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Forecasting crude oil market volatility in the context of economic slowdown in emerging markets

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Abstract. Crude Oil is a commodity with huge strategic importance to all countries in the world. But in the recent years, the oil market as well as all commodities market has crossed an intense period of changes due to a volatile international economic context. After a decade of rapid economic growth rates, China and the other emerging markets are slowing down. After a harsh and unpredictable crisis, the financial and commodity regulation has changed; the uncertainty and distrust have increased, and, implicitly, the prices volatility in financial and commodity markets has also increased. In this paper we empirically investigated the crude oil market price behaviour and proposed an econometrical GARCH model (Engle, 1982; Bollerslev, 1986) to forecast the volatility of this market. Our research questions are how crude oil price volatility has changed in the recent years? In order to answer to this question we developed an empirical analysis using daily future one month quotation of Brent, Dubai and WTI crude oil over the last three years. These quotations were extracted from Thomson-Reuters Database. Our results suggest a relatively small volatility in crude oil market on a short run with a price fluctuation around the level of 110 USD/barrel for Brent crude oil. Moreover, our final conclusion is that: the economic slowdown in emerging markets, but also the new regulations in commodity markets represent new challenges for economists and researchers, and ask for structural reforms to adjust to new context.

Keywords: crude oil market, commodity market, price behaviour forecast volatility, GARCH models.

JEL Classification: L71. **REL Classification:** 15F.

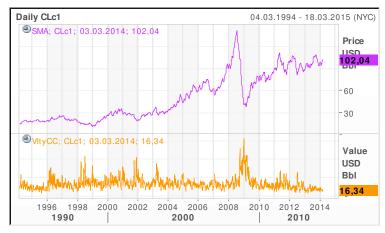
1. Brief introduction and the importance of crude oil market

Crude Oil is a commodity with huge strategic *importance* to all countries in the *world*. "Oil is an essential scarce resource, and there are still no cost effective alternatives to oil for producing vehicle fuels like petrol and diesel" (US Congressional Research Service, 2009).

Crude oil (or unrefined petroleum) is one of the most important natural resource of the industrialized countries. Since the 1850s, it can be refined to produce various derivate products such as gasoline, diesel and different forms of petrochemicals. Its components are used to manufacture almost all chemical products, such as plastics, detergents, paints, and even medicines (Wintershall, 2014).

It is widely accepted that there is a strong relationship between crude oil prices and global economic activity and crude oil is the most demanded commodity in the world. Oil industry concentrates more capital than any other industry. *The increasing prices and large volatilities observed in the last several years in oil market price are in strong relationship with the key role of oil for global economy, but also with the evolution of financial and commodity markets.*

Figure 1. Crude oil price and volatility dynamics



Source: Reuters, 2014.

Starting from all above mentioned things, the forecasting the future oil prices and volatilities in this market, but also the management of risks associated with these prices became crucial for governments, companies and researchers in several different aspects.

As we can observed crude oil reached historical peak prices (for instance, price reached 140,60 USD/Bbl for the 15th of July, 2008) and that mainly reflects increased crude oil demand as a result of strong global economic growth (this growth coming specially from the part of China, but also other emerging

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countries: Russia, India, Brasil). As we can see, during the last 20 years, crude oil prices have presented an upward trend and large volatilities.

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This upward trend is strong and directly related to the increasing demand coming from China economic boom, but also from other emerging economies (Brasil, Russia or India). Furthermore, the increasing volatility is the result of uncertainty regarding the strength of recovery of the economy after the financial and economic crisis of 2007-2009. More than that the mistrust related to other factors such as, the increased role of complex financial products, emerging trends in biofuel production and new legislation in financial and commodity markets, also has contributed to the high volatility record during the last 20 years.

2. Literature review

Although the interest regarding the study of oil price behaviour and the impact on global economy is not new, in the last decade the literature in this field has been booming based on researchers and practitioners activity.

Since crude oil is a commodity with huge strategic importance to all countries, there is a large consensus that higher oil prices and volatilities impact global economic growth and financial markets (Hamilton, 2009). Moreover the behaviour of crude oil price has sparked interest of many practitioners and researchers among which we have drawn from their works: Lynch (2002), Kaufmann et al. (2004), Merino and Ortiz (2005), Moebert (2007), Hamilton (2008), Aguilera et al. (2009), Kilian (2008), Basher et al. (2010), Elder and Serletis (2010), Richmond et al. (2013).

As we know well enough the oil market is organized and operates as an oligopolistic market (Dees et al., 2003; Mileva and Siegfried, 2012). Even if for oil producers, the long-term marginal cost is a small fraction of the price of oil (Adelman (1993), the prices in the market are quite high compared to the production costs. In order to maintain high price levels in the market, the excess supply is restricted by a cartel. How the market works?

"The higher cost producers sell all they can produce, while low-cost producers satisfy the remainder of the demand at current prices and cut back production if needed" (Mileva and Siegfried, 2012). The low-cost suppliers are especially Arabian countries. Their asymmetric behaviour is also proved by several empirical analyses, among De Santis (2000), who proves in his analysis that, in order to maintain high prices in oil market, Saudi Arabia restricts production as an answer to a negative demand shocks, but does not increase production in the case of positive demand shocks. Furthermore, as indicated by Cooper (2003), also we

have to emphasis the inelastic demand character of crude oil related to price changes.

Crude oil market price is the result of direct meeting between demand and supply and traditional fundamentals (world energy use, world production capacity and production supply, crude oil reserves) remains the key drivers for this commodity price (figures related to the evolution of crude oil fundamentals are presented in the Annex).

We have also to emphasise the need to take into consideration other new factors, considered so important for the price behaviour in commodities market: growing commodity demand from emerging countries, financial crisis and the uncertainty regarding the strength of recovery, emerging trends in bio-fuel production, and commodity market financialization.

Moreover we want to emphasis the OPEC (Organization of Petroleum Exporting Countries) key role in global oil market and the impact on global oil demand and supply. We do not intend to present into details the evolution of global oil market, but have to underline that one significant point in the history of this market is the represented by the creation of $OPEC^{(1)}$ in 1960 in Baghdad.

OPEC is considered the most important player in the oil market. Its importance and power come from the high level of oil reserves and exports. For instance, the OPEC oil reserves volume is more than 1000 million barrels and the oil supply around 35 million barrels per day. As we can see, in the bellow chart, for 2012, the average annual oil reserve stood up the value of 1200 billion barrels and the supply recorded in average the value of 36.68 million barrels per day representing 41.04 % of the world oil production.

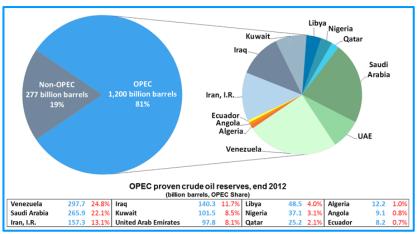
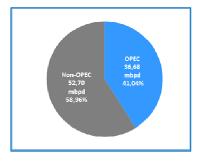


Figure 2. OPEC share of world crude oil reserves 2012

Source: OPEC Annual Statistical Buletin, 2013.



Source: Reuters, 2014.

The following two tables present the world oil supply and demand evolution during the period 2008-2013 and prevision for 2014-2015. In term of supply OPEC remains one of the main actors in the crude oil market, even if we can remark a slightly decreasing trend as percentage of global oil supply:

Actuals (mbpd)	2008	2009	2010	2011	2012	2013	2014	2015
OECD Supply				•			•	•
Total OECD	21,02	21,10	21,47	21,62	22,54	23,74	25,02	26,10
As % of World Supply	24,62	25,01	24,64	24,67	25,22	26,40	27,29	28,05
Non-OECD Supply								
Total Non-OECD	64,33	63,24	65,67	66,01	66,84	66,20	66,66	66,95
As % of World Supply	75,38	74,98	75,36	75,33	74,78	73,60	72,71	71,95
Total World Supply	85,35	84,34	87,14	87,63	89,38	89,94	91,68	93,04
OPEC Supply								
Total OPEC	35,48	33,87	35,11	35,37	36,68	35,87	35,73	35,59
As % of World Supply	41,57	40,16	40,29	40,36	41,04	39,89	38,97	38,25
Non-OPEC Supply								
Total Non-OPEC Supply	49.87	50.47	52.03	52.25	52.70	54.07	55.95	57.46
As % of World Supply	58.43	59.84	59.71	59.63	58.96	60.12	61.03	61.75

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Source: Thomson Reuters Database, 2014.

Regarding the demand part, most of energy analysts and economists agree that world oil demand will continue to increase in the next years - probably at a much faster rhythm than experienced in the last 20 years, even if after a decade of torrid growth, emerging markets are slowing down, and implicitly the demand coming from these countries is declining. As we can see from the below table the total global demand (expressed in millions barrels per day) has been increased from year to year (these trend comes from non-OECD⁽²⁾ countries specially).

2008	2009	2010	2011	2012	2013	2014	2015	
47,66	46,37	47,02	46,40	45,91	46,02	46,01	46,03	
55,70	54,70	53,79	52,39	51,49	50,94	50,22	49,50	
Non-OECD Demand								
37,91	38,41	40,39	42,16	43,26	44,33	45,61	46,96	
44,30	45,30	46,21	47,61	48,51	49,06	49,78	50,50	
85.57	84.77	87.40	88,57	89,16	90,36	91.62	92,99	
	47,66 55,70 37,91 44,30	47,66 46,37 55,70 54,70 37,91 38,41 44,30 45,30	47,66 46,37 47,02 55,70 54,70 53,79 37,91 38,41 40,39 44,30 45,30 46,21	47,66 46,37 47,02 46,40 55,70 54,70 53,79 52,39 37,91 38,41 40,39 42,16 44,30 45,30 46,21 47,61	47,66 46,37 47,02 46,40 45,91 55,70 54,70 53,79 52,39 51,49 37,91 38,41 40,39 42,16 43,26 44,30 45,30 46,21 47,61 48,51	47,66 46,37 47,02 46,40 45,91 46,02 55,70 54,70 53,79 52,39 51,49 50,94 37,91 38,41 40,39 42,16 43,26 44,33 44,30 45,30 46,21 47,61 48,51 49,06	47,66 46,37 47,02 46,40 45,91 46,02 46,01 55,70 54,70 53,79 52,39 51,49 50,94 50,22 37,91 38,41 40,39 42,16 43,26 44,33 45,61 44,30 45,30 46,21 47,61 48,51 49,06 49,78	

Table 2. World oil demand evolution

Source: Thomson Reuters Database, 2014.

As a result of all above mentioned aspects, the study and analysis of crude oil market behaviour became a challenge issue for researchers and economists. Starting from the importance of crude oil for global economy, and specially the consequences of oil price movements for producers, consumers and commodity and financial markets, many researchers and economists have done many efforts towards developing methods to forecast price and volatility levels. Thus, in order to forecast the oil price and price volatility, there was applied in the literature both quantitative and qualitative methods.

Quantitative methods, based on quantitative historical data and mathematical and econometrical models, focus specially on short and medium term predictions and can be classified into two big categories: (a) standard econometric models (time series models, financial models and structural models) and (b) non-standard computational models (models based on artificial neuronal networks). A detailed presentation on the use of all these methods in order to forecast the crude oil market behaviour can be found at Behmiri and Pires Manso (2013) research analysis.

3. Research methodology

As we mentioned, in order to forecast the behaviour of commodities and financial assets prices, in the literature are used different quantitative models, the most successful in term of cost-effectiveness being models based on time series analysis. As indicated by Behmiri and Pires Manso (2013), these models are split into three categories: 1) naïve models; 2) exponential smoothing models; and 3) autoregressive models ARIMA and (G)ARCH family of models.

Regarding the study of oil market volatility (G)ARCH models family of Engel (1982) and Bollerslev (1986) are mainly used with success. For instance, Mohammadi and Su (2010), using weekly data on 11 different crude oil spot prices for the period 1997-2009, compare out-of-sample forecasting ability of various GARCH models, and finds that exponential GARCH models perform the best. Also, Agnolucci (2009), Kang et al. (2009) and Wei et al. (2010) compares also the volatility forecasting ability of different models. They use daily or weekly spot prices for different categories of crude oil (except of Agnolucci who use daily future prices). After a detailed analysis of their results, it seems that linear GARCH models fit better for short-term volatility forecasting and the non-linear GARCH models fit better for long-term volatilities forecasting.

On the other side studies such us Xie et al. (2006), Haidar and Woff (2009) or Li Shu-rongand Ge Yu-lei (2013) proposed and applied new methods to forecast crude oil price, these methods being based on SVM (Support Vector Machines) techniques. To compare SVM with ARIMA or GARCH models performances, they used measures like: RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error). They found that the SVM techniques outperform ARIMA and GARCH models in term of forecast accuracy.

What concern us, we have greater confidence in GARCH techniques to forecast and model commodity market volatility, and further we develop this kind of models to forecast crude oil market volatility.

GARCH models are specially designed to model and forecast conditional variance. It means that variance of dependent variable is modeled as a function of past values of dependent variables and /or independent variables.

To develop an (G)ARCH model, we have to provide three distinct specifications related to: 1) conditional mean equation; 2) conditional variance; 3) conditional error distribution.

We start with the simplest version of GARCH models group, represented by GARCH (1, 1) model. The specifications of this model are the following (EViews 8 User's Guide I-II, 2013):

(1) $Y_t = X_t \theta + \varepsilon_t$ - mean equation

(2)
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2,$$

where:

 Y_t - Dependent variable;

 X_t - Exogenous variables;

 \mathcal{E}_t - Error term;

 ω - Constant term;

 σ_t^2 - Forecasted variance (conditional variance);

 ε_{t-1}^2 - The ARCH term which includes news about volatility from the previous period, measured as the lag of the squared residual from the mean equation; σ_{t-1}^2 - The GARCH term that represents last period's forecast variance.

If we recursively substitute for the lagged variance on the right-hand side of equation (2), we can express the conditional variance as a weighted average of all of the lagged squared residuals:

(3)
$$\sigma_t^2 = \frac{\omega}{1-\beta} + \alpha \cdot \sum_{j=1}^{\infty} \beta^{j-1} \varepsilon_{t-j}^2 .$$

Furthermore, we know that the error in squared returns is given by $v_t = \varepsilon_t^2 - \sigma_t^2$. Substituting for the variances in the variance equation and rearranging terms, we obtain the following expression in terms of the errors:

(4)
$$\varepsilon_t^2 = \omega + (\alpha + \beta) \cdot \varepsilon_{t-1}^2 + v_t - \beta \cdot v_{t-1}$$

The rewriting of GARCH (1,1) model as in the equations (3) and (4) helps us to interpret better the model. Thus from equation (3), we observe that GARCH (1,1) variance specification is analogous to the sampler variance, but that it downweights more distant lagged squared errors. From equation (4), we observe that the squared errors follow a heteroskedastic ARMA(1,1) process and the autoregressive root which governs the persistence of volatility shocks is $\alpha+\beta$. In many applied settings, this root is very close to unity, so that shocks die out rather slowly.

Furthermore, generalizing the above explanation, one can define GARCH(q,p) process if⁽³⁾ $\mathcal{E}_t = \sigma_t Z_t$, $t \in Z$, where (σ_t) is a nonnegative process such that:

(5)
$$\sigma_t^2 = \omega + \alpha_1 \mathcal{E}_{t-1}^2 + \dots + \alpha_p \mathcal{E}_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \dots + \beta_q \sigma_{t-q}^2, \quad t \in \mathbb{Z}$$

or

(6)
$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2$$

and

(7) $\omega > 0$, $\alpha_i \ge 0$ $i = 1, \dots, p$ $\beta_j \ge 0$ $j = 1, \dots, q$.

The conditions on parameters (7) ensure strong positivity of the conditional variance (5), where: q is the order of autoregressive GARCH term and p is the order of the moving average ARCH term.

If we were write the equation (5) in terms of the lag-operator B we obtain:

(8)
$$\sigma_t^2 = \omega + \alpha(B)\mathcal{E}_t^2 + \beta(B)\sigma_t^2,$$

where:

(9)
$$\alpha(B) = \alpha_1 B + \alpha_2 B^2 + \ldots + \alpha_p B^p$$
 and

(10) $\beta(B) = \beta_1 B + \beta_2 B^2 + \ldots + \beta_q B^q$.

If the roots of the characteristic equation, $1 - \beta_1 x - \beta_2 x^2 - \dots - \beta_q x^q = 0$, lie outside the unit circle and the process (\mathcal{E}_t) is stationary, then we can write (1) as:

$$\sigma_t^2 = \frac{\omega}{1-\beta(1)} + \frac{\alpha(B)}{1-\beta(B)} \mathcal{E}_t^2 \quad or \ \sigma_t^2 = \omega * + \sum_{j=1}^{\infty} \delta_j \, \mathcal{E}_{t-j}^2,$$

where:

$$\omega *= \frac{\omega}{1-\beta(1)},$$

and δ_i are coefficients of B^j in the expression of $\alpha(B)[1-\beta(B)]^{-1}$.

Moreover, to complete the GARCH model specification, we have to do an assumption about the conditional distribution of the error term. Starting from this assumption, GARCH models are commonly estimated by the method of maximum likelihood. There are three main assumptions usually employed when working with GARCH models: 1) Normal Gauss-Laplace distribution; 2) Student's t-distribution; 3) Generalized Error Distribution (GED). Also, in addition to the standard GARCH specification, we used for our estimations, several other variance models. In this paper we tried also: EGARCH and PARCH models.

4. Empirical analysis

In our empirical analysis, we focus on the estimation of crude oil future price and volatility. As we previously mentioned, this crude oil market represents several particularities in price evolution compared with other commodities groups. We briefly discuss proprieties of our data sets and then move on to estimate many competing GARCH-related models and assess their forecasting accuracy.

Our analysis took into consideration daily closing data for Brent Blend, Dubai Fateh, and WTI (West Texas Intermediate) crude oil. These categories of crude oil are considered as benchmarks for oil industry. There is always a spread between Brent, Dubai and WTI quotations due to the transportation cost, specially. The data used in our paper represents crude price prices expressed in US dollars per barrel. The daily prices are extracted from Eikon Thomson Reuters platform, for the period 2012-2014 and represents quotations of crude oil on Intercontinental Exchange (ICE), Dubai Mercantile Exchange (DME) and CME Group platform (the world's leading and most diverse derivatives marketplace, which includes CME, CBOT, NYMEX and COMEX exchanges). Figure 4 gives us the evolution of crude oil future prices one month over the period January 2012 to February 2014 for the three markets taken into consideration.

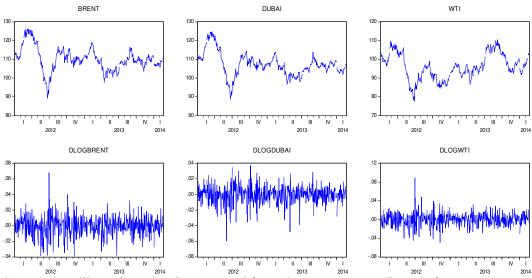


Figure 4. Daily Brent, Dubai and WTI crude oil prices and returns dynamics

Source: Own illustration using data extracted from Thomson Reuters Eikon Platform.

To make sure that our data series do no present trend, and are stationary, we investigate the dynamics of return series instead of price series. In this context we proceed to compute returns on a continuous compounding basis: $R_t = \log(P_t / P_{t-1})$ where R_t = return of crude oil price at the moment "t" and P_t = crude oil price at the moment "t".

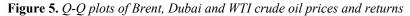
As we can observe the behaviour of prices and returns clearly indicate us the presence of volatility clustering, Mandelbrot (1963), where large changes tend to be followed by large changes, of either sign, or small changes tend to be followed by small changes.

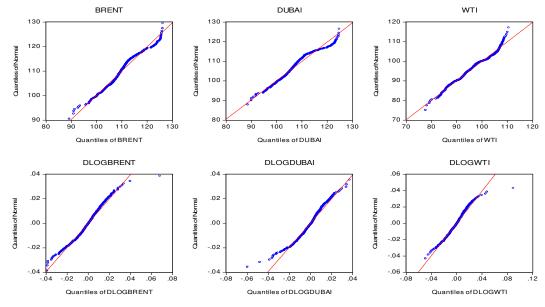
	BRENT	DUBAI	WTI	DLOGBRENT	DLOGDUBAI	DLOGWTI
Mean	110.0206	107.2297	96.15009	-3.94E-05	-4.25E-05	-1.54E-05
Median	109.8100	106.9000	95.88000	0.000679	0.000970	0.000793
Maximum	126.2200	124.8000	110.5300	0.068117	0.037334	0.089454
Minimum	89.23000	88.57000	77.69000	-0.039015	-0.059782	-0.049331
Std. Dev.	6.267985	6.193408	6.750054	0.012423	0.011412	0.013848
Skewness	0.150449	0.474626	-0.028279	-0.026563	-0.615281	0.294582
Kurtosis	3.829719	3.994740	2.453805	5.095797	5.552811	6.644335
Jarque-Bera	17.49444	42.45943	6.771816	98.52543	180.0312	305.5008
Probability	0.000159	0.000000	0.033847	0.000000	0.000000	0.000000
Sum	59301.09	57796.82	51824.90	-0.021181	-0.022861	-0.008290
Sum Sq. Dev.	21136.75	20636.77	24513.02	0.082870	0.069937	0.102981
Observations	539	539	539	538	538	538

Table 3. Descriptive statistics of Brent, Dubai, WTI oil prices and return series

Source: own calculations.

As we can observe the kurtosis value is higher than 3 in all 3 cases, thus indicating the presence of fat tails for density function comparing with density function of the standard normal distribution N (0,1). This is a very know behaviour in capital markets and suggest the presence of ARCH effects (heteroskedasticity). Furthermore, Jarque-Bera goodness-of-fit test for normality indicates that neither prices series, nor returns series (for the three oil markets taken into consideration) are normally distributed.





Source: own calculations and representations.

As we can see from the below charts, the same information is also given by QQ plots of oil prices and return series (a probability plot, which is a graphical method for comparing two probability distributions by plotting their quantiles against each other), which indicate that both large positive and negative shocks are responsible for non-normality of these series.

Before passing to the next step of our empirical study (Garch modeling of crude oil volatility), it would be normal to test for the stationarity of our return data series. As we know the data series of prices generally are not stationary, and in order to convert them into stationary data series, we proceed to compute the return of these prices using continuous transformation.

The data stationarity is analyzed using time plots (above charts), correlograms (ACF and PACF functions) and stationarity tests or unit root tests: 1) Dicky-Fuller (DF test, 1979) and Augmented Dicky-Fuller (ADF test, 1987); 2) Pilipphe Pearon (PP test, 1988); 3) Kwiatkowski–Phillips–Schmidt–Shin (KPSS test, 1982).

Low values of autocorrelation and partial correlation diagrams indicate the absence of serial correlations across return series. Furthermore the stationary tests Augmented Dicky-Fuller and Pilipphe Pearon also confirm the absence of serial dependencies in series across time (annex). The same characteristics are presented also by Dubai and WTI return series and for this reason we I have not done a detailed analysis in the present papers for Dubai and WTI.

As we mentioned, crude oil markets are characterized by persistence of shocked and cluster volatility (large changes in returns are likely to be followed by further large changes). In order to capture this feature, there were developed GARCH models (generalized autoregressive conditional heteroskedasticity models. In our paper we develop three distinct models from GARCH category in order to model crude oil market volatility: classical GARCH, EGARCH and PARCH models with three different distributional assumptions: normal, student and generalized error distributions. The use of these models allow us to understand specific features of crude oil market and further to compare them and select the best one in order to forecast volatility of this market. This paper presents a detailed analysis only for Brent crude oil market volatility and display only the best selected model (similar results were also obtained for Dubai and WTI market volatilities).

Our empirical results suggest that EGARCH(1,1,1) model with normal distribution is the best fit for Brent crude oil volatility modelling.

EGARCH (1,1,1)

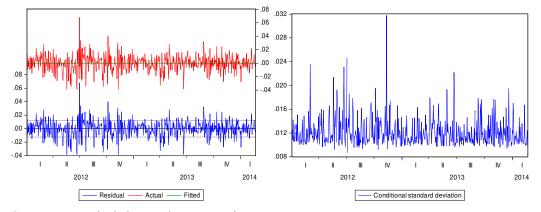
Dependent Variable: DLOGBRENT Method: ML - ARCH (Marquardt) - Normal distribution Date: 02/28/14 Time: 14:10 Sample (adjusted): 1/04/2012 2/21/2014Included observations: 538 after adjustments Convergence achieved after 30 iterations Presample variance: backcast (parameter = 0.7) LOG(GARCH) = C(1) + C(2)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(3) *BESID(1)/@SORT(CARCH(1)) + C(4)*1 OC(CARCH(-1))) + C(3)

*RESID(-1)/@SQRT(GARCH(-1)) + C(4)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equ	Variance Equation		
C(1) C(2) C(3) C(4)	-4.262462 0.294140 -0.160695 0.542929	1.211658 0.063119 0.043982 0.134413	-3.517876 4.660114 -3.653679 4.039266	0.0004 0.0000 0.0003 0.0001
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	-0.000010 0.001849 0.012411 0.082870 1612.340 2.077678	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter.		-3.94E-05 0.012423 -5.978959 -5.947079 -5.966489

The residual diagnostic analysis using Correlogram Squared Residuals and ARCH Test also confirm the validity of the selected model.

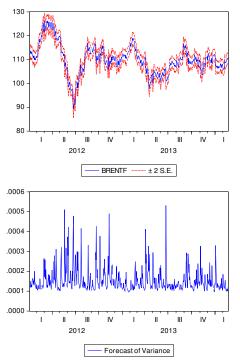
Figure 6. EGARCH (1,1,1) actual, fitted, residual and conditional standard deviation graphs



Source: own calculations and representations.

Using our EGARCH (1,1,1) selected model, and both dynamic and static forecast methods for volatility, we obtain the following results reflecting crude oil market behaviour:

Figure 7. Brent crude oil price behaviour - static forecast



Source: own calculations and representations.

Forecast: BRENTF	
Actual: BRENT	
Forecast sample: 1/03/2012	1/01/2015
Adjusted sample: 1/04/2012	2/24/2014
Included observations: 538	
Root Mean Squared Error	1.342762
Mean Absolute Error	1.014294
Mean Abs. Percent Error	0.928443
Theil Inequality Coefficient	0.006093
Bias Proportion	0.000011
Variance Proportion	0.000000
Covariance Proportion	0.999989

As we can see our estimated model fits fairly well with sample data taken into consideration. Furthermore the dynamic forecast of Brent crude oil price with two standard deviation bands indicates an average price of crude oil around 110 USD/barrel with a relatively small volatility on a short run. The value of Theil Inequality Coefficient very close to zero reflects a very good forecast model.

5. Conclusions

Crude Oil is a *commodity* with a *significant strategic role* for *global economy*. Historical peak prices and large volatilities, *observed in the last several years* in *oil market*, are strongly and directly related to the increasing demand coming from China economic boom, but also from other emerging economies as Brasil, Russia or India. But, after a decade of rapid economic growth rates, China and the other emerging markets are slowing down. After a harsh and unpredictable crisis, the financial and commodity regulation has changed; the uncertainty and distrust have increased, and, implicitly, the prices volatility in financial and commodity markets has also increased.

Therefore, understanding oil price behaviour and volatility became important for many reasons: 1) persisting changes in crude oil market volatility can affect the risk exposure of producers, intermediates and consumers; 2) high volatility can induces mistrust in the market; 3) it has weighty impact for derivatives valuation, hedging and investment decisions related to oil production or consumption; 4) volatility can affect the demand for storage, and implicitly the total marginal cost of production; 5) the higher the volatility, the higher the spot and future prices, and marginal convenience yield.

In this context, we tried to understand better the crude oil price behaviour and model the market volatility. Our selected EGARCH model results suggest a relatively small volatility in crude oil market on a short run with a price fluctuation around the level of 110 USD/barrel for Brent crude oil.

Moreover, our final conclusion is that: the economic slowdown in emerging markets, but also the new regulations in commodity markets represent new challenges for economists and researchers, and ask for structural reforms to adjust to new context.

Notes

- ⁽¹⁾ The Organization of the Petroleum Exporting Countries (OPEC) is a permanent, intergovernmental organization, created at the Baghdad Conference on September 10–14, 1960, by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. The five founding members were later joined by nine other Members: Qatar; Indonesia; Libya; United Arab Emirates; Algeria; Nigeria; Ecuador; Angola and Gabon. OPEC had its headquarters in Geneva, Switzerland, in the first five years of its existence. This was moved to Vienna, Austria, on September 1, 1965. OPEC's objective is to coordinate and unify petroleum policies among Member Countries.
- ⁽²⁾ Organization for Economic Cooperation and Development (OECD) is an international economic organization of 34 countries founded in 1961 to stimulate economic progress and world trade. The mission of the OECD is to promote policies that will improve the economic and social well-being of people around the world. Today, OECD member countries account for 59 percent of world GDP, three-quarters of world trade, 95 percent of world official development assistance, over half of the world's energy consumption, and 18 percent of the world's population.
- ⁽³⁾ $X_t = logP_t logP_{t-1}$, where P_t is the price of a financial asset or commodity at the time "t", so X_t is the return of the financial asset or commodity at the time "t".

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Annex

Null Hypothesis: DLOGBRE	NT has a unit root			
Exogenous: Constant	INT has a unit root			
Bandwidth: 1 (Newey-West a	utomatic) using Bartle	ett kernel		
	utomate) asing Bartie			
			Adj. t-Stat	Prob.*
Phillips-Perron test statistic			-24.10338	0.0000
Test critical values:	1% level		-3.442299	
	5% level		-2.866703	
	10% level		-2.569580	
*MacKinnon (1996) one-side	d p-values.			
Residual variance (no correct	ion)			0.000154
HAC corrected variance (Bar	tlett kernel)			0.000154
Phillips-Perron Test Equation Dependent Variable: D(DLOO Method: Least Squares Date: 02/27/14 Time: 17:25 Sample (adjusted): 1/05/2012 Included observations: 537 af	GBRENT) 2/21/2014			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOGBRENT(-1)	-1.040164	0.043154	-24.10368	0.0000
C	-6.66E-05	0.000536	-0.124188	0.9012
R-squared	0.520604 Mear	n dependent var		-3.47E-05
Adjusted R-squared	0.519708S.D.			0.017923
S.E. of regression		ke info criterion		-5.935131
Sum squared resid	0.082541 Schw	arz criterion		-5.919168
Log likelihood	1595.583 Hann	an-Quinn criter.		-5.928887
F-statistic	580.9876 Durb			1.997733
Prob(F-statistic)	0.000000			
Source: own calculations				
Null Hypothesis: DLOGBRE Exogenous: Constant	NT has a unit root			
Lag Length: 0 (Automatic - b	ased on SIC, maxlag=	18)		
		-7		

t-Statistic

Prob.*

Augmented Dickey-Fuller tes			-24.10368	0.0000
Test critical values:	1% level		-3.442299	
	5% level		-2.866703	
	10% level		-2.569580	
*MacKinnon (1996) one-side	d p-values.			
Augmented Dickey-Fuller Te	st Equation			
Dependent Variable: D(DLO	GBRENT)			
Method: Least Squares				
Date: 02/27/14 Time: 17:20				
Sample (adjusted): 1/05/2012	2/21/2014			
Included observations: 537 at	ter adjustments			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOGBRENT(-1)	-1.040164	0.043154	-24.10368	0.0000
С	-6.66E-05	0.000536	-0.124188	0.9012
R-squared	0.520604	Mean dependent var		-3.47E-05
Adjusted R-squared	0.519708	S.D. dependent var		0.017923
S.E. of regression	0.012421	*		-5.935131
Sum squared resid	0.082541	a.t:		-5.919168
Log likelihood	1595.583			
F-statistic	580.9876			
Prob(F-statistic)	0.000000			1.997733