MODELLING THE IMPACT OF OIL PRICE FLUCTUATIONS ON VOLATILITY OF STOCK MARKETS

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Abstract

Volatility can be referred as a measure for variation of financial instrument price over time period. It is well known that shocks in crude oil markets may have significant effects on economic activities in general.In recent years, there is substantial empirical evidence to confirm relationshipbetween volatility of stock markets and changes in crude oil prices. The aim of this paper is to examine effects of crude oil fluctuations on volatility of stock markets. In order to model mutual relationships between oil prices shocks and stock market volatilitywe utilized theDCC GARCH model. Empirical analysis is provided on illustrative example using sample data from oil-importing countries represented by France and Germany,and oil-exporting countries approximated by British and Russian stock markets. In particular, we consider daily data of CAC40, DAX, FTSE100andRTS indexes in the period of 2008 - 2014 years. Crude oil prices are represented by daily time series of Brent oil prices. We identified that changes in oil pricesmay have significant impact on volatility ofstock returns over time.

Key words: Brent oil, DCC GARCH model, oil fluctuations, stock markets, volatility

JEL Code:C58, G15, Q43

Introduction

Modelling the volatility of financial time series is essential part of theoretical and practically oriented financial analysis. Volatility itself can be interpreted as a basic measure of riskiness of financial assets. In recent years, we have observed volatile market conditions on stock markets and commodity markets as well. It seems that oil remains one of the major energy commodities for world´s economy. Last decades have been characterised by numerous significant events like Iraq war of 2003 year, the global financial crisis of 2008year or OPEC price war in 2014 year and so on. These events caused unpredictable movements of prices in stock markets and commodity markets worldwide. Therefore, an evaluation of extreme price movements may remain in the centre of our attention. In particular, this task is tightly connected with behaviour of markets in volatile conditions.

Impact of crude oil prices on macroeconomic variables was investigated in numerous papers, studies and research reports over last two decades. First paper that was focused on analysis of relationships between oil price effects and economic indicators was published by (Hamilton, 1983). Nevertheless, if we consider the number of research papers that have investigated mutual relationship between crude oil prices and stock markets, the number of studies is relatively limited. In most papers, the authors usually utilized the methods of VAR and Vector Error Correction models (Dally and Fayyad, 2011) or (Basher et al., 2012).

However, there are only a few studies that have utilized dynamic correlation between oil and stock markets. The dynamic correlation between oil prices and stock markets using data from Russia was analysed by (Bhar and Nikolova, 2010). They identified some major events that resulted in negative correlation between oil prices and Russian stock market.Multivariate constant conditional correlation (CCC) GARCH model was utilized by (Cifarelli and Paladino, 2010). They detected that oil price breaks are correlated with exchange rates and stock prices changes in a negative way. Symmetric DCCGARCH model was applied by (Choi and Hammoudeh, 2010). Theydelivered evidencethat correlation among different types of oil and gold, silver and copper is increasing during time. Nevertheless, a correlation with S&P500 stock index is decreasing. The DCC GARCH model was also employed analysing three oil-importing and three oil-importing countries (Filliset al.,2011). They found that oil innovations on demand side lead to positive correlation with stock markets. On the other hand, precautionary demand side breaks lead to negative correlation. In addition to this, they reveal that oil price innovations have a significant effect on oil price relationship during business cycle turnovers, irrespective of oil dependence status of respective country.

The aim of this paper is to examine an impact of oil prices fluctuationsapproximated by Brent type crude oil prices on volatility of oil-importing countries stock marketsrepresented by France and Germany, and oil-exporting countries stock marketsembodied by Great Britain and Russia using daily data over the period of 2008-2014 years.The studies conducted in this paper will be summarized in the following way.First, the multivariate conditional heteroskedasticity model with time varying conditional correlations and related estimation technique will be introduced. In Section 2, the data sample will be described and statistically analyzed in a simplified way. Moreover, this Section reports an empirical estimation of DCC GARCH models and corresponding dynamic conditional correlations on a set of stock market indices and crude oil prices. The achieved results are also discussed and embedded in economic environment. Section 4 concludes the analysis.

1. Methodological Background

The aim of this chapter is to describe methods that will be used for empirical analysis of potential impact of oil price fluctuations on volatility of stock markets. In this chapter, it will be specified multivariate GARCH model with time varying or dynamic conditional correlations (DCC) that will be utilized in empirical part of this paper. Univariate volatility models (Bollerslev, 1986) can be applied only when modelling the volatility that is completely independent on other financial time series. However, this fact is often too simplisticin the world of finance since there mayoccur volatility spillovers among different financial markets or among various assets traded on samefinancial market. In addition to this, when optimizing and managing various investment diversified portfolios,a correlation between particular units makes up a key determiner factor (Cipra, 2013).This group of models can be also easily used for forecasting, like ARIMA models (Gándara et al., 2013).

1.1 Multivariate GARCH model with time varying conditional correlations

In this subchapter we will define multivariate GARCH model with time varying conditional correlations or DCC GARCH model. This model was firstly introduced by (Engle, 2002). The DCC GARCH will be applied onmultivariatetime series of logarithmic returns $r_t = (r_{1,t}, r_{2,t}, ..., r_{k,t})'$ of$k$ assets. It must be emphasized that these returns are expected to have zero mean value.On the basis of fulfilment of this assumption it can be simplified mathematical notation and standed out relationshipbetween conditional correlations and vector of standardized residuals ε_t, that can be usually markedas a vector of shocks. In the case of two-dimensionaltime series $r_t = (r_{1,t}, r_{2,t})$ with constant zero mean valueits components can be written as:

$$r_{1,t} = \sqrt{E_{t-1}(r_{1,t}^2)}\varepsilon_{1,t},\ r_{2,t} = \sqrt{E_{t-1}(r_{2,t}^2)}\varepsilon_{2,t}, \tag{1}$$

where $E(\varepsilon_{i,t}) = 0$, for $i = 1, 2$ and $\mathrm{var}(\varepsilon_{i,t}) = 1$, for $i = 1, 2.$ Conditional correlation can be then written as follows:

$$\rho_{1,2,t} = \frac{E_{t-1}(\sqrt{E_{t-1}(r_{1,t}^2)}\varepsilon_{1,t}\sqrt{E_{t-1}(r_{2,t}^2)}\varepsilon_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2)E_{t-1}(\varepsilon_{1,t}^2)E_{t-1}(r_{2,t}^2)E_{t-1}(\varepsilon_{2,t}^2)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t}). \tag{2}$$

Vector of shocks ε_t therefore reflects all information about conditional correlation $r_{1,t}$ and $r_{2,t}$, and represents vector of standardized residuals. Estimation of the DCC GARCH model can be donein three basic steps. As a first step one should estimate volatility of particular components and standardised residuals.Next, it is possible to estimate correlations using standardised residuals. Finally, it is necessary to normalize and adjust estimated correlation matrix to fulfilproperties of correlation matrix (Engle, 2002).

1.2 Estimation of multivariate GARCH model with time varying conditional correlations

The estimation of the DCC GARCH model can be provided using the maximum likelihood method. It is necessary to accept an assumption that data have multivariate normal distribution with given vector ofmean valuesandcovariance matrix. This method is universal enough so thatan estimation of a modelwill be consistent ifa vector of mean values andcovariancematrix will bespecified correctly, even if anassumption of normal distributionis not fulfilled.

This universalityis very important sinceseries of logarithmic returns usually have leptokurtic distribution with more heavy tails, than anormal distribution has. Next, it can be formulated concrete DCC GARCH model. When estimating conditional quasi-correlationmatrix Q_t weutilized mean-reverting model that is also derived from GARCH(1,1) model (Engle, 2002). The specificationof the DCC GARCH model can be written as follows:

$$\begin{aligned}
&r_t \mid \Omega_{\text{t-1}} \sim N(0, D_t \rho_t D_t),\\
&D_t^2 = diag\left\{\Sigma_{\text{t}}\right\}, \Sigma_{\text{t}} = \text{cov}(r_t \mid \Omega_{\text{t-1}}),\\
&\varepsilon_t = D_t^{-1} r_t,\\
&\rho_t = diag\left\{Q_t\right\}^{-1/2} Q_t \; diag\left\{Q_t\right\}^{-1/2},\\
&Q_t = \left(1-\alpha-\beta\right)\bar{Q}_t + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1},
\end{aligned} \tag{3}$$

where $\Omega_{\text{t-1}}$ is information set, D_t represents diagonal matrix of conditional standard deviations as estimated by univariate GARCH models, $\bar{Q}_t$ denotes a matrix of unconditioned variances ε_t, ε_t are standardised residuals, α, β are nonnegative parameters that have to reach positive values and the sum $\alpha_i + \beta_i < 1$, for $i = 1,...,k.$ Parameters α a β denotehow fastnew shocksare absorbed into volatility and values of conditionalcorrelationstendedback tolong termaverage value. Their sizes andpossible changes in timetherefore showwhether thecorrelations among particular assets are sensitive on new shocks,and ifmutual relationships and properties of marketsare changing significantly over time.In order to estimate all the coefficients of the GARCH and DCC GARCH models it is usually used the maximum likelihood method (MLM) or quasi-maximum likelihood method (QMLM) respectively (Engle, 2002). Those methodsare based onmaximizing the likelihood function.

2. Empirical Findings and Discussion

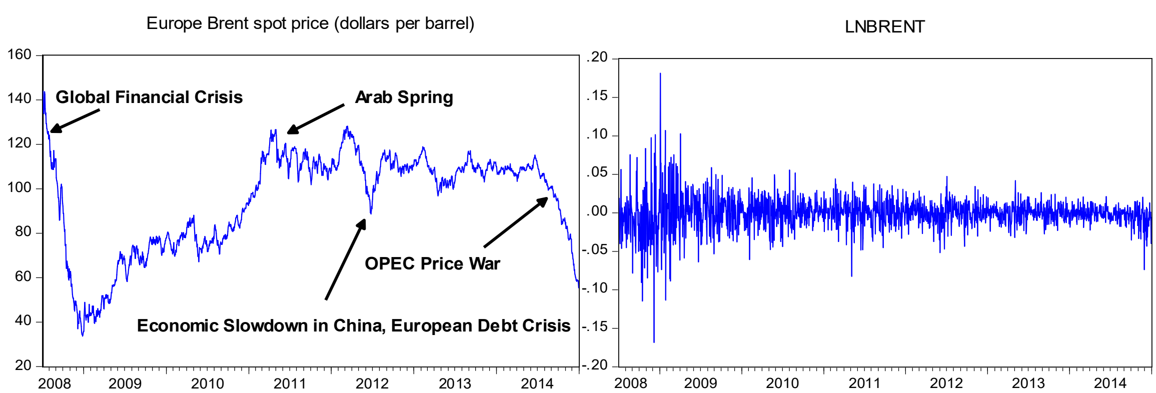
The goal of this chapter is to present and demonstrate empirical estimationsusing the methodsdiscussed and described in Section 1. First of all, we estimated the DCC GARCH models for all investigated stock markets and Brent oil prices. Next, the estimated dynamic correlations for all pairs of stock markets and Brent oil time series will be presented graphically.

2.1 Data sample

Empirical analysis is completed on daily data of closing values of stock indexes CAC40 (France) and DAX (Germany) as proxies of oil-importing countries while oil-exporting countries were represented by FTSE100 (Great Britain) and RTS (Russia) indexes. Development of oil prices is represented by Brent crude oil.Basic testing period was chosen from 3 July 2008 to 31 December 2014.The beginning of the test period was chosen intentionally since oil prices started to fall steeplyfrom that moment.

Main events determining the development of the Brent oil prices are presented in Fig. 1.In the second half of 2008 year,there was observed a sharp reversalin oil prices due to declining of aggregatedemand that was caused by the global financial crisis. In 2011,the oil price waspushed updue to politicalunrestin Arab world, especiallynervousnessoffurther developmentsin Libya.

Fig. 1: Development of the Brent oil prices with main economic or political events (left) and logarithmic returns (right) in the period of 2008-2014 years



Source: own calculations in Eviews

As demonstrated byFig.1, in 2012 it can be identifieda further declinein oil price trends. Thedevelopment of oil priceswasdeterminedmainlyby fears offurtherdeterioration ofEuropean debt crisisand unfavorableeconomicdatafrom China. The lastsignificant dropwas noted in thesecond half of2014, whenoil pricesfellby nearly 50% due to rising of oil productionin USA, and moreover, due toexpansion of shaleoil extraction process. The fall inprices acceleratedafter November 2014 when the OPEC decided not to interveneagainstfalling of pricesby limiting their production.

The daily returns r_t at time *t*were defined for all stock markets and Brent oil prices as the logarithm of index p, that is, $r_t = \ln(p_t - p_{t-1})$.Based on Fig. 1 it is possible to argue that the problem of non-stacionarity was eliminatedfor Brent oil prices. Similar results were achieved also for all four stock indexes.

2.2 Empirical estimations of DCC GARCH models

The DCC GARCH model works as two-steps procedure. First, we estimated standardised residuals using univariate linear or nonlinear conditional volatility models (Bollerslev, 1986). We assume *t*-distribution of errors that is not so strict comparing with normality. These standardised residuals then served as an input for estimation of dynamic parameters α a β ofmean-reverting model. In order to estimate the DCC GARCH model we utilized the maximum likelihood method. Parameters α a $\beta$are marked in Eviews software as theta(1) and theta(2). As mentioned in Subchapter 1.2 there must be fulfilled conditions that $\alpha > 0$, $\beta > 0$, and $\alpha + \beta < 1$ to ensure positive definiteness of matrix Q_t. Finally, we can quantify dynamic conditional correlations between particular time series.

Our attention will be devoted to significant events determining conditional correlation between oil-importing and oil-exporting countries stock markets and Brent oil prices. In the period from July 2008 till December 2014 there were identified in total three breaking events within correlation developmental trend. In general, we found that positive correlation between stock markets and development of Brent oil prices is characteristic for the whole period. Higher values of parameter α, that is marked as theta(1) in Tab. 1 and Tab. 2, makes our models much more dynamic. That is why, the DCC GARCH models are able to react on changes in measured correlations in a flexible way.

Oil Importing Countries

Estimations of the DCC GARCH models, as seen in Tab. 1, meet the requirement that the sum of dynamic parameters $\text{theta}(1)+\text{theta}(2)<1$. It means that it is fulfilled positive definiteness of matrix Q_t. In addition to his, estimated parameters of both DCC GARCH models are statistically significant. Because of high values of sum of the dynamic parameters achieved, it can be observed high persistence in conditional volatility.

Tab. 1: Estimation of DCC GARCH model for BRENT and CAC40index (left); BRENT and DAXindex (right)

	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	0.041162	0.011541	3.566678	0.0004	theta(1)	0.034407	0.011747	2.929053	0.0034
theta(2)	0.929918	0.022794	40.79598	0.0000	theta(2)	0.942841	0.024021	39.25024	0.0000
	t-Distribution (Degree of Freedom)					t-Distribution (Degree of Freedom)			
theta(3)	6.685015	0.620775	10.76883	0.0000	theta(3)	6.120271	0.532369	11.49629	0.0000
Log likelihood	9662.396	Schwarz criterion	-11.35073		Log likelihood	9769.728	Schwarz criterion		-11.47745
Avg. log likelihood	2.851947	Hannan-Quinn criter.	-11.37700		Avg. log likelihood	2.883627	Hannan-Quinn criter.		-11.50372
Akaike info criterion	-11.39244				Akaike info criterion	-11.51916			

Source: own calculations in Eviews

Based on these parameters it is possible to build a model for BRENT a CAC40 return series as referred below:

$$Q_{i,j,t} = \omega_{i,j} + 0.041162\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.929918Q_{i,j,t-1},$$

and estimated equation for BRENT a DAX time series can be expressed as follows:

$$Q_{i,j,t} = \omega_{i,j} + 0.034407\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.942841Q_{i,j,t-1}.$$

Oil Exporting Countries

In case of oil-exporting countries it is obvious that estimated parameters theta(1) and theta(2)also met conditions of positive definiteness of matrix Q_t, and moreover both parameters are again statistically significant. Estimated DCC GARCH modelsfor both return series can be considered as rather significant for expressing the development of dynamic correlations, as demonstrated by Tab. 2.

Tab. 2: Estimation of DCC GARCH model for BRENT and FTSE100 index (left); BRENT and RTSindex(right)

	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	0.036145	0.010586	3.414524	0.0006	theta(1)	0.032636	0.009819	3.323824	0.0009
theta(2)	0.943259	0.019556	48.23259	0.0000	theta(2)	0.957589	0.014300	66.96276	0.0000
	t-Distribution (Degree of Freedom)					t-Distribution (Degree of Freedom)			
theta(3)	6.910421	0.680826	10.15005	0.0000	theta(3)	6.325125	0.538916	11.73675	0.0000
Log likelihood	10150.04	Schwarz criterion		-11.92646	Log likelihood	9135.275	Schwarz criterion		-10.72839
Avg. log likelihood	2.995879	Hannan-Quinn criter.		-11.95273	Avg. log likelihood	2.696362	Hannan-Quinn criter.		-10.75466
Akaike info criterion	-11.96817				Akaike info criterion	-10.77010			

Source: own calculations in Eviews

On the basis of estimated parameters we can rewrite estimated model for BRENT and FTSE100 time series as follows:

$$Q_{i,j,t} = \omega_{i,j} + 0.036145\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.943259Q_{i,j,t-1},$$

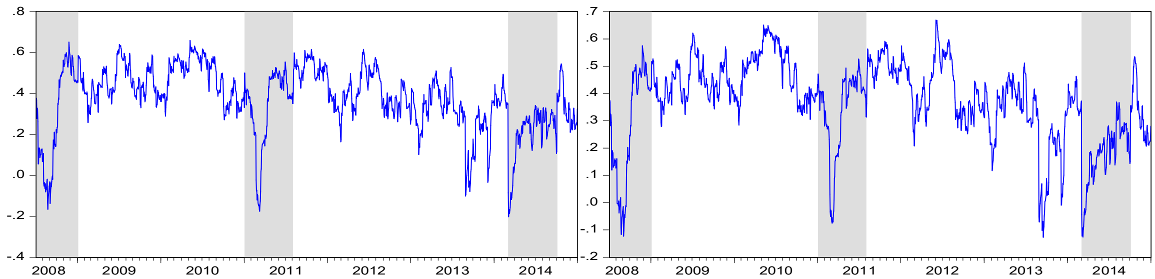
and estimated equation for BRENT a RTS time seriescan be expressedby following way:

$$Q_{i,j,t} = \omega_{i,j} + 0.032636\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.957589Q_{i,j,t-1}.$$

2.3 Visualization of Dynamic Conditional Correlations

Fig. 2 shows estimated dynamic correlations for oil-importing countries while Fig. 3 demonstrates estimated dynamic correlations for oil-exporting countries. There can be identified three significant correlation trends in total. Starting from September 2008 it can be observed that correlation coefficients, as generated by DCC GARCH models, reached just positive values for all investigated stock markets. In addition to this, there is evident positive correlation trend till the end of 2008 year. Brent oil prices fell to new minimum value of 34 USDper barrel till the end of this year. The global financial crisis can be considered as main determinant in this period. This period can be regarded as oil price shock on the side of aggregate demand. Positive values of correlations between oil prices and stock markets can be explained by the fact that global financial crisis led to "bear" trend on stock markets and this declining trend was subsequently reported in oil price development. Oil prices began to increase gradually due to increasing demand from Asian countries in 2009.

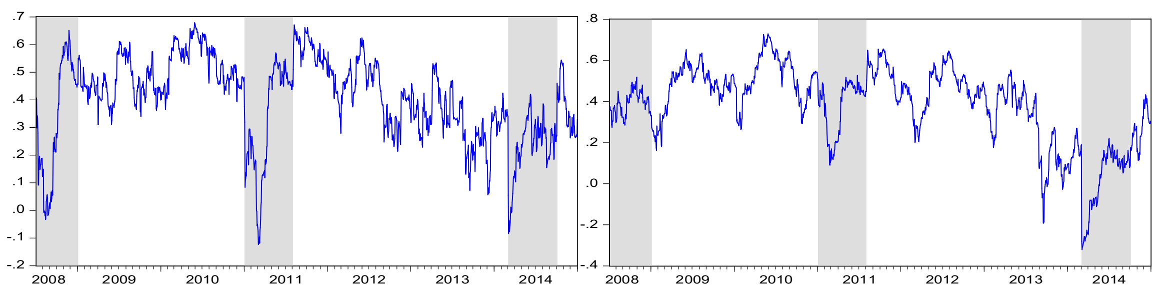
Fig. 2: Estimated correlations for BRENT and CAC40 (left); BRENT and DAX(right)



Source: own calculations in Eviews

A further increase of oil prices was due to political unrest in Arab world that began in late 2010. In April 2011 the oil prices reached the value over 120 USD per barrel.During the period of 2009-2011 years it can be detected a high correlation between oil and stock indexes in general. The correlation coefficients ranged in case of all the indices in the range of (0.3; 0.7). The influence of Arab revolution in first quarter of 2011 changed the correlation trend significantly. Correlation coefficient of stock indexes except Russian index RTS fell to negative values for all three remaining stock indexes.

Fig. 3: Estimated correlations for BRENT and FTSE100 (left); BRENT and RTS(right)



Source: own calculations in Eviews

After this downturn one can observe another increase of correlation between oil prices and stock markets. Higher fluctuations of correlations are significant at the end of 2013 year and especially in 2014 year. Period from March 2014 represents the latest turning point in correlation trend. At the beginning of this period, the correlation coefficients reached just negative values for all markets. Oil prices began gradually to decline in this period due to increasing of oil production from shale bearings in USA, and weakening global demand for oil. Another important reason was a behavior ofOPEC cartel that did not react to oil price trends and kept the same production quotas at the end of 2014. These factors caused that correlation coefficientssoon returned topositive values.

Conclusions

This paper investigatedan impact of oil prices fluctuations on volatility of stock markets with a help ofmultivariate DCC GARCH models with time varying conditional correlations using daily data in the period from July 2008 to December2014. For the purpose of this paper we utilized selected time series of stock indexes of oil-importing and oil-exporting countries and Brent oil spot prices.We identified in total three significant correlation trends that have been explained by economic or political reasons. Correlation coefficients achieved mostly positive values regardless of a type of analyzed country.The meaning of these trends is obvious. Estimated values of dynamic conditional correlations may play significant role when investing funds into oil or oil products, for instance when optimizing hedging strategy.

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