residuals is a pre-requisite for forecasting with EGARCH. We employ a version of the Lagrange Multiplier for testing for the existence of serial correlation in the residuals. The results in table 5 show that there is no serial correlation.

Table 5 Result of the test for serial correlation

Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order h

Date: 06/05/18 Time: 10:09

Sample: 1997M01 2016M12

Included observations: 238

Lags	LM-Stat	Prob
1	116.0284	0.1078
2	214.3374	0.0709
3	44.00524	0.0760
4	48.69533	0.0222
5	46.52046	0.6342
6	38.90963	0.5713
7	106.1486	0.5302
8	35.20578	0.2041
9	96.87860	0.0437
10	38.99462	0.0197
11	139.9452	0.3146
12	75.85419	0.0525

Probs from chi-square with 49 df.

3.2 Model

The appropriate choice of the model and its approropriate specificqation is an important part of any academic research.

3.2.1 Model Specification

Several studies find the presence of nonlinear connections between oil and economic activity (see Mork, 1989; Hamilton, 1996). The latter studies suggest that oil price increases exert more influence on other macroeconomic variables than oil price decreases.This implies an asymmetric behaviour of oil price shocks and their effects on output level.

In this paper, we carry out the econometric estimation with the Exponential GARCH (EGARCH) - a model which Soyemi et al. (2017) assert has been used in recent studies to measure volatility (See Lux, Segnon & Gupta, 2015, in Soyemi et al., 2017; Lawal, Somoye & Babajide, 2016; Eagle, 2017), among others.We consider this approach as a better means for accounting for the size effect of oil price movements on the dependent variable and allowing for movements in the conditional variance (see Manasseh & Omeje, 2016; Lawal et al., 2016).Proposed by Nelson (1991),the EGARCH model is important in capturing asymmetry, which is the different impacts on conditional volatility of positive and negative shocks of equal magnitude, and possibly also leverage, which is the negative correlation between returns shocks and subsequent shocks to volatility.One advantage of the EGARCH model over the basic GARCH (1,1) specification is that it is an asymmetric model that specifies the logarithm of conditional volatility and avoids the need for any parametric constraints EGARCH has some kind of leverage effects in its equation. Sadorsky (1999) reports that many authors have suggested that oil price volatility shocks may have an essential role in explaining economic activity. Some authors regard volatility of price shocks as an accurate measure of the rate of information flow in financial markets. Mokni and Mansouri(2017) report that such models are capable of capturing different volatility stylized facts which are often noticedin financial time series,namely volatility clustering , heteroskedasticity and long memory, cotemporanously..

The EGARCH[p,q] model is specified as follows: -

$$\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$$

(conditional variance equation)..(2.1)

Source : Brooks (2014).

For this study, the conditional mean and variance equations for testing the hypothesis is presented as follows:-

LOG(GARCH) **= C(1) + C(2)*DOP**

...(2.2)

LOG(GARCH) = C(3) + C(4)*ABS[RESID(-1)/@SQRT{GARCH(-1)}] + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG{GARCH(-1)} + C(7)*DOP …………………………(2.3)

LOG (GARCH) is the conditional variance of the residual; it is the dependent variable. C (3) stands for the constant which shows the last period (t-1) volatility. C(4) is the constant stands proxy for theimpact of a magnitude of a shock (size) /arch effect / spillover effect . It shows the impact of long term volatility. At five percent level of significance, if C(4) has a p-value not above 0.05, the implication is that it is significant and there is likely an impact of long term volatility..C (5) is the gamma (γ) - the leverageterm. The gamma parameter measures the asymmetry or the leverage effect. If gamma is qual to 0 , then the model is symmetric. When gamma is less than 0 , then positive shocks (good news) generate less volatility than negative shocks (bad news) do. When gamma greater than 0 , the implication is that positive innovations are more destabilizing than negative changes..C (6) re[resents the GARCH effect – the alpha. Its parameter represents a magnitude effect or the symmetric effect of the model.Beta (the GARCH term) estimates the persistence in conditional volatility notwithstandign anything happening in the market. When beta is relatively large, the implication is that volatility takes a long time to die out following a crisis in the market (see Alexander,2009). C (7) is DOP ((the explanatory variable),The statistics for the hypotheses are shown in tables 11 – 16. The decision is base on 5% level of significance. According to Brooks (2014), the model above, which is based on the assumption of normal Gaussian distribution, captures the asymmetric volatility through the variable gamma(γ). The sign of the gamma determines the size of the asymmetric volatility and whether the latter is positive or negative.

The null hypothesis is that oil price volatility had no positive and significant impact on the volatility of the trading volume. The model for testing this hypothesis is presented respectively :as follows:-

DMVOL = C(1) + C(2)*DOP
………..…………………………………………………(2.4)

LOG(GARCH) = C(3) + C(4)*ABS[RESID(-1)/@SQRT{GARCH(-1)}] + C(5)*RESID(-1)/@SQRT{GARCH(-1)} + C(6)*LOG{GARCH(-1)} + C(7)*DOP……………………(2.5)

Where DMVOL stands for the first differnce of the trading volume in the Nigeriancapital market and DOP represents the first difference of the Brent spot oil price both in their first difference forms.

4.0 Empirical results

As equation estimation(2.1 and 2.2) represents, we model the volatility of crude oil returns with an AR(1)-EGARCH(1,1) specification. Table 6 presents the test results. We find that all the parameter estimates of the EGARCH(1,1) model are highly statistically significant. We use the sum of β_1 to measure the persistence in volatility and observe that α_1 in the GARCH model is closer tounity for each period.

In equation 2.2 , the LOG (GARCH) which is the conditional variance of the residual and the dependent variable stands for the volatility of the trading volume. The constant(C(3)) indicates the last period (t-1) volatility. It is an arch (alpha) term which explains volatility clustering. C(4), which represents the impact of a magnitude of a shock (size) /arch effect / spillover effect, indicates impact of long term volatility.It has a p-value of 0.0000, implying that it is significant and that there seems to be some impact of long term volatility. In addition, C5, the leverage coefficient or gamma is positive at 1.411674 and significant with a p-value of 0.0000 .This shows that there is no leverage effect and that: bad news has less impact than good news of the same size.Further,C(6), the beta or GARCH term has a value of 0.787328 and a p-value of 0.0000.This implies that the GARCH effect is significant and that there is volatility persistence. Oil price volatility (DOP) is an exogenous variable or variance regressor as it can also contribute in the volatility of trading volume in equation 4.2. Oil price volatility (DOP) has a p-value of 0.0011. This means that the impact of oil price volatility on the volatility of trading volume (DMVOL) is significant. DOP has a negative coefficient at -0.009151 which means that its impact of on DMVOL is in the negative direction.Based onthe findings of this study using the EGARCH [1,1] esimation technique, oil price volatility has a negative and significant impact on the volatility of the trading volume in the Nigerian capital market.

5.0 Conclusion and policy implications

This study has examined the impact of oil price volatility on the volatility of the trading volume in the Nigerian capital market. We employed the EGARCH methodology to invstigate this impact. The results of the the empirical analysis show that an asymmetric behavior is present and that there is volatility persistence.We report thatoil price volatility has a negative and significant impact on the volatility of the trading volume in the Nigerian capital market. The implication is that a unit increase in oil price causes some decrease in the trading volume.The negative connection between oil price and the trading volume in Nigeria is explained by the fact that, though Nigeria is an oil-exporting country, the import bill at the moment is significantly over and above what is exported (see Adaramola,2012).The results of this study are relevant for optimal portfolio diversification strategies as well as policy making. To be proactive, the Nigrian government should take some measures to diversify her sources of energy and take steps to enhance renewable energy in primary, industrial and domestic units.According to Arnold et al.(2018), this could result in making her stock prices more independent of oil price fuctuations.

APPENDIX A

HAistorical data of Market volume (number of shares) (MVOL)and Nigerian Stock Market Performance

Year	Month	Oil price per barrel ($) (OP)	**% change in oil price (PCOP)**	**Market volume (number of shares) (MVOL)**	Exchange rate	Inflation rate
1997	1	23.47	-0.21	33,671,122	21.8861	24.1
1997	2	20.83	-11.25	191,106,820	21.8861	24.1
1997	3	19.21	-7.78	71,499,602	21.8861	22.3
1997	4	17.47	-9.06	142,113,800	21.8861	21.2
1997	5	19.14	9.56	42,142,155	21.8861	19.7
1997	6	17.55	-8.31	62,364,976	21.8861	18.7
1997	7	18.43	5.01	61,475,919	21.8861	16.4
1997	8	18.69	1.41	121,512,150	21.8861	14.8
1997	9	18.45	-1.28	71,598,094	21.8861	13.4
1997	10	20.05	8.67	91,426,119	21.8861	12
1997	11	19	-5.24	78,220,368	21.8861	11
1997	12	17.1	-10	116,343,390	21.8861	10.2
1998	1	15.09	-11.75	75,476,819	21.8861	10.2
1998	2	14.06	-6.83	114,405,677	21.8861	9.8
1998	3	13.08	-6.97	177,465,258	21.8861	9.3
1998	4	13.39	2.37	113,920,654	21.8861	9.3
1998	5	14.39	7.47	111,526,252	21.8861	7.6
1998	6	12.06	-16.19	110,848,908	21.8861	7.2
1998	7	12.04	-0.17	283,550,519	21.8861	7.2
1998	8	11.88	-1.33	110,993,947	21.8861	7.5
1998	9	13.36	12.46	124,313,524	21.8861	7.5
1998	10	12.56	-5.99	129,084,808	21.8861	7.7
1998	11	10.92	-13.06	446,889,141	21.8861	7.7
1998	12	9.8	-10.26	206,464,014	21.8861	7.9
1999	1	10.95	11.73	84,680,503	86.00000	8.3

1999	2	10.2	-6.85	104,918,443	86.00000	8.8
1999	3	12.12	18.82	181,440,055	86.96590	9.1
1999	4	15.16	25.08	145,601,803	90.00000	9.9
1999	5	15.22	0.4	170,110,027	94.88000	10.5
1999	6	15.6	2.5	244,810,917	94.88000	10.6
1999	7	18.71	19.94	161,742,610	94.88000	10.2
1999	8	20.17	7.8	1,145,294,546	94.88000	10.6
1999	9	22.11	9.62	688,232,901	94.88000	9.6
1999	10	22.12	0.05	170,231,951	94.88000	8.5
1999	11	24.55	10.99	195,184,378	94.88000	7.6
1999	12	25.48	3.79	368,987,262	96.45410	6.6
2000	1	25.22	-1.02	198,284,430,015	98.78000	5.2
2000	2	27.63	9.56	538,326,556	99.91430	3.9
2000	3	27.47	-0.58	486,536,480	100.93790	2.7
2000	4	22.54	-17.95	198,560,542	100.37830	1.8
2000	5	27.4	21.56	236,971,989	101.82860	1.1
2000	6	29.68	8.32	335,108,202	101.82860	0.9
2000	7	28.51	-3.94	400,707,163	105.32860	1.2
2000	8	29.89	4.84	612,619,747	102.80480	2.2
2000	9	32.62	9.13	340,281,416	102.36170	3.3
2000	10	30.93	-5.18	454,371,592	102.47730	4.5
2000	11	32.52	5.14	333,506,610	102.52050	5.8
2000	12	25.28	-22.26	372,157,537	106.71110	6.9
2001	1	25.64	1.42	548,483,766	110.50450	8.6
2001	2	27.41	6.9	474,095,973	110.70500	10.3
2001	3	24.4	-10.98	433,111,105	110.65500	11.9
2001	4	25.55	4.71	387,606,692	113.70000	13.9
2001	5	28.45	11.35	400,734,446	118.56670	15.7
2001	6	27.72	-2.57	360,422,023	112.47500	16.6
2001	7	24.54	-11.47	714,402,235	111.5455	17.7
2001	8	25.67	4.6	811,552,946	111.6953	18.1
2001	9	25.54	-0.51	310,364,314	111.6	18.4
2001	10	20.48	-19.81	477,033,192	111.6	15.8
2001	11	18.94	-7.52	437,155,678	111.5205	18.7
2001	12	18.6	-1.8	487,815,953	106.7111	18.9
2002	1	19.48	4.73	371,286,464	113.5045	18.9
2002	2	22.29	4.16	403,265,569	114.2759	18.9
2002	3	23.69	16.76	626,646,656	116.04	18.6
2002	4	25.65	8.27	424,642,544	116.128	17.9
2002	5	25.43	-0.86	336,716,197	116.55	16.8
2002	6	24.13	-5.11	798,704,555	118.49	16.4

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2002	7	25.77	6.8	625,529,006	123.7232	16.2
2002	8	26.63	3.34	942,529,256	125.7547	15.6
2002	9	28.34	6.42	722,738,938	126.4491	13.6
2002	10	27.55	-2.79	39,562,621	126.7886	13.6
2002	11	24.5	-11.07	332,543,852	126.8294	13.2
2002	12	28.52	16.41	619,112,524	126.8833	12.9
2003	1	31.29	9.71	925,999,379	127.0695	12.3
2003	2	32.65	4.35	594,649,880	127.315	11.4
2003	3	30.34	-7.08	1,117,793,090	127.164	10.5
2003	4	25.02	-17.53	592,264,656	127.37	10.1
2003	5	25.81	3.16	471,545,733	127.6676	10
2003	6	27.55	6.74	1,070,304,491	127.8817	10
2003	7	28.4	3.09	1,623,127,751	127.772	10
2003	8	29.83	5.04	1,078,114,948	127.895	10
2003	9	27.1	-9.15	1,367,557,002	128.515	12.7
2003	10	29.59	9.19	1,501,260,544	129.7866	12.3
2003	11	28.77	-2.77	1,952,143,625	129.7866	12.3
2003	12	29.85	-2.77	1,952,143,625	137.2233	14
2004	1	31.18	4.35	2,472,287,064	136.0823	15
2004	2	30.87	-0.99	1,272,272,631	135.1625	16.5
2004	3	33.8	9.49	1,335,893,138	184.4717	17.8
2004	4	33.36	-1.3	1,424,953,130	188.5091	18
2004	5	37.92	13.67	1,457,083,993	133.0116	19.4
2004	6	35.19	-7.2	2,260,070,007	112.7506	19.4
2004	7	38.37	9.04	1,694,448,189	132.7992	19.1
2004	8	43.03	12.14	1,227,978,745	132.8295	19.1
2004	9	43.38	0.81	1,018,054,618	132.8445	17.1
2004	10	49.77	14.73	1,076,098,922	132.8552	17.1
2004	11	43.05	-13.5	1,599,398,458	132.864	16.1
2004	12	43.38	0.81	1,018,054,618	132.86	15
2005	1	44.28	11.68	1,568,875,707	132.86	14
2005	2	45.56	2.69	998,858,923	132.85	12.9
2005	3	53.08	16.51	1,255,256,544	132.85	12.5
2005	4	51.86	-2.3	1,037,890,542	132.85	12.6
2005	5	48.67	-6.15	1,617,761,306	132.85	12.5
2005	6	54.31	11.59	3,355,488,149	132.87	i 12.9
2005	7	57.58	6.02	2,066,078,778	132.87	14.2
2005	8	64.09	11.31	2,320,612,627	133.3271	15.5
2005	9	62.98	-1.73	4,015,308,986	130.8102	16.8
2005	10	58.52	-7.08	3,543,095,633	130.8392	17.4
2005	11	55.53	-5.11	2,385,721,495	130.6271	17.8

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2005	12	62.98	-1.73	4,015,308,986	130.39	17.9
2006	1	63.57	12.02	1,480,032,197	130.29	17.9
2006	2	59.92	-5.74	2,068,833,277	129.5931	17.8
2006	3	62.25	3.89	1,700,273,023	129.7043	17.4
2006	4	70.44	13.16	2,121,338,334	128.4652	16.9
2006	5	70.19	-0.35	2,595,460,189	128.4516	16.4
2006	6	68.86	-1.89	2,343,296,927	128.4543	15.8
2006	7	73.9	7.32	3,351,561,566	128.3811	13.5
2006	8	73.61	-0.39	5,111,095,706	128.8273	11.4
2006	9	62.77	-14.73	3,414,197,745	128.2902	10
2006	10	58.38	-6.99	4,775,257,847	128.283	9
2006	11	58.48	0.17	4,023,456,102	128.2858	8.5
2006	12	58.38	-6.99	4,775,257,847	128.2919	8
2007	1	54.3	-12.86	5,637,065,621	128.2772	8
2007	2	57.76	6.37	9,181,447,332	128.2687	7.7
2007	3	62.14	7.58	1,394,353,969	128.1513	7.2
2007	4	67.4	8.46	2,531,215,703	127.9814	6.5
2007	5	67.48	0.12	693,918,767	127.5595	6
2007	6	71.32	5.69	422,053,966	127.409	5.9
2007	7	77.2	8.24	452,025,715	127.1859	6
2007	8	70.8	-8.29	505,939,341	126.6753	6.1
2007	9	77.13	8.94	410,415,386	125.8926	5.9
2007	10	83.04	7.66	402,874,795	124.276	5.7
2007	11	92.53	11.43	1,206,587,942	126.1236	5.5
2007	12	70.8	-8.29	505,939,341	118.2007	5.4
2008	1	91.92	0.51	20,081,009,894	117.9768	5.5
2008	2	94.82	3.15	888,191,023	118.2687	5.5
2008	3	103.28	8.92	388,447,107	117.9218	5.8
2008	4	110.44	6.93	467,595,958	117.8137	6.5
2008	5	123.94	12.22	1,519,286,364	117.8342	6.5
2008	6	133.05	7.35	1,244,510,970	117.8086	7
2008	7	133.9	0.64	1,716,441,483	117.7671	7.8
2008	8	113.85	-14.97	4,489,525,492	117.725	8.5
2008	9	99.06	-12.99	1,560,170,655	117.7243	9.2
2008	10	72.84	-26.4 7	5,851,999,328	117.7433	10.1
2008	11	53.24	-26.91	7,972,898,388	117.7433	10.9
2008	12	41.58	-21.9	9,684,671,827	128.4756	11.6
2009	1	44.86	7.89	4,793,539,995	145.7803	12
2009	2	43.24	-3.61	6,603,151,163	147.1444	12.6
2009	3	46.84	8.33	7,800,671,995	147.7226	13.1
2009	4	50.85	8.56	7,956,903,916	147.2272	13.5

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2009	5	57.94	13.94	7,961,281,227	147.8427	13.8
2009	6	68.59	18.38	205,102,830	148.2018	12.7
2009	7	64.92	-5.35	9,921,024,638	148.589	13.4
2009	8	72.5	11.68	9,910,905,917	157.358	13.3
2009	9	67.69	-6.63	9,053,230,710	152.3017	13.1
2009	10	73.19	8.13	419,847,660	149.355	12.8
2009	11	77.04	5.26	9,335,586,291	150.8469	112.6
2009	12	74.67	-3.08	7,572,469,803	149.6226	12.5
2010	1	76.37	2.28	8,281,823,360	149.7791	12.6
2010	2	74.31	-2.7	7,858,148,444	150.2224	12.7
2010	3	79.27	6.67	259,884,860	149.3285	12.8
2010	4	84.93	7.14	431,613,925	149.8927	12.9
2010	5	76.25	-10.22	8249621689	150.3125	12.9
2010	6	74.84	-1.85	7,105,511,532	150.1915	13.1
2010	7	74.74	-0.13	7,638,050,081	150.6986	13.3
2010	8	76.69	2.61	5,265,589,620	150.2267	13.5
2010	9	77.79	1.43	4,836,603,913	151.0332	13.8
2010	10	82.92	6.59	6,714,188,097	151.25	13.9
2010	11	85.67	3.32	7,434,138,490	150.221	13.9
2010	12	91.8	7.16	6,627,104,060	150.4799	13.7
2011	1	96.29	4.89	295,574,863	151.5455	13.5
2011	2	103.96	7.97	6,497,107,332	151.9391	13.2
2011	3	114.44	10.08	7,839,883,859	152.5074	13
2011	4	123.15	7.61	2,170,765,373	153.9673	12.7
2011	5	114.46	-7.06	6,585,723,649	154.806	12.6
2011	6	113.76	-0.61	7,614,574,399	154.5029	12.3
2011	7	116.46	2.37	5,512,662,763	151.8646	13
2011	8	110.08	-5.48	6,461,101,829	152.7154	11.6
2011	9	110.88	0.73	4,513,119,409	155.2636	11.4
2011	10	109.4 7	-1.27	6,767,898,640	153.2569	11.11
2011	11	110.5	0.94	5,119,936,515	153.7693	11
2011	12	107.97	-2.29	6,183,451,240	158.2074	10.8
2012	1	110.99	2.8	4,088,327,501	158.3868	10.9
2012	2	119.7	7.85	8,059,336,233	177.8681	11
2012	3	124.93	4.37	7,487,272,112	157.5875	10.9
2012	4	120.59	-3.47	7,366,664,577	157.3314	11.1
2012	5	110.52	-8.35	8,519,172,890	157.2762	11.1
2012	6	95.59	-13.51	4,325,534,996	157.4388	11.3
2012	7	103.14	7.9	6,297,059,021	157.4342	11.6
2012	8	113.34	9.89	5,502,802,787	157.3796	11.8
2012	9	113.38	0.04	2,271,730,715	157.3429	11.9

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2012	10	111. 97	-1.24	3,171,356,231	157.3156	11.9
2012	11	109.71	-2.02	5,504,556,782	157.308	12.1
2012	12	109.64	-0.06	5,152,687,772	151.321	12.2
2013	1	112.93	3	361,246,496	157.3012	11.9
2013	2	116.46	3.13	351,540,246	157.2994	11.7
2013	3	109.24	-6.2	8,119,205,976	157.5115	11.4
2013	4	102.88	-5.82	8,301,154,015	157.3052	11.1
2013	5	103.03	0.15	8,477,752,976	157.3008	11.8
2013	6	103.11	0.08	9,728,882,072	157.3065	10.4
2013	7	107.72	4.47	1,071,123,117	157.3157	10.5
2013	8	110.96	3.01	6,060,441,669	157.3135	9.8
2013	9	111.62	0.59	5,393,672,256	157.3157	9.5
2013	10	109.48	-1.92	6,827,725,319	157.4166	9.2
2013	11	108.08	-1.28	6,827,725,319	157.2734	8.8
2013	12	110.63	2.36	930,335,094	157.2742	8.5
2014	1	107.57	-2.77	8,228,678,774	157.2918	8.4
2014	2	108.81	1.15	4,630,735,522	157.6075	8.3
2014	3	107.41	-1.29	7,791,420,664	157.3008	8.2
2014	4	107.88	0.44	7,422,571,102	157.2918	8.1
2014	5	109.68	1.67	7,571,787,789	157.2873	8
2014	6	111.87	2	9,437,263,833	157.2873	8
2014	7	106.98	-4.37	8,318,638,689	157.2373	8
2014	8	101.96	-4.73	5,445,750,526	157.2873	8
2014	9	97.34	-4.49	2,050,387,820	157.3006	8
2014	10	87.27	-10.35	7,979,950,461	157.3141	8
2014	11	78.44	-10.12	9,078,340,494	157.9961	8
2014	12	62.16	-20.75	3,537,969,885	169.68	8
2015	1	48.42	-22.1	8,004,991,757	184.6611	8.1
2015	2	57.93	14.64	7,735,341,390	196.3427	8.1
2015	3	55.79	-3.69	1,402,115,443	198.3366	8.2
2015	4	59.39	6.45	1,146,154,942	197.36574	8.2
2015	5	64.56	8.71	7,952,562,657	197.5658	8.3
2015	6	62.35	-342	6,113,490,411	197.9818	8.4
2015	7	55.87	-10.39	6,192,688,806	197.9504	8.5
2015	8	46.99	-15.89	2,529,468,994	197.0525	8.6
2015	9	47.23	0.51	6,963,114,639	197.3765	8.7
2015	10	48.12	1.88	4,965,828,035	197.3765	8.76
2015	11	14.42	-7.69	6,167,650,274	198.1227	8.88
2015	12	37.72	-15.08	7,237,559,835	197.4135	9.01
2016	1	30.8	-18.35	5,668,576,502	196.9394	9.13
2016	2	33.2	7.79	3,285,739,119	197.3936	9.39

2016	3	39.07	17.68	6,669,101,350	196.8329	9.75
2016	4	42.25	8.14	6,676,861,560	197.7628	10.18
2016	5	47.13	11.55	7,855,000,727	197.948	10.75
2016	6	48.48	2.86	7,712,472,745	219.9499	11.37
2016	7	45.07	-7.03	4,934,484,795	288.2376	12.04
2016	8	46.14	2.37	5,621,108,259	321.4032	12.74
2016	9	46.19	0.11	7,950,765,747	321.5451	13.45
2016	10	49.73	7.66	3,671,071,128	313.4051	14.21
2016	11	46.44	-6.62	6,093,377,809	312.4617	14.96
2016	12	54.07	16.43	5,568,424,075	311.4057	15.7

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