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The Impact of Oil Price Volatility to Oil and Gas Company Stock Returns and Emerging Economies

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ABSTRACT

In this paper, we examine the impact of oil price shocks on both selected companies and emerging markets. The novelties of this study can be described as: (i) It also includes the recent oil price crisis compared to previous articles in this field, (ii) our study considers in details the oil and gas company business acumen to explain the results of the econometric models which is not the case in previous studies, (iii) we also include the impact of oil price volatility on emerging markets since oil prices have an importance as explanatory variable of exchange rate movements which makes out study a very comprehensive one. As mostly preferred in many previous studies in this literature, we employed the exponential GARCH (EGARCH) estimation methodology, we concluded that the volatility effect of a given shock to the oil prices and oil and gas company stock price returns are highly persistent and the successive forecasts of the conditional variance converge to the steady state slowly. In addition, we also present the news impact curves which indicate that the behavior of commodity prices and company stock prices react differently to bad and good news.

Keywords: Oil Prices, Time Series, Asymmetric Volatility, Stock Returns, Oil and Gas Companies, News Impact Curves
JEL Classifications: Q4, Q43

1. INTRODUCTION

Crude oil prices fluctuated heavily in the past three decades and become more volatile than they were over the period from World War II to the early 1970s. Since oil prices are denominated in US dollars, and so their fluctuations in domestic currencies depend closely on the dollar exchange rates, oil and non-oil economies are not affected by the oil price increases in the same manner.

High volatility and specialness in energy markets result in more challenging trade execution, larger capital requirements and decreasing effectiveness of benchmark hedging compared to other asset classes. Major sources of energy are often discovered at considerable distances from the locations of ultimate consumption which created regional imbalances with consequences raging from international capital flows to geopolitical risks to the reliability of energy supply.

With an enthusiast for fossil fuels in the white house and former head of Exxon Mobil as US secretary of state the oil industry is expected to be a hot topic again while renewables continue to rise worldwide. Diminishing oil prices in the last years forced the energy giants such as BP, Exxon, Shell, Total, Chevron etc. BP had to contend with collapse of crude oil prices while at the same time paying out tens billions of dollars in compensation and clean-up costs caused of UK group's 2010 oil spill in the Gulf of Mexico.

A recovery in the industry is crucial for those companies in an environment where renewable energy grows substantially with the support of Paris Agreement. However Royal Dutch and Chevron better positioned themselves compared to BP and Exxon by investing aggressively amid the downturn. Shell acquired BG Group of the UK for 35bn £ during the depths of the oil crash. This strong portfolio acquired from BG including energy assets in Australia and deep water oil fields of Brazil recovered the Anglo-Dutch Company.

On the other hand Exxon is interested in new asset acquisitions and it struck deals worth up to 6.6bn £ to buy shale oil companies with drilling right on a large area of the Permian basin in New

Mexico. BP is also rebuilding however the oil price needed to cover investment and its dividend-to 60$ per barrel this year from 55$ at the end of last year.

The stabilization of oil prices is more important than price itself since volatility makes it difficult to predict both for the major players and the countries as well. Oil price dynamics influenced economic activity, equity markets and the strategies of the energy companies. In this context modeling and forecasting the comovements between oil priced and the dollar exchange rates are crucial.

The paper is organized as follows: Section 2 includes the literature review on previous research on the interaction between oil prices and exchange rates along with macroeconomic implications of oil price shocks. Section 3 describes the empirical methodology and Section 4 presents the data used and we discussed our empirical results in Section 5. Finally, section 6 provides conclusion remarks and further study areas within this topic.

Results show that the volatility of a given shock to the oil prices and oil and gas company stock prices are highly persistent and the successive forecasts of the conditional variance converge to the steady state slowly. The news impact curve (NIC) indicates that the behavior of commodity prices and company stock prices react differently to bad and good news.

2. LITERATURE REVIEW

Before global financial crisis, there was a positive relationship between oil price prices and dollar value. Chen and Chen (2007) studied the long run relationship between real oil prices and real exchange rates and concluded that world oil prices constitute the dominant source of exchange rate movements. Narayan et al. (2008) examined the relationship between oil prices and the Fiji-US exchange rate and concluded that a rise in oil prices leads to an appreciation of the Fijian-dollar. Krugman (1983) and Golub (1983) document the potential importance of oil prices as an explanatory variable of exchange rate movements. Kang et al. (2015) examine the effects of global oil price shocks on the stock market return and volatility contemporaneous relation using a structural VAR model which they conclude that the spillover index between the structural oil price shocks and covariance of stock return and volatility is large and highly statistically significant.

Coherently, Ratti and Vespignani (2016) state that global money, global industrial production and global oil prices are cointegrated. A rise in oil prices result in significant increases in global interest rates. Causality goes from global liquidity to oil prices and from oil prices to the global interest rate, global industrial production and global CPI. Positive shocks to global M2[1], to global CPI and to global industrial production lead to statistically significant and persistent increases in global oil prices. Aloui et al. (2013) claim that the negative relationship between the oil prices and the price of dollar can be explained by the fact that oil is a hedge against rising inflation and serves as a safe haven against growing risk.

In the study of Lizardo and Mollick (2010), cointegration tests and forecasts show that increases in real oil prices lead to a significant depreciation of the USD dollar against currencies of net oil exporting countries (Canada, Mexico and Russia). On the other hand the value of dollar relative to currencies of net oil importing countries such as Japan increases when the real oil prices go up.

Moreover, it is documented that oil shocks may have an asymmetric impact on macroeconomic variables. Federer (1996) and Lee et al. (1995) have found that changes in oil price volatility significantly affect macroeconomic variables.

After more than two decades of research on volatility forecasting, there is still considerable disagreement on how volatility should be modeled. One respectful example of volatility forecasting is the observation that equity returns and volatility are negative correlated. The phenomenon can be explained by a leverage effect, or a volatility feed-back effect. Takaishi (2017) propose a new ARCH-type model that uses a rational function to capture the asymmetric response of volatility to returns, which is leverage effect. Coherently, we also included analysis to find out the effect of shocks on stock returns of the major industry players in to this study.

In addition to macroeconomic impact, commodity prices such as oil have significant effects of company stock returns. Jorion (1990) estimates exchange rate exposure of US multinationals over the period from January 1971 to December 1987. Blose and Shieh (1995) examine the impact of gold prices' changes on the returns of gold mining stocks. Due to their findings the gold price sensitivity of a mining stock was found to be greater than one. The hypothesis of unity gold price sensitivity was not rejected using monthly data over the period 1981–1990 for a sample of commonly traded companies. Those studies guide us to analyze the impact of oil price volatility on emerging market currencies to understand the macroeconomics aspect of energy price movements since for most of those countries it is the most important input of the whole economics activity.

Due to the results of the previous literature there is a clear asymmetric behavior between oil prices and other assets classes like company equities and currencies. Also since the effect of oil price shocks can be persistent for a long time period there are cyclical impacts on both microeconomics and macroeconomics indicators. In this respect one of the crucial points of this study is that it includes the recent oil price crisis period in the dataset. Narayan and Narayan (2007) paper appears to be the only notable paper that has attempted to model oil price volatility using different sub periods in order to judge the robustness of their results. This is the main reason why we will also use three sub periods in our analysis which will cover both 2008 global crisis and 2014 oil price crisis.

1 M2 is a measure of the money supply that includes all elements of M1 as well as "near money." M1 includes cash and checking deposits, while near money refers to savings deposits, money market securities, mutual funds and other time deposits. These assets are less liquid than M1 and not as suitable as exchange mediums, but they can be quickly converted into cash or checking deposits.

3. METHODOLOGY

Firstly, we used exponential GARCH (EGARCH) instruments to model the volatility behavior of oil prices. Major advantage of the model is that, instead of considering heteroskedasticity as a problem to be corrected, ARCH and GARCH models treat it as a variance to be modeled. Usually financial data suggests that some time periods are riskier than others; that is, the expected value of the magnitude of error terms at sometimes is greater than at others. The goal of such models is to provide a volatility measure, like a standard deviation, then can be used in financial decisions related with risk analysis, portfolio selection and derivative pricing (Engle 1982; 1993; 2001).

ARCH model assumes that the variance of t u_t in period t, σ_t^2 depends on the square of the error term in t−1 period, $u_{t-1.}$

In this context, ARCH(q) and GARCH(q) models are as follows;

α0>0, αi>0

$$h_t=\alpha_0+\alpha_1\varepsilon_{t-1}{}^2+\alpha_2\varepsilon_{t-2}{}^2+\ldots+\alpha_q\varepsilon_{t-q}{}^2+\nu_t \qquad (1)$$

GARCH models which express the generalized form of ARCH models were developed by Engle (1982) and Bollerslev (1986) to provide reliable estimations and predictions. GARCH models consist of conditional variance, in equation (2) in addition to conditional mean in equation (1).

$$h_t=\alpha_0+\sum_{i=1}^{q}\alpha_i r^2{}_{t-i}+\sum_{i=!}^{p}\beta_j h_{t-j} \qquad (2)$$

In this context, restrictions of variance model are as follows;

for αi≥0 and βi≥0, αi+βi<1

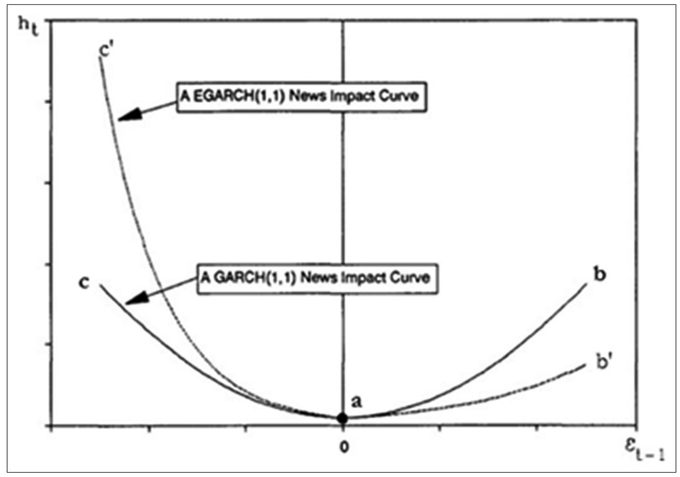
If αi+βi≥1 it is termed as non-stationary in variance. For non-stationarity in variance, the conditional variance forecasts will not converge on their unconditional value as the horizon increases (Brooks, 2008).

In this context ARCH and GARCH models have become very popular as they enable the econometrician to estimate the variance of a series at a particular point in time. Clearly asset pricing models indicate that the risk premium will depend on the expected return and the variance of that return (Enders, 2004).

An interesting feature of asset prices is that "bad" news seem to have a more pronounced effect on volatility than does "good" news. For many stocks, there is a strong negative correlation between the current return and the future volatility. The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage effect.

The idea of the leverage effect is captured in the Figure 1, where "new information" is measured by the size of ε_{t-1}. If $\varepsilon_{t-1}=0$, expected volatility (h_t) is 0a. Any news increases volatility; however, if the news is "good" (i.e., if ε_t is positive), volatility increases along ab (or ab' for EGARCH model). If the news is "bad," volatility increases along ac (or ac' for EGARCH model). Since ac and ac' are steeper than ab and ab', a positive ε_t shock will have a smaller effect on volatility than a negative shock of these same magnitude (Figure 1).

Figure 1: News impact curves



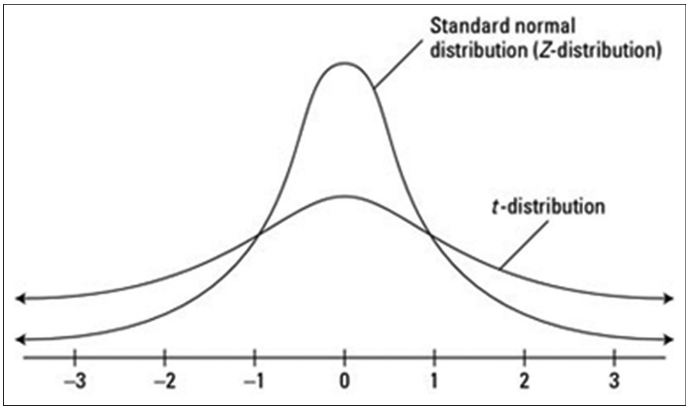
Asymmetric or leverage volatility models, in which good news and bad news have different predictability for the future volatility are the most interesting approaches in the literature. Overall, Chen and Ghysels (2010) found that moderately good (intra-daily) news reduces volatility (the next day), while both very good news (unusual high intra-daily positive returns) and bad news (negative returns) increase volatility, with the latter having a more severe impact. The asymmetries disappear over longer horizons.

The NIC characterizes the impact of past return shocks on the return volatility which is implicit in a volatility model. In the next sections we discuss several models of oil price and oil and company stock prices volatility and present the NIC.

Coherent with that GARCH models allow us to test the effect of news on oil prices quantitatively and help us to understand if the markets absorb these closely tracked data by people. For most financial assets, the distribution function for the rate of return is fat-tailed. A fat-tailed distribution has more weight in the tails than a normal distribution. Suppose that the rate of return on a particular stock has a higher probability of a very large loss (or gain) than indicated by the normal distribution. As such, you might not want to perform a maximum likelihood estimation using a normal distribution. Figure 2 below compares the standardized normal distribution to a t-distribution. You can see that the t-distributions places a greater likelihood on large realizations than does the normal distribution. As such, many computer packages allow you to estimate a GARCH model using a t-distribution.

Another model that allows for asymmetric effect of news is the EGARCH model. One problem with a standard GARCH model is that it is necessary to ensure that all of the estimate coefficients are positive. Nelson (1991) proposed a specification that does not require nonnegativity constrains.

Figure 2: Normal distribution versus students-t distribution



Consider:

$$\ln\left(h_t\right)=\alpha_0+\alpha_1\left(\frac{\varepsilon_{t-1}}{h_{t-1}^{+0.5}}\right)+\lambda_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right|+\beta_1\ln(h_{t-1}) \quad (3)$$

Equation (3) is called the exponential-GARCH or EGARCH model. There are three interesting features to notice about EGARCH model:

1. The equation for the conditional variance is in log-linear form. Regardless of the magnitude of ln (h_t), the implied value of h_t can never be negative. Hence, it is permissible for the coefficients to be negative.
2. Instead of using the value of ε_{t-1}^2, the EGARCH model uses the level of standardized value of ε_{t-1}^2 [i.e.,, ε_{t-1}^2 divided by $(h_{t-1})^{0.5}$]. Nelson argues that this standardization allows for a more natural interpretation of the size and persistence of shocks. After all, the standardized value of ε_{t-1}^2 is a unit-free measure.
3. The EGARCH model allows the leverage effects. If ε_{t-1}^2 $(h_{t-1})^{0.5}$ is positive, the effect of the shock on the log of conditional variance is $\alpha_1+\lambda_1$. If ε_{t-1}^2 $(h_{t-1})^{0.5}$ is negative, the effect of the shock on the log of the conditional variance is $-\alpha_1+\lambda_1$.

Most financial decisions involve a trade-off between future risks and asset returns. The volatilities and correlations of securities are often major components of risk. Second moments evolve over-time as the economy changes and new information is released. Volatilities and correlations measured from historical data may miss changes in risk unless methods are carefully designed to update estimates rapidly (Cappiello and Engle, 2006).

In the case of EGARCH models the NIC has its minimum at $\varepsilon_{t-1}=0$ and is exponentially increasing in both directions but with different parameters.

The NIC are drawn by using the estimated conditional variances equation for the model under consideration, with its given coefficient estimates and with the lagged conditional variance set to the unconditional variance.

Consider EGARCH (1,1)

$$\ln(h_t)=\alpha_0+\beta\ln(h_{t-1})+\alpha_1 z_{t-1}+\gamma(|z_{t-1}|)-E(|z_{t-1}|)|) \quad (4)$$

Where $z_t=\varepsilon_t/\sigma_t$. The NIC is

$$h_t=\begin{cases}A\exp\dfrac{\alpha_1+\gamma}{\sqrt{h_t}} & \text{for } \varepsilon_{t-1}>0\\ A\exp\dfrac{\alpha_1-\gamma}{\sqrt{h_t}} & \text{for } \varepsilon_{t-1}<0\end{cases} \quad (5)$$

$$A\equiv h_t^{\beta}\exp\left[\alpha_0-\gamma\sqrt{2/\pi}\right] \quad (6)$$

$$\alpha_1<0 \;\; \alpha_1+\gamma>0 \quad (7)$$

Although in our analysis GARCH and EGARCH model results did not differ from each other significantly we proceeded with EGARCH models for NIC. Further details can be found in Section 5.

ECONOMETRIC DATA DESCRIPTION

The NYMEX WTI futures contract is one of the world energy benchmarks. The notional quantity for one contract is 1000 barrels, which, as mentioned earlier, is one lot. As with all futures, trading for a given contract month ceases at a defined futures expiration date prior to the contract month.

In the case of the WTI contract, this is roughly two-thirds of the way through previous contract month. However, in the recent years the idiosyncrasies related to the delivery location of the WTI contract resulted in substantial and prolonged decoupling from global crude oil prices. As a result, despite complications of its own, the Brent futures contract which trades on ICE[2] is now viewed as the dominant crude oil benchmark. The settlement and delivery mechanism of Brent contracts are more complex than WTI futures. The Brent contract is described by the exchange physically settling with an option to settle financially on the ICE Brent Index. However Salisu and Fasanya (2012) state that their choice of the crude oil price is underscored by the fact that WTI has remained dominant in the world oil market. The crude oil is either traded themselves or their prices are reflected in other types of crude oil. In this respect we also decided to use WTI in our models however we also incorporated Brent in the same models instead of WTI and experienced no significant result changes.

Our dataset contains daily crude oil, hard currencies such as Canadian dollar (CAD), Euro (EUR), Swiss Franc (CHF), UK

2 Intercontinental Exchange (traded as ICE) is an American business and finance company founded on May 11, 2000 by Jeffrey Sprecher, headquartered in Atlanta, Georgia. It owns exchanges and clearing houses for financial and commodity markets, and operates 23 regulated exchanges and marketplaces. ICE futures exchanges in the United States, Canada and Europe, Liffe futures exchanges in the US and Europe, New York Stock Exchange, Equity options exchanges, OTC energy, credit and equity markets.

Table 1: Model dataset descriptions

Variable	Description	Frequency
RWTI	Returns** of NYMEX light sweet crude oil (WTI) closing prices	Daily
RWTI (−1)	1 day lagged returns of NYMEX light sweet crude oil (WTI) closing prices	Daily
RCAD	Returns of USD Dollar/Canadian Dollar (CAD) closing prices	Daily
REUR	Returns of USD Dollar/Euro (EUR) closing prices	Daily
RCHF	Returns of USD Dollar/Swiss Franc (CHF) closing prices	Daily
RGBP	Returns of USD Dollar/UK Pound Sterling (GBP) closing prices	Daily
RJPY	Returns of USD Dollar/Japanese Yen (JPY) closing prices	Daily
RDXY	Returns of USD Dollar index*	Daily
RMXN	Returns of USD Dollar/Mexican Peso (MXN) closing prices	Daily
RRUB	Returns of USD Dollar/Russian Ruble (RUB) closing prices	Daily
RBrent	Returns of ICE brent crude electronic energy futures closing prices	Daily
RBrent (−1)	1 day lagged returns of ICE brent crude electronic energy futures closing prices	Daily
RTRY	Returns of USD Dollar/Turkish Lira (TRY) closing prices	Daily
RXOM	Returns of Exxon Mobil Corp (XOM) stock closing prices	Daily
RCVX.N	Returns of Chevron Corp (CVX.N) stock closing prices	Daily
RCOP.N	Returns of Conoco Phillips (COP.N) stock closing prices	Daily
RHES.N	Returns of Hess Corp (HES.N) stock closing prices	Daily
RMRO.N	Returns of Marathon Oil Corp (MRO.N) stock closing prices	Daily
RBP.L	Returns of BP PLC (RBP.L) stock closing prices	Daily
RDSa.AS	Returns of Royal Dutch Shell PLC (RDSa.AS) stock closing prices	Daily
RTOTF.PA	Returns of Total SA (TOTF.PA) stock closing prices	Daily

*The US Dollar Index is an index of the value of the United States dollar relative to a basket (57.6% Euro, 13.6% Japanese Yen, 11.9% pound sterling, 9.1% Canadian dollar, 4.2% Swedish krona, 3.6% Swiss franc) of foreign currencies, often referred to as a basket of US trade partners' currencies **returns are calculated as $\ln\left(\frac{x_t}{x_{t-1}}\right)$

Pound Sterling (GBP), Japanese Yen (JPY) as well as emerging currencies such as such as Turkish Lira (TRY), Mexican Peso (MXN), Russian Ruble (RUB) and dollar index (DXY) over the period from January 4, 2000 to February 9, 2017[3] (Table1). Furthermore, we have major industry players' daily stock prices which are Exxon Mobil, Chevron Corp, Conoco Phillips, Hess Corp, Marathon Oil Corp, BP, Shell and Total. Detailed business descriptions of the mentioned companies are exhibited at Appendix Table 1 in Appendices part. We computed the returns on crude oil price indices, exchange rates and stock prices by taking the difference in logarithm of the two successive daily prices.

At a glance all the currencies and oil prices fluctuate significantly on 2008 global financial crisis as we can see in Figure 3. In addition we narrowed the period from September 15, 2008 to February 9, 2017 which we will emphasize as "Global Financial Crisis Period" in our GARCH models. In Figure 4 after global financial crisis we can clearly observe that after from 2014 to present there is an increase in oil price return volatility (RBRent and RWTI) as well as emerging market currencies go on to fluctuate after 2008 crisis.

Oil prices have fallen sharply since mid-2014 and reached a 10-year low in early 2016. From their peak in June 2014 to the trough in January 2016, Brent crude oil prices dropped by USD 82 per barrel (70%).

There are five key moments in oil price decline which are:

i. November 2014: OPEC decides not to cut output
ii. April 2015: Shell and Total delay west African projects
iii. January 2016: Brent hits 12 years low
iv. November 2016: OPEC agrees to reduce output
v. December 2016: BP approves expansion of Mad Dog field.

3 Dataset is provided by Thomson Reuters Eikon.

Descriptive statistics and distributional characteristics of return series are reported in Appendix Tables 2 and 3. The normal distribution has a skewness of zero. But in reality, data points may not be perfectly symmetric. So, an understanding of the skewness of the dataset indicates whether deviations from the mean are going to be positive or negative. The hard currency returns like GBP and CAD are negative skewed which means that the left tail is longer; the mass of the distribution is concentrated on the right of the figure. Emerging market currency returns like TRY and ARS are positive skewed which means that the right tail is longer; the mass of the distribution is concentrated on the left of the figure.

The kurtosis of any univariate normal distribution is 3. It is common to compare the kurtosis of a distribution to this value. Distributions with kurtosis less than 3 are said to be platykurtic which has thinner tails. It means the distribution produces fewer and less extreme outliers than does the normal distribution. Distributions with kurtosis greater than 3 are said to be leptokurtic. All the series in our dataset is highly leptokurtic which has fatter tails which is expected for financial assets.

Thus we will also analyze the oil prices in a third sub-sample namely "oil price crisis" which includes the data between November 1st, 2014 and February 7th, 2017. We will also analyze industry company stock prices in the same sub-period in order to find out the effect of oil price volatility on company stock returns and their business strategies.

APPLICATIONS AND FINDINGS

We applied all our models by using Brent instead of WTI and any significant difference was not detected. The analysis for countries and company stock returns are exhibited in two separate sub-sections in order to make the reader focus easier on the fundamental differences of results and NIC behaviors of the assets.

Figure 3: Return graph for overall period

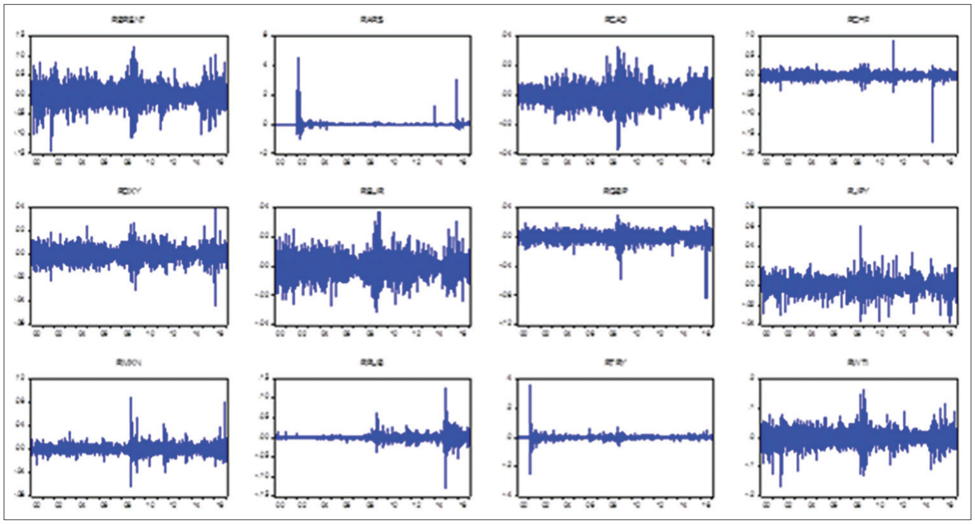
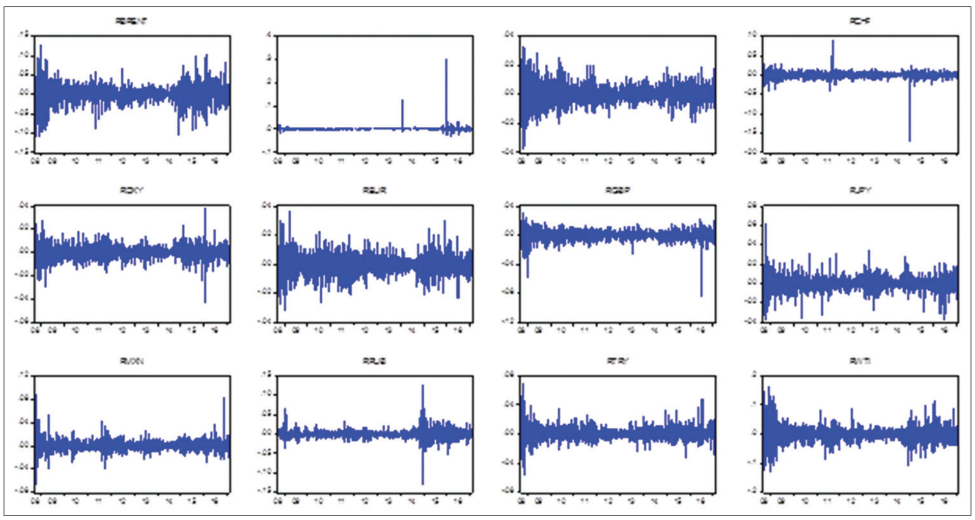


Figure 4: Return graph for global financial crisis period



Country Implication Analysis

We present our results in Tables 2 and 3 by fitting GARCH and EGARCH models with both normal and student-t distributions. The series were modeled by GARCH (1,1) and EGARCH (1,1) satisfactory. Note that for all models the parameter β is close to 0,9 (even 1,0 in EGARCH model with student-t distribution) highly significant which thus indicates that conditional volatility is past dependent and very persistent over time.

While Tables 2 and 3 exhibit models for overall period Appendix Tables 4 and 5 exhibit models for global financial crisis period in which we see that the parameter β is still close to 0.9 and highly significant but slightly less than overall period models. The effect of ε_t and past values of ε_t on y_t is the effect of shocks which include news effect or extra ordinary days.

In Appendix Tables 6 and 7 models exhibit results for oil crisis period which shows that the effect of news and extra ordinary days increase compared to overall period and global financial crisis period. It appears that there is a high level of persistence in the oil price volatility that may be associates with crisis such as 2008 and 2014.

In all EGARCH (1,1) models exhibited in Tables 3, Appendix Tables 5 and 6, λ_1 is negative for all periods. This validates the conclusion that negative shocks have the tendency of reducing volatility more than positive shocks thereby suggesting asymmetric effects in the volatility of crude oil prices.

Moreover, we included first lags of WTI, CAD, EUR, CHF, GBP, JPY, DXY, MXN and RUB returns in the mean equation for the all models. Russia and Canada are among top world oil producers while Switzerland is a net oil importer without domestic oil production. Japan's current account balance and reliance on nuclear energy help weakening the dependence of the Yen value on changes in the price oil even though this country is one of the biggest oil importers following China, US, India and South Korea. Mail EU countries such as Germany, Italy, Netherland and France are also in the list of biggest oil importers.

In this context, EUR, CAD, RUB returns have a negative effect on WTI returns while JPY returns are expected to have a positive

Table 2: RWTI GARCH model for overall period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.04	−2.69			−0.04	−3.17		
RCAD	−0.88	−14.29			−0.89	−14.67		
REUR	−0.52	−5.22			−0.40	−3.44		
RCHF	0.00	0.00			0.08	1.27		
RGBP	0.04	0.65			0.08	1.20		
RJPY	0.29	6.66			0.25	5.32		
RDXY	−0.87	−6.95			−0.74	−4.84		
RMXN	−0.09	−2.02			−0.12	−2.73		
RRUB	−0.66	−21.75			−0.66	−18.28		
α_0			0.00	4.61				
α_1			0.07	14.00			0.06	8.31
β_1			0.92	155.23			0.94	132.1
Observations				4266				4266
R^2				0.177				0.178
DW				2.029				2.087

Table 3: RWTI EGARCH model for overall period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.03	−2.61			−0.04	−3.16		
RCAD	−0.89	−14.37			−0.90	−14.79		
REUR	−0.48	−4.78			−0.37	−3.26		
RCHF	−0.02	−0.40			0.06	1.02		
RGBP	0.08	1.33			0.09	1.48		
RJPY	0.26	6.01			0.24	5.19		
RDXY	−0.76	−5.74			−0.69	−4.50		
RMXN	−0.10	−2.35			−0.13	−2.84		
RRUB	−0.64	−20.03			−0.63	−17.22		
α_0			−0.21	−9.20			−0.16	−6.38
α_1			0.15	15.17			0.12	8.70
λ_1			−0.04	−6.68			−0.04	−4.58
β_1			0.99	423.1			1.0	416.6
Observations				4266				4266
R^2				0.180				0.178
DW				2.030				2.080

effect. Since Canada[4] and Russia[5] are oil producers and exporters while Japan is an importer country, the signs of the coefficients are quite coherent with macroeconomics theory. Oil prices are traded as US dollar denominated. Therefore when Russia and Canada export oil, RUB and CAD will come down since there will be US dollar inflow in to these markets while JPY will rise as there will be US dollar outflow from Japanese market.

Wang et al. (2013) found that the magnitude, duration, and even direction of response by stock market in a country to oil price shocks highly depend on whether the country is a net importer or exporter in the world oil market, and whether changes in oil price are driven by supply or aggregate demand. In Appendix Table 8, we performed Granger Causality tests in order to understand the signs of coefficients better in the mean equation. Based on our findings the causality between CAD and oil prices is one way from CAD to oil prices however it is just in the opposite way for RUB. Flexible exchange rates can provide a measure of protection to countries like Russia which mitigated some of the impact of low oil prices with fallen ruble: In dollar terms. Lower oil revenues are offset by cheaper domestic expenditures. Consequently since Mexico[6] is an oil producer two way causality between crude oil prices (Brent and WTI) and MXN is also relevant.

In Appendix Table 9 results show that there is one-way causality from crude oil prices (Brent and WTI) to TRY given by the fact that Turkey is an oil importing country. Oil prices increase pressure over TRY since oil is traded as US dollar denominated. As Berk and Aydoğan (2012) suggest that the global financial liquidity conditions are the most plausible explanation for the changes in Turkish stock market returns. There exists some evidence that purified oil price shocks still have an impact on stock market

4 215.5 million tonnes in 2015 (4.9% of total production), BP Statistical Review of World Energy June 2016.

5 540.7 million tonnes in 2015 (12.4% of total production), BP Statistical Review of World Energy June 2016.

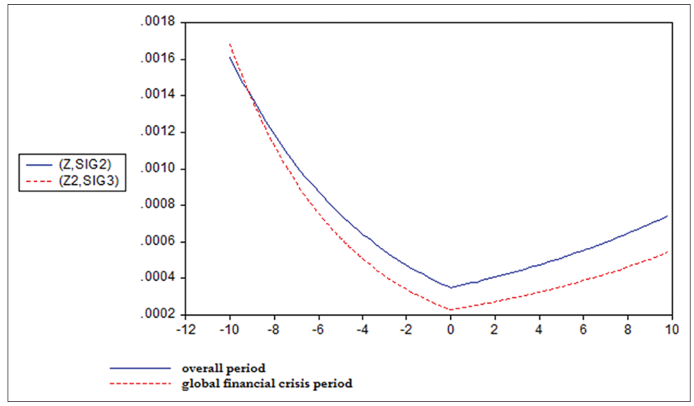
6 127.6 million tonnes in 2015 (2.9% of total production), BP Statistical Review of World Energy June 2016.

returns where this effect is smaller and less significant than the liquidity constraints.

Hamilton (1985) stated that a given oil price increases seems to have a smaller macroeconomic effect after 1973 than an increase of same magnitude would have had before 1973. The article concluded with the statement: "The political history of the Middle East makes it almost inevitable that sometime within the next decade economists will be granted some more data with which to assess the economic effects of oil supply disruptions." This is exactly what happened in 1990 when Iraq invaded Kuwait, and surely this oil shock was a key factor in the recession that followed (Hamilton, 1996). Considering the latest oil price crisis and macroeconomic developments in the world we can conclude that Hamilton's statement is still valid.

In Figure 5[7], the NIC of the EGARCH (1,1) is compared for overall and global financial crisis sub-periods. As we can see both NIC are asymmetric, with negative shocks having more impact on future volatility than positive shocks of the same magnitude. However, after 2008 global financial crisis we can see that NI on volatility decreases.

Figure 5: News impact curves



Company Analysis

Appendix Table 10 exhibits models for oil crisis period in which we see that the parameter β is below 0.9 and highly significant. The effect of ε_t and past values of ε_t on y_t is the effect of shocks which include news effect or extra ordinary days. Table shows that the effect of news and extra ordinary days in company stocks volatility forecast models has more effect compared to oil price volatility forecast models.

In most of the EGARCH (1,1) models exhibited in Appendix Tables 10 λ_1 is positive which validates that negative shocks generate less volatility than positive shocks in company stock returns. Diaz et al. (2016) investigate the role of real oil price shocks on real stock returns of four oil and gas corporations[8] where they conclude that both linear and non-linear specifications oil price changes have a positive significant impact on real stock returns of these companies in the short-run.

Initially we display the impulse response functions using the oil price changes of WTI (Figure 6). In summary, we detect a negative impact of the linear specification of oil price on stock returns within 2 days after the shock and then a positive impact which is absorbed within nearly one week. In all cases, the impulse responses revert to zero usually within 6–8 days. The impulse response analysis was also tested with overall period data and any significant behavior change was not detected.

NI curves of the major industry players' differentiate from oil price NI curves in a way that most of them are either close to symmetric or good news increase volatility more than bad news (Figure 7). NI curves of Exxon, Conoco Phillips and Shell are almost symmetric which shows that both good and bad news increase volatility in the same way. For Chevron, BP and Total good news increase volatility more while for Hess Corp and Marathon Oil bad news have more impact to increase volatility of stock returns.

NI curves of asymmetric ARCH-type models exhibit for BP stock returns that the higher volatility response to negative stocks in the oil prices period while it is the opposite for the oil prices period. The tragic accident and oil spill in the Gulf of Mexico may be one of the key factors in this behavior change however further analysis can be provided by using proxy variables in the EGARCH variance equations to drill down more.

Exxon and Chevron react to the shocks equally based on their NI curves which suggest that bad or good, any kind of news increases the volatility of the stock returns significantly more in the oil prices period compared to overall period. As of January 31st, 2017 Exxon and Chevron have stronger financial positions compared to Shell, Total, BP and others. Both companies focused on investing in higher return investments with shorter-cycles and optimizing their costs via flexible capex programs which enabled them to improve their cash flows in the oil crisis period.

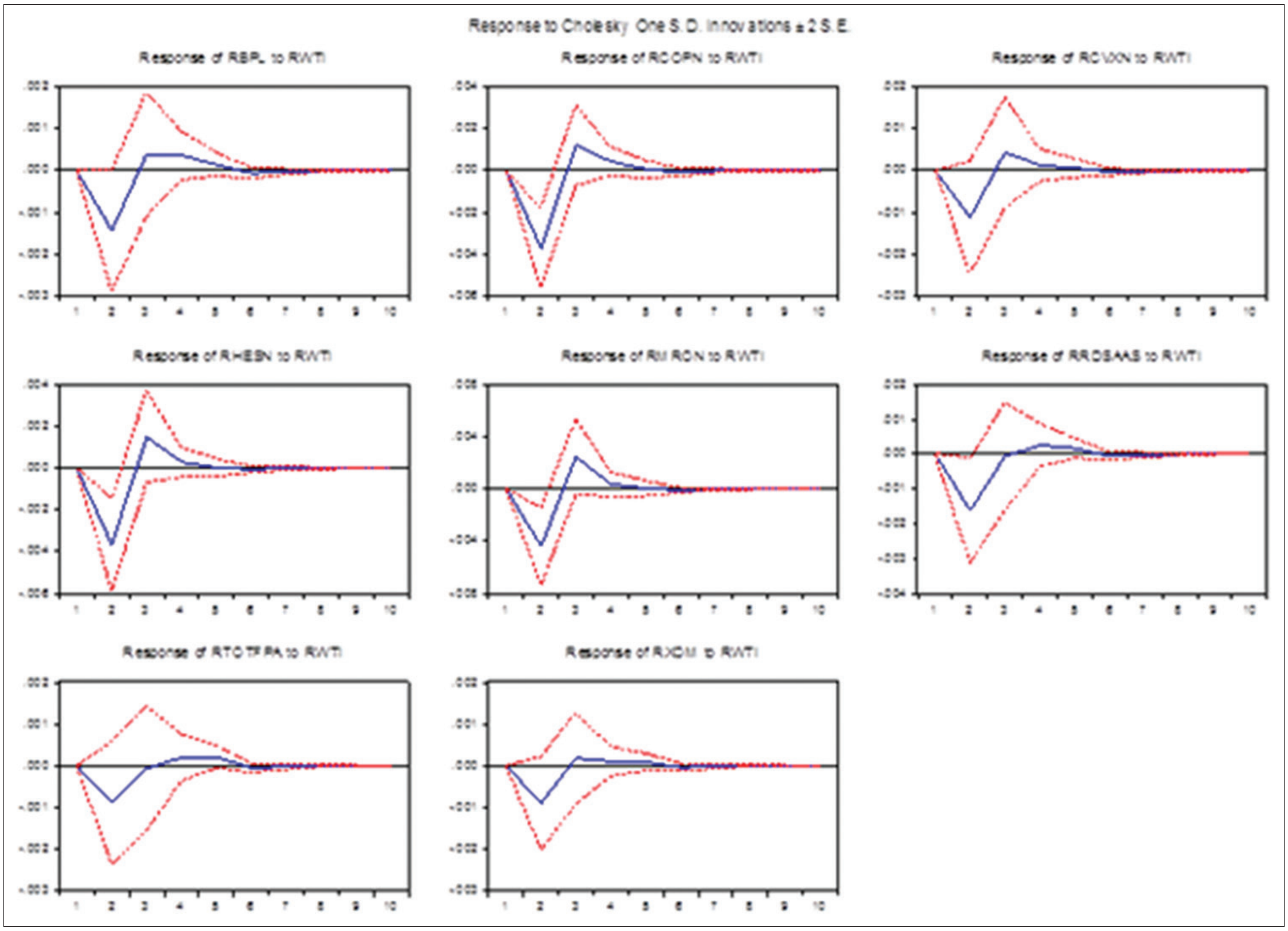
For Hess and Marathon, negative shocks have greater impact on volatility both in overall and oil prices period. Considering Shell NIC, we can conclude that while in overall period good news increase the volatility more in the oil crises period both bad and good news have a balanced impact on the volatility of stock returns.

Finally for total we see that news effect changes for overall and oil crises period significantly where good news have a significant

7 We follow the EViews syntax and firs generate the conditional variance series (GARCH01). Next, we store the median by entering "scalar med =@median(garch01)" in the command window, where GARCH01 is the name of the conditional variance series produced in Table 2 and 3 above (If Eviews give a range error in this step use "pagestruct" command before creating series z and make your data type "unstructed/unfitted"). Third, we generate the z series, which is the x -axis amount of the news impact curve, using the commands "smpl 1 100" and "series z = −10 + @trend(1)*20/100," which constructs an equispaced series between -10 and 10. Fourth, we generate the ht series using the variance equation in Table 2-3 and the command "series log(SIG2) = eq01.c(3) + eq01.c(6)*log(med) + eq01.c(4)*abs(z) + eq01.c(5)*z , where SIG2 is the name for the ht series. Finally, the EViews automatically creates the series SIG2 from the log specification. Highlighting the two series Z and SIG2 shows a customized graph depicting the estimated news impact curves from EGARCH model fitted to the oil prices and company stock prices.

8 Exxon, BP, Chevron, Shell.

Figure 6: Impulse response analysis for oil and gas company stock returns



impact on volatility in the oil prices period. Total has a diversified portfolio of gas developments both in downstream and upstream and implements its strategy through portfolio management. However, countries do not have such flexibilities to optimize their spending or changing the dynamics of macroeconomy and production schemes against oil shocks in order to adjust themselves like oil and gas companies can do.

We should also keep in mind that Shell and Total stocks are quoted in Amsterdam stock exchange and Euronext respectfully. Since the exchange markets of the other companies are US, there will be different systemic and unsystemic risks for the stocks that can affect the returns and volatiles rather than oil price fluctuations.

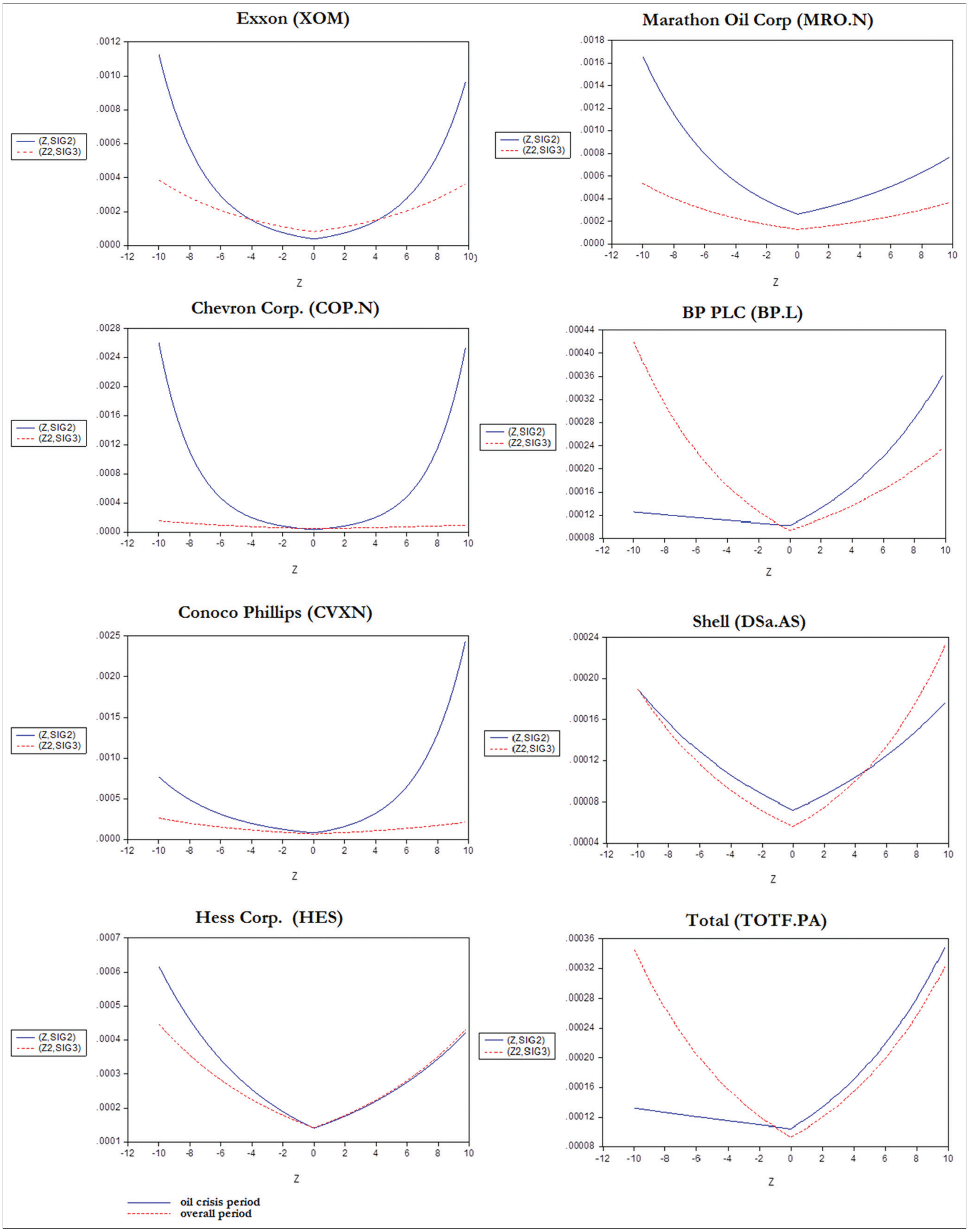
CONCLUSION

In this paper we examined the oil price and oil and gas company stocks volatility forecast and the impact of oil price shocks to both selected companies and emerging markets. The innovation part in this paper are: (i) We analyze the oil price across three sub-periods which also includes the recent oil price crisis, (ii) we use alternative models to model volatility forecast, (iii) we make the analysis both in macroeconomics and microeconomics level considering both production and consumption areas of oil as a commodity. First we analyzed the country specific models and both EGARCH models and causality tests showed that based on if the country is an oil exporter or importer, the magnitude and sign of the currency of the related country as an explanatory variable in oil price change compatible with macroeconomics theory.

We also showed that bad news increase volatility more than bad news for oil prices which is coherent with the theory. It is quite coherent with the theory since a slowdown in global economy is likely to result in a further decline in crude oil prices. The view expressed in Hamilton (1998a, b) is that oil shocks affect the macroeconomy preliminary by depressing demand for key consumption and investment goods. If that is indeed the mechanism by which oil shocks affect the economy, then a decrease in oil price would not create a positive effect on the economy. However on the supply side, significant investment and technological innovations (especially in shale oil extraction) caused oil production to fluctuate in a slowing world growth putting downward pressure on oil prices.

NI curves of the company stock returns clearly exhibits that NI on volatility changed significantly during oil price crisis compared to overall period.

Figure 7: News impact curves for major industry player's EGARCH models



All those companies we have chosen for the analysis operate both in upstream and downstream businesses along with alternative energy segments. Leveraging their business portfolio and dividend payments provided them room for maneuvers in oil price crisis period. This is one of the major reasons why bad and good NI differentiates for commodity prices and industry company stock prices.

Strong (1991) analyses the ability of oil equities portfolios to hedge oil price risk. Using monthly data over the period 1975–1987, the oil price sensitivity of firms' returns appears to be low or not significant, and on average the percentage of oil price changes offset by the returns of the hedge portfolio is only about one-third. In this context, further improvements and additional studies can be achieved by examining the relation between the commodity hedge market and the underlying commodity itself along with its permanent effects on the real industry and macroeconomics activities.

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APPENDICES

Table 1: Business descriptions of selected companies for models (1/2)

Company name	Business description	Country of Exchange
Exxon Mobil Corporation	Exxon Mobil Corporation is an energy company. The Company is engaged in the exploration and production of crude oil and natural gas, manufacturing of petroleum products, and transportation and sale of crude oil, natural gas and petroleum products. The Company also manufactures and markets petrochemicals, including olefins, aromatics, polyethylene and polypropylene plastics, and various specialty products. The Company operates through the Upstream, Downstream, Chemical, and Corporate and Financing segments. The Upstream segment operates to explore for and produce crude oil and natural gas. The Downstream segment operates to manufacture and sell petroleum products. The Chemical segment operates to manufacture and sell petrochemicals. The Company's projects include the Kearl project, Heidelberg project, the Point Thomson project, the Hadrian South project, the Lucius project, the Barzan project, the Arkutun-Dagi project, and the Upper Zakum 750 project, among others	United States of America
Chevron Corporation	Chevron Corporation (Chevron) manages its investments in subsidiaries and affiliates and provides administrative, financial, management and technology support to the United States and international subsidiaries that engage in integrated energy and chemicals operations. Chevron operates through two business segments: Upstream and Downstream. The Upstream segment consists primarily of exploring for, developing and producing crude oil and natural gas; transporting crude oil by international oil export pipelines; transporting, storage and marketing of natural gas, and a gas-to-liquids plant. Downstream operations consist primarily of refining crude oil into petroleum products; marketing of crude oil and refined products; transporting crude oil and refined products by pipeline, marine vessel, motor equipment and rail car, and manufacturing and marketing of commodity petrochemicals, plastics for industrial uses and fuel and lubricant additives	United States of America
ConocoPhillips	ConocoPhillips (ConocoPhillips) is an independent exploration and production company. The Company explores for, produces, transports and markets crude oil, bitumen, natural gas and liquefied natural gas (LNG). The Company operates through six operating segments, which are primarily defined by geographic region: Alaska; Lower 48; Canada; Europe and North Africa; Asia Pacific and Middle East, and Other International. The Company's continuing operations are producing in the United States, Norway, the United Kingdom, Canada, Australia, Timor-Leste, Indonesia, China, Malaysia and Qatar. The Company's portfolio includes North American unconventional assets and oil sands assets in Canada; assets in North America, Europe, Asia and Australia; several international developments, and an inventory of global conventional and unconventional exploration prospects.	United States of America
Hess Corp	Hess Corporation is an exploration and production (E&P) company. The Company is engaged in exploration, development, production, transportation, purchase and sale of crude oil, natural gas liquids, and natural gas. Its segments include E&P, which is engaged in the sale of crude oil, natural gas liquids and natural gas, and Bakken Midstream, which provides services, including crude oil and natural gas gathering, processing of natural gas and the fractionation of natural gas liquids, transportation of crude oil by rail car, terminaling and loading crude oil and natural gas liquids, and the storage and terminaling of propane, located in the Bakken shale play of North Dakota. Its Bakken Midstream assets include Tioga gas plant, Tioga gas plant, Crude oil train units, Ramberg truck facility, Gathering pipelines and Gathering pipelines. It has production operations located in the United States, Denmark, Equatorial Guinea, the Joint Development Area of Malaysia/Thailand, Malaysia and Norway	United States of America

Table 2: Descriptive statistics (1/2)

	RARS	RBRENT	RCAD	RCHF	RDXY	REUR	RGBP	RJPY	RMXN	RRUB	RTRY	RWTI
Mean	0.0006	0.0002	0.0000	−0.0001	0.0000	0.0000	−0.0001	0.0000	0.0002	0.0002	0.0005	0.0002
Median	0.0000	0.0006	−0.0001	−0.0001	0.0000	0.0001	0.0001	0.0000	−0.0001	0.0000	0.0000	0.0006
Maximum	0.4616	0.1271	0.0330	0.0893	0.0390	0.0372	0.0304	0.0622	0.0877	0.1240	0.3567	0.1641
Minimum	−0.1036	−0.1444	−0.0377	−0.1714	−0.0437	−0.0318	−0.0841	−0.0378	−0.0654	−0.1288	−0.2513	-0.1654
SD	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Skewness	21.88	-0.16	0.14	−2.52	−0.05	−0.01	−1.10	−0.07	1.09	0.56	5.56	-0.10
Kurtosis	775.07	5.90	5.83	74.39	6.20	4.62	15.44	7.47	18.64	45.51	228.35	6.93
Observations	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4.267	4,267

Table 3: Descriptive statistics (2/2)

	RBP_L	RCVX_N	RHES_N	RTOTF_PA	RXOM	RCOP_N	RRDSA_AS	RMRO_N
Mean	−0.0001	0.0003	0.0003	0.0001	0.0002	0.0002	24.9696	0.0002
Median	0.0000	0.0007	0.0006	0.0006	0.0003	0.0006	25.2050	0.0006
Maximum	0.1058	0.1894	0.1544	0.1279	0.1586	0.1536	37.5000	0.2099
Minimum	−0.1404	−0.1334	−0.2127	−0.0964	−0.1503	−0.1487	15.3800	0.2177
SD	0.02	0.02	0.03	0.02	0.02	0.02	4.08	0.02
Skewness	−0.14	0.09	−0.66	0.00	0.04	−0.30	0.34	0.17
Kurtosis	7.51	13.43	11.05	7.46	13.06	8.53	2.81	10.68
Observations	4.189	4.189	4.189	4.189	4.189	4.189	4.189	4.189

Table 4: RWTI GARCH model for global financial crisis period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.05	−2.95			−0.05	−2.92		
RCAD	−1.12	−14.49			−1.12	−14.72		
REUR	−0.64	−4.99			−0.51	−3.89		
RCHF	0.10	1.55			0.15	2.03		
RGBP	0.06	0.77			0.10	1.45		
RJPY	0.42	8.00			0.37	6.71		
RDXY	−1.14	−6.52			−0.96	−5.36		
RMXN	0.00	−0.01			−0.04	−0.84		
RRUB	−0.61	−20.87			−0.59	−16.53		
α_0			0.00	4.71			0.00	3.26
α_1			0.09	9.64			0.08	6.50
β_1			0.89	88.79			0.90	66.3
Observations				2118				2118
R^2				0.321				0.322
DW				2.078				2.079

Table 5: RWTI EGARCH model for global financial crisis period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.05	−2.79			−0.05	−2.88		
RCAD	−1.09	−13.95			−1.12	−14.84		
REUR	−0.56	−4.35			−0.47	−3.53		
RCHF	0.06	0.98			0.12	1.80		
RGBP	0.06	0.85			0.09	1.34		
RJPY	0.38	7.48			0.35	6.63		
RDXY	−1.00	−5.55			−0.89	−4.96		
RMXN	−0.03	−0.62			−0.05	−1.04		
RRUB	−0.57	−18.34			−0.56	−15.32		
α_0			−0.25	−7.90			−0.21	−5.70
α_1			0.15	10.20			0.14	7.15
λ_1			−0.06	−6.39			−0.06	−4.55
β_1			0.98	314.74			0.99	282.4
Observations				2118				2118
R^2				0.320				0.322
DW				2.081				2.078

Table 6: RWTI GARCH model for oil crisis period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	Z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.05	−1.54			−0.05	−1.61		
RCAD	−2.09	−11.19			−2.12	−11.01		
REUR	−0.19	−0.54			−0.09	−0.26		
RCHF	0.16	0.77			0.19	0.79		
RGBP	0.08	0.50			0.07	0.49		
RJPY	0.45	3.00			0.42	2.76		
RDXY	−0.03	−0.06			0.10	0.22		
RMXN	0.03	0.31			0.01	0.14		
RRUB	−0.54	−13.44			−0.54	−11.47		
α_0			0.00	2.75			0.00	2.01
α_1			0.11	4.02			0.10	2.99
β_1			0.83	20.85			0.84	16.2
Observations				594				594
R^2				0.440				0.441
DW				2.110				2.115

Table 7: RWTI EGARCH model for oil crisis period

Distribution	Normal distribution				Student t-distribution			
	Mean equation		Variance equation		Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats	Coefficient	z-Stats
RWTI (−1)	−0.05	−1.50			−0.07	−2.24		
RCAD	−2.02	−10.64			−2.10	−10.82		
REUR	−0.20	−0.65			−0.08	−0.25		
RCHF	0.08	0.72			0.14	0.90		
RGBP	0.08	0.54			0.04	0.28		
RJPY	0.40	2.76			0.36	2.39		
RDXY	0.06	0.13			0.15	0.37		
RMXN	−0.01	−0.06			−0.04	−0.42		
RRUB	−0.53	−13.47			−0.51	−11.41		
α_0			−0.47	−2.92			−0.22	−1.82
α_1			0.18	4.42			0.09	2.14
λ_1			−0.06	−2.40			−0.08	−3.39
β_1			0.96	51.43			0.98	72.3
Observations				594				594
R^2				0.439				0.442
DW				2.130				2.088

Table 8: Granger causality tests for major oil exporter countries

Null hypothesis	Overall period		Global financial crisis period	
	F-Statistic	P	F-Statistic	P
WTI does not granger cause CAD	1.26	0.17	1.31	0.14
CAD does not granger cause WTI	1.62	0.03	1.34	0.12
WTI does not granger cause RUB	2.21	0.00	1.79	0.01
RUB does not granger cause WTI	0.92	0.58	1.08	0.36
MXN does not granger cause WTI	2.70	0.00	1.82	0.01
WTI does not granger cause MXN	2.67	0.00	1.90	0.01
BRENT does not granger cause CAD	1.05	0.40	1.20	0.23
CAD does not granger cause BRENT	2.25	0.00	2.03	0.00
BRENT does not granger cause RUB	2.05	0.00	1.49	0.06
RUB does not granger cause BRENT	0.91	0.58	0.85	0.67
MXN does not granger cause BRENT	3.29	0.00	1.51	0.05
BRENT does not granger cause MXN	2.27	0.00	2.29	0.00
Observations		4243		2095
Lags		24		24

Table 9: Granger causality tests for Turkey

Null hypothesis	Overall period		Global financial crisis period	
	F-Statistic	P	F-Statistic	P
WTI does not granger cause TRY	1.72	0.02	1.58	0.04
TRY does not granger cause WTI	1.13	0.30	0.98	0.49
TRY does not granger cause BRENT	1.09	0.35	1.07	0.37
BRENT does not granger cause TRY	1.21	0.22	1.67	0.02
TRY does not granger cause EUR	0.89	0.61	1.29	0.16
EUR does not granger cause TRY	1.18	0.24	1.13	0.30
TRY does not granger cause MXN	1.40	0.09	1.39	0.10
MXN does not granger cause TRY	5.79	0.00	2.92	0.00
TRY does not granger cause RUB	2.19	0.00	2.31	0.00
RUB does not granger cause TRY	1.81	0.01	2.08	0.00
Observations		4243		2095
Lags		24		24

Table 10: Major industry players' EGARCH model for oil price crisis period with student-t distribution

RXOM	Mean equation		Variance equation		RCVX.N	Mean equation		Variance equation		RCOP.N	Mean equation		Variance equation		RHES.N	Mean equation		Variance equation	
	Coefficient	z-Stats	Coefficient	z-Stats		Coefficient	z-Stats	Coefficient	z-stats		Coefficient	z-Stats	Coefficient	z-Stats		Coefficient	z-Stats	Coefficient	z-Stats
RCVXN	0.63	25.81			RXOM	0.66	23.76			RCVXN	0.28	5.60			RCOPN	0.39	10.33		
RHESN	0.04	2.56			RWTI	0.02	1.68			RXOM	0.17	3.47			RXOM	0.26	5.40		
RWTI	0.01	0.80			RBPL	0.10	5.50			RWTI	0.03	1.76			RWTI	0.12	5.27		
REUR	−0.06	−1.55			RCOPN	0.20	11.24			RBPL	0.04	1.70			RMRON	0.27	11.92		
RMXN	−0.08	−2.63								RHESN	0.27	9.59							
										RMRON	0.21	11.47							
α_0			−1.41	−2.68	α_0			−2.27	−3.26	α_0			−1.58	−2.37	α_0			−0.37	−2.09
α_1			0.33	3.62	α_1			0.43	4.62	α_1			0.29	3.50	α_1			0.13	2.95
λ_1			0.00	−0.08	λ_1			0.00	0.05	λ_1			0.06	1.17	λ_1			−0.02	−0.59
β_1			0.88	17.76	β_1			0.80	11.9	β_1			0.85	12.30	β_1			0.97	52.3
Observations				564					564					564					564
R^2				0.682					0.757					0.785					0.747
DW				2.0353					2.045					1.788					1.832
RMRO.N	**Mean equation**		**Variance equation**		**RBP.L**	**Mean equation**		**Variance equation**		**RDSa.AS**	**Mean equation**		**Variance equation**		**RTOTF.PA**	**Mean equation**		**Variance equation**	
	Coefficient	**z-Stats**	**Coefficient**	**z-Stats**		**Coefficient**	**z-Stats**	**Coefficient**	**z-Stats**		**Coefficient**	**z-Stats**	**Coefficient**	**z-Stats**		**Coefficient**	**z-Stats**	**Coefficient**	**z-Stats**
RHESN	0.48	12.04			RCOPN	0.09	3.98			RWTI	0.04	2.22			RMRON	0.03	1.94		
RCOPN	0.59	12.67			RWTI	0.07	4.10			RTOTFPA	0.45	13.67			RBPL	0.73	29.94		
RBPL	0.10	2.65			RTOTFPA	0.68	28.26			RGBP	0.24	3.34			RXOM	0.15	3.99		
RWTI	0.08	3.22								REUR	−0.28	−3.91							
										RXOM	0.09	2.71							
										RBPL	0.42	14.72							
α_0			−0.20	−2.27	α_0			−1.03	−1.27	α_0			−15.13	−9.84	α_0			−12.50	−1.42
α_1			0.15	3.16	α_1			0.07	1.16	α_1			0.22	3.23	α_1			0.07	0.64
λ_1			−0.04	−1.42	λ_1			0.05	1.28	λ_1			0.08	1.75	λ_1			0.05	0.70
β_1			0.99	112.43	β_1			0.89	10.2	β_1			−0.58	−3.5	β_1			−0.37	−0.4
Observations				564					564					564					564
R^2				0.752					0.649					0.78					0.648
DW				1.916					1.940					1.945					2.037