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Volatility transmission between oil prices and European stock market

Bachelor thesis

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Abstract

This thesis examines transmissions of returns and volatility between crude oil and stock indices from different sectors of economy. We will be using daily Brent crude futures and Euro Stoxx sector indices from 1992 to 2017. For the analysis we employ bivariate VAR BEKK-GARCH model to simultaneously estimate the conditional mean and variance equations, to investigate the causal relationships between the variables. In addition we use the results of our estimation to calculate optimal portfolio weights and hedge ratios. The results show Granger causality from oil to most of the individual sectors, reverse relationship exists in two cases. We found unidirectional volatility spillovers from stock sectors to oil in majority of cases and in 4 sectors the spillover was bidirectional.

Keywords

volatility transmissions, VAR GARCH model, crude oil prices, stock sector indices

Abstrakt

Tato bakalářská práce se zabývá přenosy výnosů a volatility mezi ropou a akciovými indexy z různých sektorů ekonomiky. Budeme využívat denní data od roku 1992 do roku 2017. Naše proměnné budou Brent crude futures a Euro Stoxx indexy pro jednotlivé sektory. Pro analýzu využijeme VAR BEKK-GARCH model, který dokáže zachytit jak přenosy výnosů, tak i volatility. Na závěr využijeme našich výsledků pro výpočet optimálního složení portfolia a zajišťovacího poměru. Výsledky nám ukazují, že ve většině případů ropa Granger způsobuje změny na akciovém trhu, opačná kauzalita existuje pouze ve dvou případech. Nalezli jsme signifikantní přenosy volatility ze sektorů akciového trhu na ropu ve většině případů a ve 4 případech oboustranný přenos volatility.

Klíčová slova

přenosy volatility, VAR GARCH model, ceny ropy, sektory akciového trhu

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, 18 May 2017

Signature

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Bachelor Thesis Proposal

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Proposed topic: Volatility transmission between oil prices and European stock market

Research question and motivation

The aim of my thesis is to find whether there is a transmission of returns and volatility between crude oil and individual European stock market sector indices (utilities, financials, technology, etc.). The choice to study individual sectors instead of an aggregate index is to see which sectors are affected by crude oil (or affect crude oil).

Contribution

I hope to identify which sectors are the most affected by oil price changes. Identifying how different sectors are interlinked with crude oil can help us gain an insight into the behaviour of these markets and can be a valuable information that can help to make a well-diversified portfolio.

Methodology

To analyse how oil returns and sector indices are interconnected we employ VAR BEKK-GARCH model to see return and volatility transmissions. This will be done using daily data of Brent crude and Euro Stoxx indices.

Outline

- Introduction
- Literature review
- Theoretical framework

- Statistical tests
- Empirical part
- Conclusion

Core bibliography

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Contents

List of Tables

List of Figures

Acronyms

ACF	Autocorrelation function
AIC	Akaike Information Criterion
AR model	Autoregressive model
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA model	Autoregressive Moving Average model
BEKK model	Baba, Engle, Kraft and Kroner model
BIC	Schwarz Bayesian Information Criterion
GARCH	General Autoregressive Conditional Heteroskedasticity
LM	Lagrange Multiplier
LR	Likelihood Ratio
MLE	Maximum Likelihood Estimation
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
Quasi-MLE	Quasi-Maximum Likelihood Estimation
VAR model	Vector Autoregressive model

Introduction

Crude oil accounts for one third of gross energy consumption in the European Union. The EU currently relies on imports for 88% of its crude oil supply (Cambridge Econometrics, 2016). This makes crude oil greatly important for the whole economy as oil shock transmits to economy via increased costs (of transportation, production, heating, etc.) or increased inflation. With increased financialization of crude oil market over the past decades it is increasingly interlinked with other sectors of the economy with increased transmission of risk (Cheng and Xiong, 2014). Understanding return and volatility transmissions is important for financial market participants so they can make optimal portfolio allocation decisions.

In this thesis we will focus on identifying return and volatility transmission between crude oil futures market and euro area stock sector indices. We want to study different sector indices to see whether they differ in their reactions to shocks from oil market and whether any of them affect crude oil more heavily.

To study this we will employ VAR BEKK-GARCH model which allows us to inspect return and volatility spillovers simultaneously. We will be using daily data from 1992 to 2017 of Brent crude futures and Euro Stoxx sector indices. We also show possible implications for portfolio management by computing optimal portfolio weights and hedge ratios.

Regarding the results of our study, we show evidence of significant return and volatility spillovers, return spillovers are going mainly from oil to different stock sectors while volatility spillovers mainly from stock sectors to crude oil.

The structure of the thesis is following: in? Chapter 1 we will review previous research related to the topic. In Chapter 2, we will focus on the theoretical background needed for our empirical part. VAR model, the concept of Granger causality and selected ARCH models are presented here. Chapter 3 is dedicated to statistical tests that we will be using in the empirical part to make sure our models are correctly specified. Chapter 4 consists of empirical application, where we first examine the dataset, and continue with the econometric analysis. The conclusion summarizes the main findings of the thesis.

1 Literature review

In this section we present some of the literature regarding links between oil and stocks, with the emphasis on papers studying stock sectors.

Research using monthly data has the advantage of having oil supply and demand, industrial production index, interest rate, economics activity and other monthly data available. These studies usually use variants of VAR model.

For example Kilian and Park (2007) studied the impact of oil price shocks on U.S. market with a monthly data, differentiating between supply and demand shocks. Their conclusion is that increased oil price causes lower stock return only in case of demand shocks (i.e. concerns about oil supply shortfalls) while oil supply shocks showed no effect on U.S. stocks.

Another example of utilizing the VAR model is by Diaz et al. (2016) who analysed G-7 economies fiding negative response of increased oil volatility on stock returns.

Recent research is more focused on modelling volatility spillovers using multivariate GARCH models.

Khalfaoui et al. (2015) are examining the link between crude oil market and stock market of G-7 countries, using BEKK methodology and wavelet analysis to see the effects over various time horizons, with results overall indicating that crude oil is leading.

Hassan and Malik (2007) focused on U.S. sector indices and oil transmission, using multivariate BEKK GARCH and found significant transmission of shocks and volatility across different sectors

Hamma et al. (2014) employ VAR BEKK methodology to Tunisian stock sectors finding spillovers mainly from oil to stocks. They compared hedging effectiveness of different types of models and found that the BEKK is the best performing model in the Tunisian case.

Literature regarding links between oil and European stock market sectors is presented in the following three paragraphs.

Arouri and Nquyen (2010) examine short term linkages between oil price and European sector indices, focusing on a reaction of stock indices to oil price changes. They also used Granger causality test to see returns transmission and found that changes in European stock indices affect oil prices.

Arouri et al. (2011) analyse European and American stock sectors using BEKK model, finding bidirectional volatility transmission in case of American stocks and mostly unidirectional spillovers from oil to stock in European case. The also examine optimal portfolio composition and hedging effectiveness.

Degiannakis et al. (2013) study time varying correlations between oil prices returns and European sector indices at a monthly frequency employing diagonal VECH model. Results suggest that correlation is significantly varying over time and is higher during crises periods.

Concerning the causes of volatility, Fleming et al. (1998) studied linkages in stock, bond and money markets and suggest that volatility spillovers are caused by either change in common information (i.e. news about inflation) or because of the cross market hedging.

Another cause of volatility spillovers is being attributed to financial contagion, due to a co-movement where a shock in one country affects stocks in other country. This was studied for instance by Kodres and Pritsker (2002) who focused on cross market rebalancing, when investors adjust their portfolios to account for macroeconomic risks. They found that the amount of contagion depends on the sensitiveness of the sector to macroeconomic risks.

2 Theoretical framework

In this section we will present models and concepts which are of a main interest in our analysis.

2.1 VAR model

One of the ways to study relationship between more variables are vector autoregression (VAR) models. VAR(P) model is used to capture relationship between more time series, via lagged values of each variable, up to Pth lag.

VAR(P) model:

$$y_t = v + \Phi_1 y_{t-1} + \cdots + \Phi_P y_{t-P} + \varepsilon_t \tag{1}$$

where y_t is $n \times 1$ vector of our n time series at time t, v is $n \times 1$ vector of intercept parameters, Φ_1,...,Φ_P are $n \times n$ matrices of parameters, ε_t is $n \times 1$ vector of error terms.

From the estimated VAR equation we can see the effect of own past values and past values of other variables in the model (both up to Pth lag) on the variable. y_t is stable VAR(P) process if all roots of the characteristic equation

$$|I - \lambda\Phi_1 - \lambda\Phi_2 - \cdots - \lambda\Phi_P| = 0 \tag{2}$$

are in absolute value less than one.

The VAR model in itself is not enough to sufficiently capture our data, due to the heteroskedasticity in it, but the VAR model can be used together with a model which deals with ARCH effects.

2.2 GARCH model

Volatility clustering is a feature of time series, which can be described as "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" (Mandelbrot, 1963, p.418).

Autoregressive conditional heteroskedasticity (ARCH) process was introduced by Engle (1982) as a way to describe volatility clustering and the high kurtosis of data. This is done by using squared error terms to model conditional variance. This was later developed into a more general form - generalized autoregressive conditional heteroskedasticity (GARCH) by Bollerslev (1986). He included an additional term in the conditional variance equation - past conditional variances. A visual inspection of sample ACF and PACF of a squared times series can tell us whether the series has ARCH effects or not. If there are a lot of significant correlations it is a sign of ARCH effects. This can be subsequently formally tested by the Ljung-Box Q or LM tests.

A GARCH model estimates conditional variance of ε_t, which is a process with zero mean and conditional variance h_t, i.e.

$$E(\varepsilon_t|\Omega_{t-1}) = 0,\ Var(\varepsilon_t|\Omega_{t-1}) = h_t \tag{3}$$

$$\varepsilon_t = z_t\sqrt{h_t} \qquad z_t \sim i.i.d.N(0,1) \tag{4}$$

where Ω_{t-1} is the information revealed at the time $(t-1)$

The conditional variance h_t is modelled by univariate GARCH(p,q) as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{5}$$

where z_t is i.i.d.N(0,1). $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ for all i are conditions to ensure strictly positive conditional variance h_t. The conditional variance is based on residuals ε_t from the mean equation of a model. $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ is the ARCH term, which captures past volatilities, p tells us how many lags of squared errors are added to the equation. It shows us how shocks or new from previous periods change the variance. In GARCH(1,1) case, if $\alpha_1 > 1$ then the shock will have destabilizing effect, causing variance to increase over time to infinity. $\sum_{i=1}^{p} \beta_i h_{t-i}$ is the GARCH term, capturing how is the current conditional variance affected by conditional variances from previous periods (up to qth lag), that is the persistence of conditional variance. In GARCH(1,1) β_1 that is smaller than one, but close to it will cause high persistence of shocks, while β_1 closer to zero means that shocks do not last long.

GARCH(p,q) model has a stationary unconditional variance $Var(\varepsilon_t)$ if $\left[\sum_{i=1}^{q}\alpha_i + \sum_{i=1}^{p}\beta_i\right] < 1$.

GARCH is estimated via maximum likelihood estimation (MLE). That is done by maximizing log likelihood function $\mathscr{L}_T$ which might take the following form (apart from constant):

$$\mathscr{L}_T = \frac{1}{T}\sum_{t=1}^{T}\ell_t \tag{6}$$

$$\ell_t = -\frac{1}{2}\ln(h_t) - \frac{1}{2}\varepsilon_t^2 h_t^{-1} \tag{7}$$

as suggested by Bollerslev (1986).

2.3 BEKK-GARCH model

First multivariate modelling of GARCH processes, known as a VECH model, was proposed by Bollerslev, Engle and Wooldridge (1988). Although it is a very general model, it is not suitable to use it in our case. The first drawback of it is the large number of parameters, making it impractical to use for more than two time series. The second one is that we cannot ensure the positive definiteness of the conditional covariance matrix H_t. These problems can be solved by using diagonal a VECH model, which significantly reduces the number of parameters and ensures positive definiteness, but the diagonal model does not allow for transmissions of volatility between the variables. A solution to these problems, while allowing for volatility transmission, is BEKK model proposed by Engle and Kroner (1995) (Baba, Engle, Kraft and Kroner worked on early versions of the paper which led to the acronym BEKK).

The BEKK-GARCH model is a restricted version of a VECH model, requiring less parameters and ensuring positive definiteness under very weak conditions. Because of that, the BEKK-GARCH model is widely used in the literature dealing with volatility transmission to model conditional covariance matrix. It is a parsimonious model for a low number of variables, though it is not that useful for higher dimensions as the number of parameters becomes too high.

BEKK-GARCH is models a conditional covariance matrix of the error term ε_t, which is a vector of residuals from the mean equation.

Let ε_t be a martingale difference sequence, a stochastic process with zero conditional mean, i.e.

$$E(\varepsilon_t|\Omega_{t-1}) = 0 \ \ \textit{almost surely for every } t \tag{8}$$

with conditional covariance matrix being:

$$Cov(\varepsilon_t|\Omega_{t-1}) = H_t^{-1/2} Cov(z_t|\Omega_{t-1}) H_t^{-1/2'} = H_t \tag{9}$$

where $H_t^{1/2}$ is a symmetric positive definite square root of H_t which can be obtained by Cholesky factorisation (Lütkepohl, 2005)

$$\varepsilon_t = H^{1/2} z_t, \qquad z_t \sim i.i.d.(0, I) \tag{10}$$

I is $n \times n$ identity matrix, n being the number of variables.

The BEKK-GARCH(p,q) model:

$$H_t = C'C + \sum_{i=1}^{q} A_i' \varepsilon_{t-1} \varepsilon_{t-1}' A_i + \sum_{i=1}^{p} B_i' H_{t-1} B_i \tag{11}$$

C is a $n \times n$ lower triangular matrix, A_i and B_i are $n \times n$ matrices of parameters. Given how H_t is defined it is a symmetrical matrix with positive definiteness of H_t achieved when at least one of the matrices C or B_i has a full rank.

Coefficients a_{ii} are capturing own volatility spillovers, b_{ii} own volatility persistence of ith variable. Off-diagonal elements of A and B show us the spillover of volatility. Off-diagonal element a_{ij} captures the transmission of volatility from ith to jth variable, while off-diagonal coefficient b_{ij} measures the dependence of volatility of jth variable on past volatility of ith variable.

Now we consider the BEKK-GARCH(1,1) i.e. case when $p = q = 1$. In bivariate case matrices from the BEKK model are following:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} \quad C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

Individual conditional variances and the covariance from the H_t matrix can be expanded as:

$$\begin{aligned} h_{11,t} = c_{11}^2 + c_{21}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 \\ + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \end{aligned} \tag{12}$$

$$\begin{aligned} h_{22,t} = c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 \\ + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} \end{aligned} \tag{13}$$

$$\begin{aligned} &h_{12,t} = c_{21}c_{22} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{11}a_{22} + a_{21}a_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ &+a_{22}a_{21}\varepsilon_{2,t-1}^2 + \ b_{11}b_{12}h_{1,t-1} + (b_{11}b_{22} + b_{21}b_{12})h_{12,t-1} + b_{22}b_{21}h_{2,t-1} \end{aligned} \tag{14}$$

The BEKK model is covariance stationary if and only if all the eigenvalues of $[\sum_{i=1}^{q} A_i \otimes A_i + \sum_{i=1}^{p} B_i \otimes B_i]$ are less than one in modulus (the symbol $\otimes$ denotes Kronecker product)

Univariate standardized residuals:

$$\varepsilon_{i,t}^{US} = h_{ii,t}^{-1/2}\varepsilon_{i,t} \tag{15}$$

$\varepsilon_{i,t}$ is residual from mean equation of ith variable at time t, $h_{ii,t}$ is the corresponding conditional variance from estimated covariance matrix

Jointly standardized residuals:

$$\varepsilon_t^{JS} = H_t^{-1/2}\varepsilon_t \tag{16}$$

where ε_t is residual vector $n \times 1$ from mean equations.

Univariate standardized residuals will be used when checking the model fit of each times series independently, while jointly standardized residuals are used in multivariate tests. Analysing both is recommended by Lütkepohl (2005).

BEKK model can be estimated via maximum likelihood estimation (MLE), as suggested Engle and Kroner (1995), but as MLE assumes normality of standardized residuals, our estimates are likely to be inconsistent. This is due to the fact that the normality of standardized residuals is usually rejected when using daily or weekly data because of the excess kurtosis (when using MLE on our data, normality was strongly rejected in all cases).

Because of this, it is more suitable to use quasi-MLE which can treat this problem. Quasi-MLE is a procedure of maximizing the normal log-likelihood function but with the assumption of normality violated. It was shown by Comte and Lieberman (2003) that quasi-MLE is consistent and asymptotically normal estimator of BEKK-GARCH model. That is, under the assumption of correctly specified conditional mean and conditional variance our estimates will be consistent and asymptotically normal.

Quasi-MLE standard errors (Bollerslev and Wooldridge, 1988) will be used so that our results are valid under non-normality.

A suggested by Malik and Hammoudeh (2007), we are going to estimate the mean simultaneously with the conditional variance equation to avoid generated regressor problem that would arise in case we used 2-step estimation, that is by firstly estimating the mean equation and subsequently estimating the conditional variance equation on estimated residuals. The problem with 2-step approach is that in the first step it is not accounted for the GARCH effects in the mean equation which could lead to inconsistent results.

Estimates are obtained by maximizing the quasi log likelihood function

$\mathscr{L}_T(\theta)$ (Engle and Kroner, 1995)

$$\mathscr{L}_T(\theta) = \sum_{t=1}^{T} \ell_t(\theta) \tag{17}$$

$$\ell_t(\theta) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}(\theta)\varepsilon_t \tag{18}$$

where θ is the parameter vector to be estimated, ℓ_t is the conditional log-likelihood function for a single period t, T is the total number of observations, n is the number of variables and $|H_t|$ is the determinant of conditional covariance matrix.

Ling and McAleer (2003) provide us with asymptotic theory to vector ARMA-GARCH model, the consistency of the model under quasi-MLE, making it possible for us to use VAR model in the mean equation in our analysis.

2.4 Granger causality

The concept of Granger causality was proposed by Granger (1969) as a way to describe causality between two times series, without the need to understand the underlying structure of causality. The definition of Granger causality is based on forecasts, if x_t is Granger causing y_t then the forecast of y_t can be predicted better when taking into account the information about x_t. Granger causality can be defined in terms of conditional expectations (Lütkepohl, 2005). Time series variable x_t is causal to y_t if

$$E(y_{t+1}|y_t, y_{t-1}, ...) \neq E(y_{t+1}|y_t, y_{t-1}, ...x_t, x_{t-1}, ...) \tag{19}$$

That is, this definition gives us the Granger causality in mean.

The definition of Granger causality can be directly extended to a higher order conditional moment. x_t is said to be causal for y_t in the rth moment if

$$E(y^r_{t+1}|y_t, y_{t-1}, ...) \neq E(y^r_{t+1}|y_t, y_{t-1}, ...x_t, x_{t-1}, ...) \tag{20}$$

If we for rth moment use the second central moment, we get the causality in variance. Causality in variance can be interpreted in the same way as mean causality, x_t is causal in variance for y_t when y_t is predicted better when including x_t information. In this thesis volatility transmission, volatility spillover and causality in variance are interchangeable, consistent with previous studies regarding this topic (Arouri et al, 2011; Khalfaoui et al. 2015).

In practice, we test for a Granger causality by setting the null hypothesis of Granger non-causality, which can be tested in a simple VAR(P) via an F-test by testing the model with and without the x_t in the y_t equation:

$$y_t = \alpha + \sum_{i=1}^{P} \gamma_i y_{t-i} + \sum_{i=1}^{P} \delta_i x_{t-i} + \varepsilon_t \tag{21}$$

$$y_t = \alpha + \sum_{i=1}^{P} \gamma_i y_{t-i} + \varepsilon_t \tag{22}$$

However, when variables have significant ARCH effects, we must account for that by firstly dealing with the heteroskedasticity as the transmission in volatility could affect our results (Woźniak, 2012).

When testing for noncausality in mean we can use the Wald test (Lütkepohl, 2005). Testing for noncausality in variance can be done via the Wald test as well, when working with BEKK-GARCH model estimated with quasi maximum likelihood, as was shown in Hafner and Herwartz (2008).

3 Statistical tests

This section is devoted to presenting tests needed for a proper model selection, checking the fit of a model and testing our hypotheses.

3.1 Unit root test

A times series is said to have a unit root if one root of the process equals to one and other roots lie within a unit circle. If times series has a unit root then shocks ε_t have a permanent effect which does not decay over time. Variance of unit root process is dependent on time and goes to infinity.

Augmented Dickey-Fuller test is widely used to determine between stationarity and unit root process. To test for unit root on y_t series, we begin by estimating the following equation (Kočenda and Černý, 2014):

$$\Delta y_t = \mu + \beta t + \gamma y_{t-1} + \sum_{i=1}^{K} \rho_i \Delta y_{t-i} + \varepsilon_t \tag{23}$$

Depending on the type of test we want to use, we may have to restrict the equation (23). For stationarity test we set $\mu = 0$ and $\beta = 0$, for level stationarity $\beta = 0$ and for trend stationarity we use the full equation. Afterwards, we compute the t-statistic of $\hat{\gamma}$:

$$t = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$

H_0: $\gamma = 0$ that the times series contains unit root against H_1: $\gamma < 0$ that the time series is stationary. We compare the t-statistic to Dickey-Fuller critical values.

3.2 Jarque-Bera test

The Jarque-Bera normality test is based on third and fourth moments of a distribution of our variable, comparing it to a standard normal distribution.

Sample skewness $\hat{S}(x)$ and sample kurtosis $\hat{K}(x)$ of variable x_t are defined as:

$$\hat{S}(x) = \frac{1}{(T-1)\hat{\sigma}_x^3}\sum_{t=1}^{T}(x_t - \hat{\mu}_x)^3 \qquad \hat{K}(x) = \frac{1}{(T-1)\hat{\sigma}_x^4}\sum_{t=1}^{T}(x_t - \hat{\mu}_x)^4$$

The Jarque Bera statistic is given as follows (Tsay, 2010):

$$JB = \frac{T}{6}\left(\hat{S}^2(x) + \frac{(\hat{K}^2(x) - 3)^2}{4}\right) \tag{24}$$

where T is the number of observations. H_0: $\hat{S}(x) = 0$ & $\hat{K}(x) = 3$ (normality of a time series). JB statistic is asymptotically distributed as χ^2 with two degrees of freedom.

3.3 Cointegration

Let x_t and y_t be two time series integrated of order one (it contains a unit root and differenced series is stationary). These two series are said to be cointegrated if there exists a non-trivial linear combination of them, $z_t = \alpha x_t + \beta y_t$, such that z_t is integrated of order 0 (a stationary series).

The reason to inspect the cointegration is that if there was a cointegration between crude oil and any stock index then it would be more suitable to use vector error correction model (VECM) as a mean equation instead of VAR model with returns (Sakthivel et al. 2012).

To test for cointegration, we will use the Engle and Granger cointegration test (Engle and Granger, 1987). Firstly, we estimate the following equation using OLS regression:

$$y_t = c + \beta x_t + e_t \tag{25}$$

or if we want to allow for a trend:

$$y_t = c + \gamma t \beta x_t + e_t \tag{26}$$

Afterwards, we test the residuals e_t for a unit root, using augmented Dickey-Fuller test (no constant or trend should be added as it was already included in the previous equation) with special critical values (they are different from the classic ADF test as we had to estimate e_t).

3.4 Optimal lag length

Choosing the suitable number of lags to include is important, as it can greatly change our outcomes. This can be done by using the likelihood ratio (LR) test which compares two models, a restricted and an unrestricted one. However in case we want to compare non-nesting models (i.e. different specifications of GARCH(p,q) model) LR test does not allow that. For this purpose, information criteria are used.

Information criteria are computed for competing models. Information criteria are computed using log likelihood of the model and they penalize for a large number of parameters (the penalty term is dependent on the type of criterion). The number of observation has to be the same for all of the models to make a comparison possible. The best fitting model will have the lowest information criterion. The great advantage of information criteria is that we can compare non-nesting models

Two of the frequently used criteria are Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC). They are defined as follows (Tsay, 2010):

$$AIC = -2LL + 2k \tag{27}$$

$$BIC = -2LL + k \cdot \ln(T) \tag{28}$$

where LL is log likellihood of the model, k is the number of parameters in the model.

The AIC penalizes the number of parameters less compared to the BIC and it tends to choose an over-parametrized model. The BIC is asymptotically consistent, meaning that in large samples BIC should not choose an over-fitted model (Kočenda and Černý, 2014).

3.5 Engle ARCH test

To test for the presence of ARCH effect up to sth lag we can use Lagrange multiplier (LM) ARCH test suggested by Engle (1982).

We take squared returns and run the OLS regression to estimate

$$r_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \cdots + \alpha_p r_{t-p}^2 + e_t \tag{29}$$

$$H_0 : \alpha_i = 0, \textit{for } i = 1, 2, ..., p$$

$$H_1 : \alpha_i \neq 0, \textit{for at least one } i$$

Under the null hypothesis (of no ARCH effects) the test statistic $LM = TR^2$ will be distributed as χ^2 with p degrees of freedom.

3.6 Multivariate ARCH test

We will use a natural extension of LM ARCH test to multivariate case described by Pfaff (2008). To test for joint ARCH effects up to qth lag in our jointly standardized residuals we start by regressing the products and crossproducts of the standardized residuals on a constant and its lags (up to qth lag) that is, we estimate the equations:

$$vech(\varepsilon_t^{JS} \varepsilon_t^{JS'}) = \beta_0 + B_1 vech(\varepsilon_{t-1}^{JS} \varepsilon_{t-1}^{JS'}) + ... + B_q vech(\varepsilon_{t-q}^{JS} \varepsilon_{t-q}^{JS'}) + v_t \tag{30}$$

where $vech$, half vectorisation is a matrix operator which stacks the lower triangular part of a symmetric matrix, creating a vector. β_0 is $[\frac{1}{2}n(n+1) \times 1]$ vector, $B_1, ..., \; B_q$ are $[\frac{1}{2}n(n+1) \times \frac{1}{2}n(n+1)]$ matrices, n is the number of variables used in our analysis and v_t is an error process.

$$H_0 : \; B_1 = ... = B_q = 0$$

$$H_1 : \; B_i \neq 0 \quad i = 1, 2, ..., q$$

LM statistic is computed as:

$$LM(q) = \frac{1}{2} Tn(n+1) R_m^2 \tag{31}$$

where

$$R_m^2 = 1 - \frac{2}{n(n+1)} tr(\hat{\Omega} \hat{\Omega}^{-1}) \tag{32}$$

$\hat{\Omega}$ is the residual covariance matrix estimator of equation (30), $\hat{\Omega}^{-1}$ is covariance matrix of restricted equation when q is set to zero, T is the total number of time observations. Under the null hypothesis of no ARCH effects $LM(q)$ follows χ^2 distribution with $[qn^2(n+1)^2/4]$ degrees of freedom.

3.7 Ljung-Box Q-test

Ljung Box Q-statistics tests whether autocorrelation up to sth lag is significant. It is defined as:

$$Q(s) = T(T+2)\sum_{i=1}^{s}\frac{\rho_i^2}{T-1} \tag{33}$$

T is the number of observations, s is the number of lags tested, ρ_i is ith sample ACF. H_0 is that all autocorrelations up to sth lag are zero. Under the H_0 the Q statistic follows χ^2 distribution with s degrees of freedom. Ljung Box Q-test on squred returns or squared standardized residuals is performed in the same way in order to test for ARCH effects of the time series and is denoted $Q^2(s)$.

3.8 Multivariate Ljung-Box Q-test

To test whether there is a residual autocorrelation after fitting a multivariate model, we will be using multivariate generalisation of Ljung-Box Q-test proposed by Hosking (1980). This test is performed on jointly standardized residuals. The Q statistic to test for autocorrelation up to sth lag:

$$Q(s) = n(n+2)\sum_{j=1}^{s}\frac{1}{T-j}tr[\hat{C}_{0j}\hat{C}_{00}^{-1}\hat{C}'_{0j}\hat{C}_{00}^{-1}] \tag{34}$$

$$\hat{C}_{0j} = T^{-1}\sum_{t=j+1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}'_{t-j} \tag{35}$$

n is the number of variables in our model, tr(A) denotes trace of a matrix, T is total number of observations. Under the null hypothesis Q(s) follows χ^2 distribution with $[n^2(s-P)]$ degrees of freedom, P being number of lags used in VAR model in the mean equation.

3.9 Wald test

The Wald test (Wooldridge, 2002) is a useful way to test multiple linear hypotheses as we only need to estimate the full model (under H_1) but not the restricted one. To test our model for Q linear restrictions on K total parameters in a model, we rewrite our restrictions in a matrix form:

$$H_0 : \; R\beta = r$$

where R is $Q \times K$ matrix with rank Q, β is $K \times 1$ vector of our estimated coefficients and r is $Q \times 1$ vector of our restrictions. The Wald statistic has following form:

$$W = (r - R\hat{\beta})'[R\Sigma_x R']^{-1}(r - R\hat{\beta}) \tag{36}$$

where Σ_x is the estimated covariance matrix of coefficients. Under the H_0 the Wald statistic follows asymptotically χ^2 distribution with Q degrees of freedom.

4 Empirical part

In this section we will describe the data and apply the methods described in previous two sections to find out whether there are mean and volatility spillovers between crude oil and euro area stock sectors. We also discuss possible implications of our findings for portfolio management.

For the analysis econometric software RATS (Regression Analysis of Time Series) version 9.0 and Gretl version 2016d were used. Finding suitable software for estimation of the BEKK model was challenging as multivariate GARCH models are insufficiently covered in the most of the econometric software packages.

All figures and tables are my own calculations. Figures were made using Gretl.

4.1 Data description

As a proxy for crude oil price Brent crude one-month futures were used. Brent crude futures are traded on Intercontinental Exchange Futures Europe (a subsidiary of an American company Intercontinental Exchange). Following the example of Sadorsky (2001) and Elyasiani et al. (2011), who argue that futures are less affected by temporary random noises than spot prices, we use future prices rather than spot prices.

Brent crude is a future contract developed in 1988 by the oil industry together with International Petroleum Exchange (now Intercontinental Exchange Futures Europe). Brent Crude is an important benchmark of oil price worldwide, currently are up to two thirds of oil is priced relative to Brent Crude (Intercontinental Exchange, 2017), and especially suppliers from Europe, Africa and the Middle East use it, which makes it suitable for use in our analysis which is centred in Europe.

Euro Stoxx indices are used as a proxy for euro area individual sectors. These indices include companies from 12 euro area countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain). Euro Stoxx sector indices are divided into 10 sectors: basic materials, consumer goods, consumer services, financials, healthcare, industrials, oil and gas energy, technology, telecommunications, utilities. We use indices from these sectors, Euro Stoxx 50 and Euro Stoxx broad index.

Both Brent crude and Euro Stoxx indices are expressed in euros. Brent crude was converted to euros using euro/dollar exchange rate to avoid any influence of changing exchange rate on our variables that might occur.

The data are at a daily frequency, daily closing price (from Monday to Friday) was obtained from Thomson Reuters Eikon spanning from 2 January 1992 to 26 April 2017 with a total number of observations being 6605. When a holiday occurs, the closing price from the previous trading day was used, as suggested by Malik and Hammoudeh (2007). Holidays are treated the same as workdays in our analysis, no dummy variables were added to keep our model parsimonious.

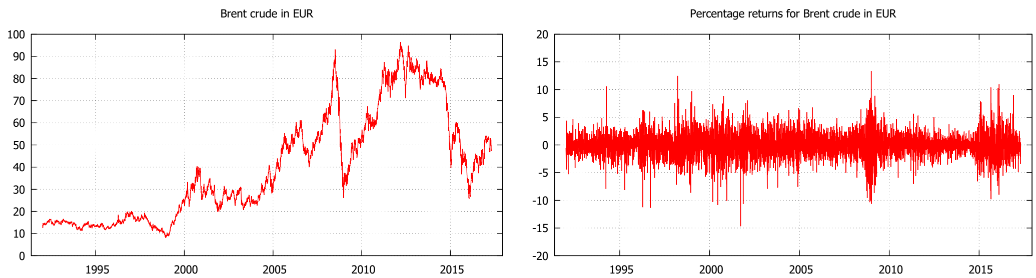
In most of our empirical part we will be working with percentage returns, which are defined as log-differences of prices multiplied by 100.

$$r_{i,t} = 100 \cdot [\ ln(y_{i,t}) - ln(y_{i,t-1})\ ] \tag{37}$$

4.1.1 Overview of oil price development

In the Figure 1 are presented graphs of Brent crude futures in EUR and its percentage returns.

The first notable downturn of oil price was during East Asian economic crisis in 1997-1998. Countries affected by the crisis were not suppliers of oil but it was rather the belief that the growth in the area would continue which



(a) Brent crude

(b) Returns of Brent crude

Figure 1: Price and percentage returns of Brent crude

boosted the prices prior to crisis (Hamilton, 2011). In 1999 Organization of the Petroleum Exporting Countries (OPEC) cut production to increase the price (Atkinson, 1999), oil consumption was increasing during this time as well, until the regression began in the U.S. in 2001. After that, there was a continuous growth of oil price from 2002 to 2008 as the economy was in expansion, demand going up. After 2005 the production of oil did not go up, while the demand was still strong, resulting in higher price growth up to 2008. The spike in 2008, with oil exceeding $140 was caused by high demand, stagnant production of oil and possibly by speculations in the oil futures market. On July 14th 2008 U.S. President Bush lifted an executive order banning oil drilling in the U.S (CNN, 2008). This, together with the global financial crisis caused prices to fall significantly, bottoming around $40. Early in 2009 OPEC started to cut the production (Blas, 2009), which caused prices to go steadily upwards during 2009 and 2010 as OPEC maintained the quotas and the demand grew. During 2011 prices stayed high, to which contributed the civil war in Libya, high demand for petroleum and oil transportation issues in the U.S.. In 2012 U.S. oil production rose, but is still remained net oil importer. At the same time disruption in petroleum production in South Sudan, Yemen, Syria and North Sea added an upward pressure on prices (U.S. Energy Information Administration, 2012; 2013). During the first half of 2014 prices remained similar to 2013 level but from

June, prices began to decline rapidly. This was caused by more factors: weak economic activity and low demand; America became the largest supplier of oil; despite turmoil in Iraq and Libya, their oil supply was not affected. On 27 November 2014 OPEC did not reach an agreement about its quotas which made prices fall even more (E.L., 2014). This situation was unfavourable for non-OPEC countries as they have much higher costs of extracting oil. During 2015 prices recovered slightly but fallen to 40 dollars at the end of year. In October 2016 OPEC cut the production, which was followed by non-OPEC countries cutting the production as well causing prices to increase (Fletcher, 2016).

4.1.2 Euro Stoxx indices

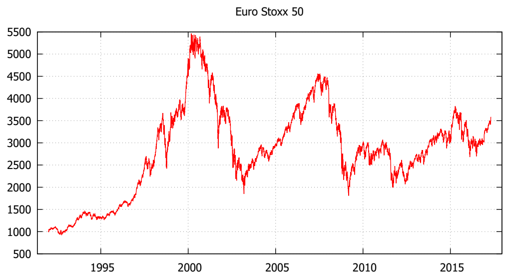
In Figure 2 are sector indices in levels together with corresponding returns.

From 1995 a dot-com bubble started to develop. It was caused by massive speculations into information technology stocks and burst at the end of the year 2000 (this affected mostly telecommunication, technology and consumer services sectors) increasing the return volatility in all sectors. In 2001, 9/11 attacks caused a drop, which together with the aftermath of the dot-com bubble caused stocks to decline until 2003. After that, stocks rise steadily until the end of the year 2007 when global financial crisis hit. Drop in 2010 was caused by sovereign debt crisis in Europe, followed in 2011 by U.S. rating being downgraded (Appelbaum, 2011). In the summer of 2015 Chinese stock market crashed (Hsu, 2016) and concerns around Greek debt crisis caused markets to downturn. Currently there is an upward trend in the stock market.

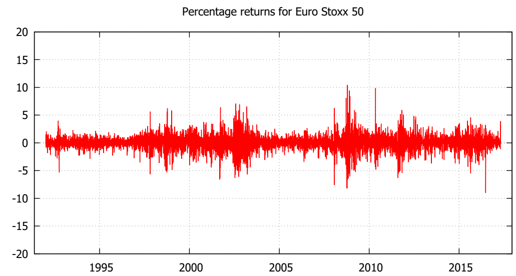
4.2 Descriptive statistics and preliminary analysis

In table 1 are presented summary statistics for returns of our variables.

Sample mean is similar for all the variables being between 0.01 and 0.03 percent. The highest in variance is Brent crude (4.4) followed by technology

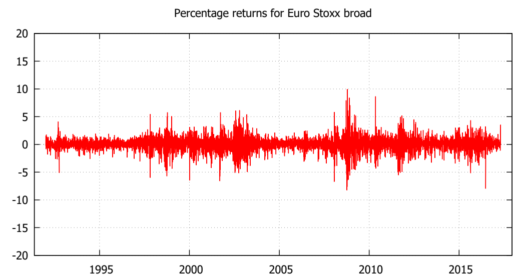


(a) Euro Stoxx 50



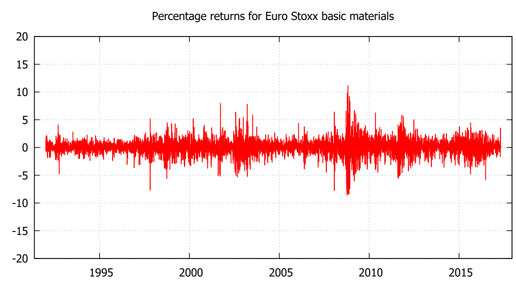
(b) Returns of Euro Stoxx 50

(c) Euro Stoxx broad



(d) Returns of Euro Stoxx broad

(e) Basic materials



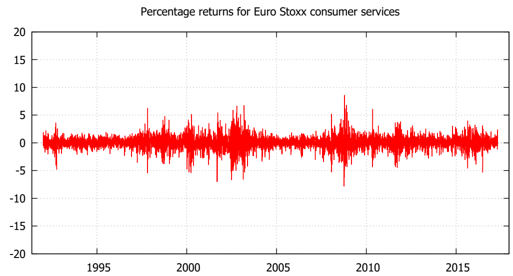
(f) Returns of basic materials

(g) Consumer goods

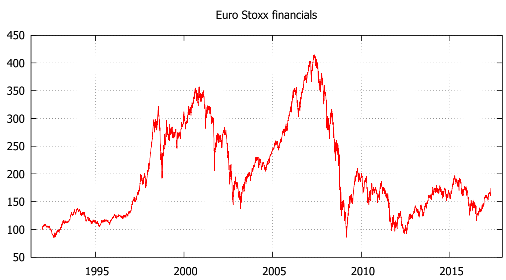
(h) Returns of consumer goods

Figure 2: Price and percentage returns of Euro Stoxx indices

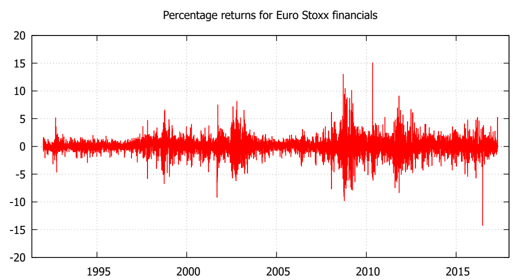
(i) Consumer services



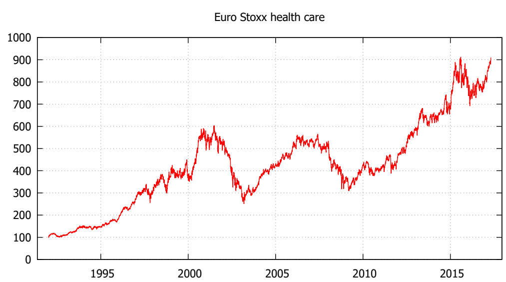
(j) Returns of consumer services



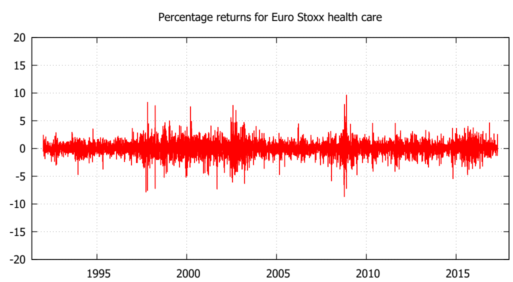
(k) Financials



(l) Returns of financials

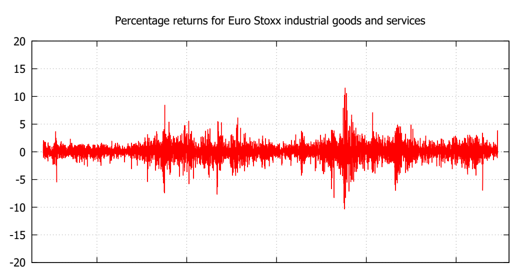


(m) Health care



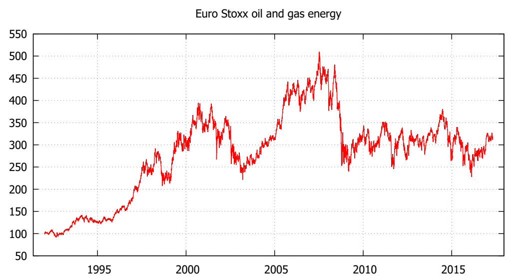
(n) Returns of health care

(o) Industrial goods and services

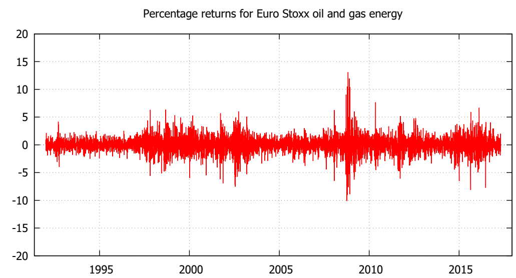


(p) Returns of industrial goods and services

Figure 2: Price and percentage returns of Euro Stoxx indices (cont.)

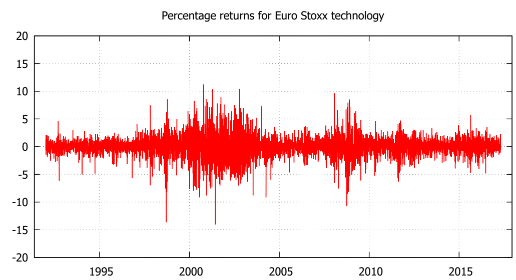


(q) Oil and gas energy

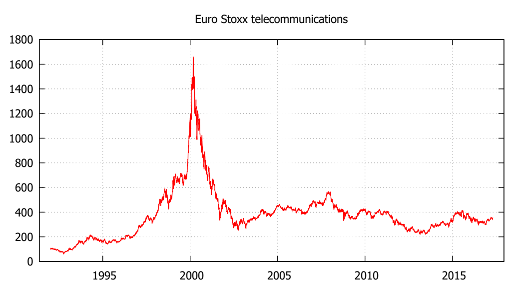


(r) Returns of oil and gas energy

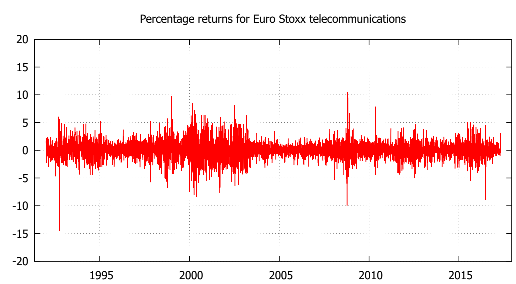
(s) Technology



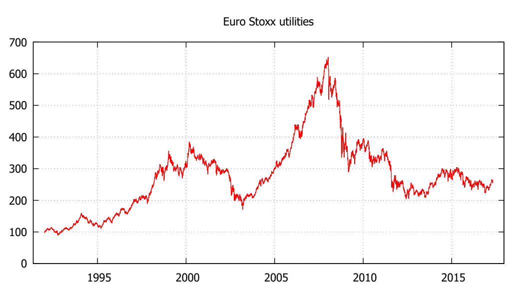
(t) Returns of technology



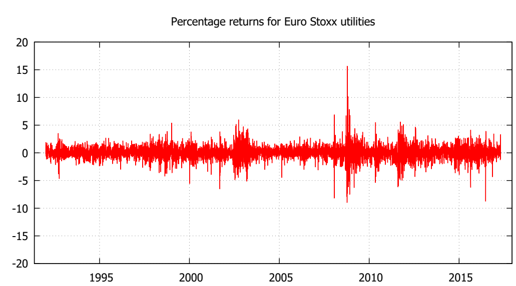
(u) Telecommunications



(v) Returns of telecommunications



(w) Utilities



(x) Returns of utilities

Figure 2: Price and percentage returns of Euro Stoxx indices (cont.)

Table 1: Summary statistics of percentage returns

	Mean	Variance	Skewness	$\hat{K}(x)$ - 3	JB	$\rho_{(\text{Brent, Euro Stoxx})}$
Brent Crude	0.0187	4.42	-0.13	3.23	2880.2	1.000
Euro Stoxx 50	0.0192	1.86	-0.11	5.14	7286.3	0.172
Euro Stoxx broad	0.0203	1.57	-0.21	5.18	7442.8	0.178
Basic materials	0.0306	1.81	-0.15	5.87	9508.9	0.165
Consumer goods	0.0273	1.60	0.61	23.47	151974.8	0.124
Consumer services	0.0172	1.37	-0.20	4.67	6052.2	0.139
Financials	0.0084	2.45	-0.05	7.94	17329.5	0.151
Healthcare	0.0333	1.68	-0.11	4.17	4799.8	0.101
Industrials	0.0313	1.81	-0.20	6.43	11419.2	0.172
Oil and gas	0.0175	2.08	-0.05	6.28	10854.7	0.274
Technology	0.0232	3.26	-0.21	4.98	6867.8	0.116
Telecommunications	0.0193	2.41	-0.07	4.45	5461.3	0.114
Utilities	0.0146	1.54	-0.03	9.20	23315.8	0.152

sector (3.26) and financials (2.45). All of the variables are skewed to the left with the exception of consumer goods, which are skewed to the right. There is an excess kurtosis in all cases, as expected, which is the highest in case of consumer goods, utilities and financials. Jarque-Bera normality test is strongly rejected in all cases (critical value of χ^2_2 at 10% significance level is 4.605 while Jarque Bera statistics are in thousands). The correlation between crude oil and indices returns is positive in all cases, which could be explained that crude oil serves as an indicator of economic situation in the world to some degree. So that while in some sectors increased price of oil increases costs, the overall effect seems to be positive for all sectors. We performed several test statistics on our data to make sure that it is suitable for the analysis we want to perform. Results are presented in the Table 2.

Checking for a unit root is the first step. In case of our level data, we are choosing between testing for level stationarity or for trend stationarity. To give the level data more linear structure, we take natural logarithms of it. After that, we test for trend stationary using augmented Dickey-Fuller

Table 2: Statistical tests

	ADF test		Cointegration	$Q^2(20)$	$LM(20)$
	Log-levels	Returns		Returns	Returns
Brent Crude	-2.238	-84.476***		2250.01***	704.57***
Euro Stoxx 50	-1.929	-39.441***	-2.239	5423.90***	1213.98***
Euro Stoxx broad	-2.049	-38.805***	-2.229	5367.90***	1222.28***
Basic materials	-3.176*	-80.297***		6679.77***	1516.28***
Consumer goods	-2.388	-59.509***	-2.668	2937.87***	1072.42***
Consumer services	-1.883	-38.949***	-2.426	5246.35***	2490.72***
Financials	-1.836	-38.513***	-2.274	4609.62***	936.052***
Healthcare	-1.969	-35.668***	-2.277	3045.46***	1436.48***
Industrials	-2.177	-76.653***	-2.218	6066.23***	1437.57***
Oil and gas	-2.040	-39.061***	-2.292	6300.99***	1182.92***
Technology	-1.850	-78.963***	-2.259	4793.93***	1089.85***
Telecommunications	-1.907	-76.677***	-2.239	2745.51***	773.31***
Utilities	-1.627	-59.857***	-2.448	5283.67***	1592.85***

Note: ***,**,*, denote the significance level (1% ,5% and 10% respectively) at which the null hypothesis of the test can be rejected.

test, where the Schwarz Bayesian information criterion was used to choose the number of lags in the equation. Series have a unit root present in them except for the basic materials sector where we reject the null hypothesis of unit root at 5% significance level and conclude it is stationary. Consequently basic materials will not be tested for cointegration.

When we look at the return series, from a visual inspection we can see that there are no structural breaks in them so we can utilize standard ADF test for level stationarity (otherwise there would be a need to include dummy variables to correct for this fact). Number of lags to be included in the equation is again selected based on BIC.

Now that we know that all our time series in log-levels are integrated of order one, we can continue with examining the existence of cointegration relationship. We regressed Brent crude on a constant, a time trend and a particular Euro Stoxx index and tested residuals from this regression for a unit root. Result of this test are presented in Table 2. None of the Euro Stoxx indices are found to be cointegrated with Brent crude, as we cannot reject the null hypothesis of cointegration at any conventional significance level.

To check that we have ARCH effects in the data we perform Ljung-Box Q tests and LM tests, both of them with 20 lags. Returns from both Brent crude and stocks show strong ARCH effects.

4.3 VAR BEKK-GARCH model

The model we are going to estimate is VAR(1;5) BEKK-GARCH(1,2). That is the first and the fifth lags of returns in the mean equation. In the variance equation we will add two lags of ARCH term and one lag of GARCH term.

Mean equation:

$$r_t = v + \Phi_1 r_{t-1} + \Phi_5 r_{t-5} + \varepsilon_t \qquad \varepsilon_t = H_t^{1/2} z_t \qquad z_t \sim i.i.d(0, I) \tag{38}$$

Conditional variance equation:

$$H_t = C'C + A_1' \varepsilon_{t-1} \varepsilon_{t-1}' A_1 + A_2' \varepsilon_{t-2} \varepsilon_{t-2}' A_2 + B' H_{t-1} B \tag{39}$$

We will test the following hypotheses using the Wald test:

To test Granger causality from Brent crude to stock market we set the null hypothesis of no Granger causality:

$$H_0 : \ \varphi\{1\}_{12} = \varphi\{5\}_{12} = 0 \tag{40}$$

Sector index is not Granger causing Brent crude:

$$H_0 : \ \varphi\{1\}_{21} = \varphi\{5\}_{21} = 0 \tag{41}$$

To test whether there is a volatility spillover from Brent crude market to sector stock index we will test:

$$H_0 : \ a\{1\}_{12} = a\{2\}_{12} = b_{12} = 0 \tag{42}$$

To test for volatility transmission in the other direction, from stocks to oil, we will test the null hypothesis:

$$H_0: \ a\{1\}_{21} = a\{2\}_{12} = b_{21} = 0 \tag{43}$$

Schwarz Bayesian information criterion was used to select appropriate specifications for our model as it does not choose over-parametrized model. This is important as each added lag to the model means that four additional parameters have to be estimated which could cause convergence issues. The ACF and PACF of fifth lag are the highest in most stock sectors so we tried models with specific lags in the mean equation along with the usual VAR(P) specification. Minimized BIC was in VAR(1;5) BEKK-GARCH(1,2), with 25 parameters to be estimated. The same specifications for all sectors will be useful for comparison purposes.

To estimate the models we first refined our initial estimates by using 20 simplex iterations, a derivative free-method which allows us to refine our initial estimates. Afterwards, BFGS (named after Broyden, Fletcher, Goldfarb, Shanno) algorithm was used, as was suggested by Khalfaoui et al. (2015). All of our models converged successfully and the number of iterations needed for convergence was between 47 and 92.

In Table 3 are reported results of the estimation, together with the results of Wald tests for each hypothesis and largest eigenvalues. Regarding the mean equation, the number in curly brackets of individual coefficients $\{i\}$ signifies ith lag in the VAR model, subscript number denotes the position in Φ_i matrix from VAR equation, similar applies for the variance equation where we differentiate between the first and second ARCH term.

We will start with the examination of the mean equation. In the mean equation of Brent crude its own first lag ($\varphi\{1\}_{11}$) is statistically significant in all cases, with coefficient being around -0.03. Fifth own lag of crude oil ($\varphi\{5\}_{11}$) is found to be insignificant for crude oil.

Looking at the results of the Wald test for Granger causality from stock

Table 3: Estimation results from VAR-BEKK-GARCH model

	Euro Stoxx 50	Euro Stoxx broad	Basic materials	Consumer goods	Consumer services	Financials
Mean equation of Brent crude returns						
$\varphi\{1\}_{11}$	-0.028**	-0.029**	-0.032***	-0.034***	-0.030**	-0.026**
$\varphi\{5\}_{11}$	-0.003	-0.004	-0.004	-0.007	-0.005	-0.004
$\varphi\{1\}_{12}$	0.015	0.021	0.044**	0.040**	0.018	0.006
$\varphi\{5\}_{12}$	-0.0230	-0.023	-0.007	-0.015	-0.015	-0.024*
v_1	0.036*	0.034	0.030	0.032	0.028	0.031*
Mean equation of Euro Stoxx index percentage returns						
$\varphi\{1\}_{21}$	0.013**	0.0102*	0.017***	0.0002	-0.003	0.003
$\varphi\{5\}_{21}$	0.008	0.009	0.016***	0.003	0.005	0.012**
$\varphi\{1\}_{22}$	-0.015	0.007	0.007	0.016*	0.026***	0.043***
$\varphi\{5\}_{22}$	-0.044***	-0.046***	-0.038***	-0.035***	-0.031***	-0.038***
v_2	0.057***	0.055***	0.068***	0.051***	0.047***	0.045***
Conditional variance equation						
c_{11}	0.143***	0.141***	0.140***	0.142***	0.146***	0.147***
c_{21}	-0.032	-0.026	-0.053*	-0.019	-0.003	-0.027
c_{22}	0.141***	0.135***	0.141***	0.149***	0.132***	0.117***
$a\{1\}_{11}$	0.209***	0.208***	0.191***	0.194***	0.192***	0.196***
$a\{1\}_{21}$	-0.020	-0.015	-0.008	-0.035	0.011	-0.00005
$a\{1\}_{12}$	-0.004	-0.004	-0.008	-0.004	-0.003	-0.001
$a\{1\}_{22}$	0.205***	0.212***	0.245***	0.234***	0.256***	0.248***
$a\{2\}_{11}$	-0.057**	-0.058*	0.098***	-0.084***	0.094***	-0.093***
$a\{2\}_{21}$	0.075***	0.086***	-0.075***	0.089***	-0.080***	0.057***
$a\{2\}_{12}$	0.016**	0.012*	-0.024***	0.025***	-0.019**	0.016**
$a\{2\}_{22}$	0.224***	0.225***	-0.165***	0.196***	-0.149***	0.191***
b_{11}	0.974***	0.974***	0.974***	0.975***	0.975***	0.974***
b_{21}	-0.001	-0.003	0.003	0.003	-0.006	-0.002
b_{12}	0.003	0.003	0.005**	0.003	0.003	0.002
b_{22}	0.945***	0.943***	0.946***	0.942***	0.946***	0.947***
Largest eigenvalue of $[\Sigma(A_i \otimes A_i)+\Sigma(B_i \otimes B_i)]$						
	0.995	0.995	0.995	0.995	0.996	0.997
Wald test H_0: Brent crude does not Granger cause X						
	6.367**	5.661*	13.299***	0.228	1.328	5.767*
Wald test H_0: X does not Granger cause Brent crude						
	2.628	2.730	5.144*	5.790*	1.543	3.654
Wald test H_0: there are no transmission of volatility from Brent crude to X						
	6.503*	5.195	10.052**	12.233***	5.357	5.595
Wald test H_0: there are no transmission of volatility from X to Brent crude						
	19.482***	25.992***	30.285***	26.944***	11.312**	18.342***

Notes: ***, **, * indicate significance of coefficients (i.e. rejection of H_0: coefficient equals zero) at 1%, 5%, 10% significance level respectively. In the case of Wald test it indicates rejection of the null hypothesis of joint significance of coefficients.

Table 3: Estimation results from VAR-BEKK-GARCH model (cont.)

	Healthcare	Industrials	Oil and gas	Technology	Telecommunications	Utilities
Mean equation of Brent crude returns						
$\varphi\{1\}_{11}$	-0.025**	-0.029**	-0.031**	-0.028**	-0.029**	-0.025**
$\varphi\{5\}_{11}$	-0.006	-0.005	-0.001	-0.006	-0.006	-0.004
$\varphi\{1\}_{12}$	-0.022	0.019	0.024	0.013	0.009	0.005
$\varphi\{5\}_{12}$	-0.011	-0.003	-0.011	-0.008	-0.019	-0.012
v_1	0.032	0.028	0.030	0.029	0.032	0.034
Mean equation of Euro Stoxx index percentage returns						
$\varphi\{1\}_{21}$	-0.005	0.010*	0.088***	0.005	-0.018**	0.010
$\varphi\{5\}_{21}$	0.004	0.015***	0.011	0.013	0.005	-0.005
$\varphi\{1\}_{22}$	-0.030**	0.044***	-0.035***	0.031**	0.065***	0.007
$\varphi\{5\}_{22}$	-0.045***	-0.037***	-0.024**	-0.027**	-0.011	-0.013
v_2	0.054***	0.059***	0.046***	0.058***	0.041***	0.052***
Conditional variance equation						
c_{11}	0.153***	0.136***	0.146***	0.161***	0.140***	0.146***
c_{21}	-0.050	-0.032	-0.037	0.035	0.006	-0.035
c_{22}	0.156***	0.123***	0.140***	0.127***	0.149***	0.174***
$a\{1\}_{11}$	0.178***	0.198***	0.186***	0.201***	0.190***	0.171***
$a\{1\}_{21}$	-0.024	0.002	-0.010	-0.017	-0.016	0.022
$a\{1\}_{12}$	0.019*	-0.007	-0.008	0.010	0.009	0.005
$a\{1\}_{22}$	0.256***	0.225***	0.252***	0.199***	0.216***	0.264***
$a\{2\}_{11}$	0.124***	-0.078***	-0.113***	0.090***	-0.092***	0.128***
$a\{2\}_{21}$	-0.034	0.096***	0.057**	-0.066***	0.063***	-0.045
$a\{2\}_{12}$	-0.047***	0.008	0.0134*	0.007	0.008	-0.022***
$a\{2\}_{22}$	-0.125***	0.199***	0.118***	-0.137***	0.172***	-0.137***
b_{11}	0.973***	0.975***	0.973***	0.972***	0.975***	0.975***
b_{21}	0.014	-0.007	0.0103	-0.003	-0.004	0.001
b_{12}	0.003	0.003*	0.005**	-0.003	0.00002	0.003
b_{22}	0.945***	0.949***	0.953***	0.967***	0.956***	0.941***
Largest eigenvalue of $[\Sigma(A_i \otimes A_i)+\Sigma(B_i \otimes B_i)]$						
	0.995	0.995	0.995	0.995	0.995	0.995
Wald test H_0: Brent crude does not Granger cause X						
	0.973	9.173**	168.746***	2.730	6.282**	3.444
Wald test H_0: X does not Granger cause Brent crude						
	2.043	1.563	1.945	1.669	2.186	0.418
Wald test H_0: there are no transmission of volatility from Brent crude to X						
	23.939***	3.090	5.923	0.846	3.126	11.391***
Wald test H_0: there are no transmission of volatility from X to Brent crude						
	4.980	24.083***	23.190***	19.173***	9.565**	11.321**

Notes: ***, **, * indicate significance of coefficients (i.e. rejection of H_0: coefficient equals zero) at 1%, 5%, 10% significance level respectively. In the case of Wald test it indicates rejection of the null hypothesis of joint significance of coefficients.

sectors to oil, stock sector index is Granger causing oil in the case of basic materials and consumer goods at 10% significance level. Fifth lag of financial sector slightly affects oil (at 10% level, but we cannot reject the null hypothesis of the Wald statistic).

Turning to the mean equation of different stock sectors we find that the majority of them are affected by their own past values ($\varphi\{1\}_{22}$, $\varphi\{5\}_{22}$) as well (except for utilities). Fifth lag was significant in more cases having with negative coefficients ranging between -0.01 and -0.04 while the first lag has mostly positive coefficients.

Brent crude Granger causes stock return changes in seven cases. Out of these significant coefficients ($\varphi\{1\}_{21}$, $\varphi\{5\}_{21}$), only telecommunication sector has a negative sign. The positive coefficients support the intuition that increased oil price reflects increased demand due to economic growth which can outweigh the increased costs. This result is consistent with the findings of Degiannakis et al. (2013) who suggest as an explanation that the increased price of oil causes uncertainty in the telecommunications investment thus decreasing the stock value. These findings are also consistent with Arouri and Nguyen (2010) who reach the same conclusion regarding European stock sectors, finding positive causality from oil to stock sectors in most cases (in the same sectors as in our analysis)

Particular coefficients of the variance equation are not easy to interpret due to the quadratic form of them. All the diagonal elements of the ARCH term ($a\{1\}_{11}$, $a\{1\}_{22}$, $a\{2\}_{11}$, $a\{2\}_{22}$) and the GARCH term (b_{11}, b_{22}) are significant in all cases. Coefficients of ARCH term are quite low for both oil and stock sectors (there are squared or cross multiplied in the variance equation) so the immediate effect of the shock will not be that severe. When we look at the GARCH terms, all the diagonal coefficients are significant and high, with crude oil having higher persistence than sector indices. Out of sector indices, technology has the highest persistence.

Looking at the off-diagonal elements which determine the volatility spillovers from oil to stock sectors the first lag of ARCH term ($a\{1\}_{12}$) is not significant in all cases but one (healthcare sector is significant at 10% level). The second lag of ARCH term ($a\{2\}_{12}$) is significant in 9 sectors. Although the coefficients $a\{2\}_{12}$ are significant in most cases we must note that the coefficients are low and when they are squared in the conditional variance equation they get close to zero. The GARCH coefficients (b_{12}) are not significant in most cases. Regarding the results of the Wald test, there is volatility transmission from oil to stocks in 5 cases out of 12, and oil and gas energy sector is close to significance(with the p-value of 0.115). This result is consistent with findings of Arouri et al. (2011). They study slightly different sectors than us but the three sector that showed no volatility transmission from crude oil to stock sector in their study were telecommunications, industrials and technology. These three sectors have the lowest Wald statistic out of the sectors we studied (thus being unable to reject H_0).

Regarding the volatility transmissions from stock sectors to crude oil the first lag of ARCH term ($a\{1\}_{21}$) and GARCH term (b_{21}) are insignificant in all cases and the second lag of ARCH term ($a\{2\}_{21}$) is highly significant in all cases except for healthcare sector. Volatility transmission from stocks to Brent crude was found to be significant by the Wald test in 11 cases, where only the healthcare sector seems to be unaffected by oil. Similar results with regards to spillovers were found in the U.S. stock sectors and oil analysis by Arouri et al. (2011). In the same study they examined the European stock market (Stoxx Europe indices) as well, but found volatility spillovers going from stock sector to oil only in case of financial and utilities sectors. This difference could be potentially caused by the different stocks indices chosen, as euro area might be more interlinked with oil than Europe as a whole. This could be because countries included in the Euro Stoxx index have higher petroleum consumption per capita (BP Global, 2017). Other reasons for this could be different frequency or span of the data (weekly data from 1998 to 2009 were used in their study).

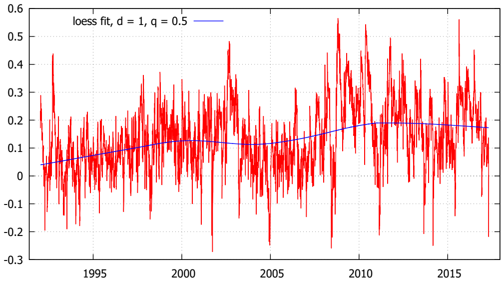
Table 4: Analysis of residuals

	Q(10)		$Q^2(20)$		Jarque Bera		Q(10)	LM(20)
	Brent	Euro Stoxx	Brent	Euro Stoxx	Brent	Euro Stoxx	Multivariate	Multivariate
Euro Stoxx 50	13.87	8.59	20.49	17.26	625.6***	770.7***	29.83	153.07
Euro Stoxx broad	14.02	7.40	20.69	17.07	630.3***	859.5***	29.63	152.83
Basic materials	16.11*	10.21	22.68	18.54	664.5***	690.6***	29.98	180.90
Consumer goods	16.78*	12.56	23.36	15.67	621.7***	376.8***	31.34	170.24
Consumer services	15.41	9.04	22.42	15.18	634.6***	296.9***	37.12	158.47
Financials	14.52	10.23	21.63	22.42	642.6***	1135.1***	29.64	212.74**
Health care	17.58*	12.97	24.65	19.99	679.1***	602.3***	46.20**	182.17
Industrials	15.34	7.032	22.26	23.98	650.8***	397.3***	22.09	188.87
Oil and gas energy	17.90*	19.19**	24.57	25.46	698.2***	343.0***	49.77**	194.49
Technology	15.57	6.43	21.67	11.77	600.6***	1579.5***	32.86	165.71
Telecommunications	18.06*	9.32	24.62	28.92*	591.1***	815.8***	37.08	202.69
Utilities	18.46**	9.43	26.19	11.80	691.9***	1069.5***	31.53	211.68*

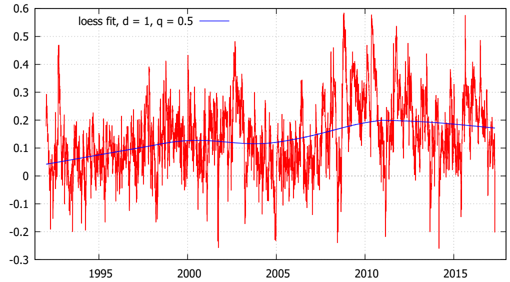
Note: ***,**,*, denote the significance level (1% ,5% , 10%) at which the null,hypothesis of the test can be rejected.

Eigenvalues of $[\Sigma(A_i \otimes A_i)+\Sigma(B_i \otimes B_i)]$ are in all cases less than one, implying that all our models have stationary unconditional covariance. As the eigenvalues are extremely close to one we can say that there is high co-persistence of volatility in the data but it is slowly reverting to the mean.

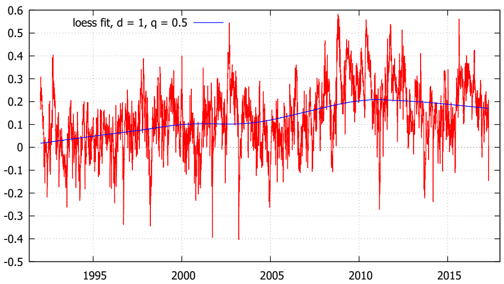
Individual conditional correlations between oil and sectors are shown in figure 3. Because the data is greatly fluctuating, locally weighted scatter-plot smoothing regression was fitted to the correlations allowing us to spot changes over time more easily. From these graphs we can see that in almost all cases correlation increased overall, being higher during crises (more pronounced during the financial crisis than in case of dot.com bubble). Oil and gas sector has a notably growing conditional correlation, compared to other sectors, with values from the beginning of period being around 0.1 and at the end around 0.4. These findings are consistent with the findings of Degiannakis et al. (2013) who also found evidence of greater conditional correlation between stock sectors and oil during crisis period.



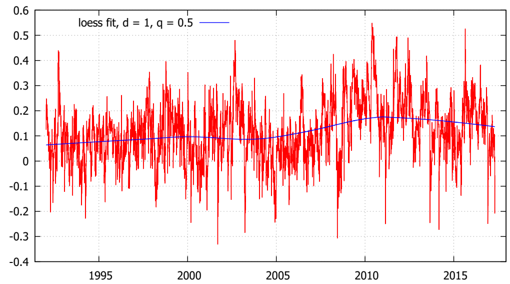
(a) Euro Stoxx 50



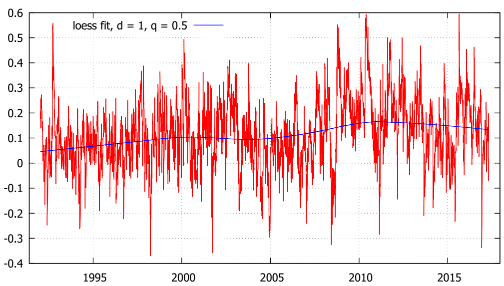
(b) Euro Stoxx broad



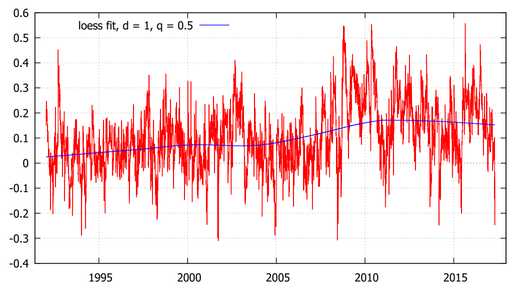
(c) Basic materials



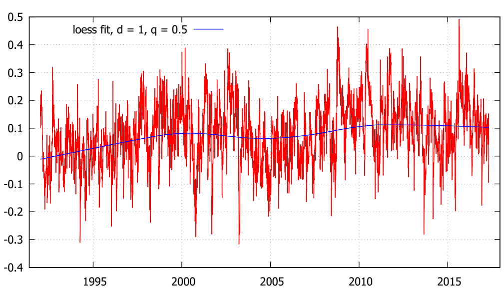
(d) Consumer goods



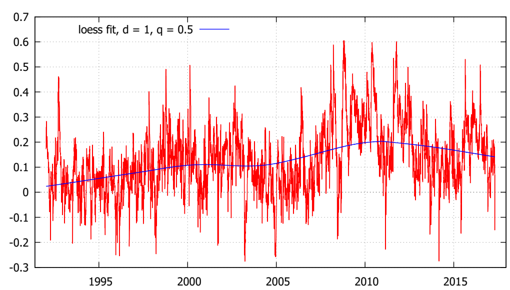
(e) Consumer services



(f) Financials

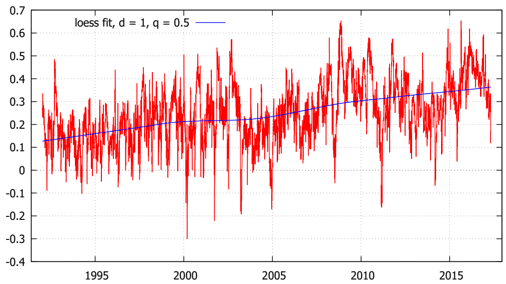


(g) Health care

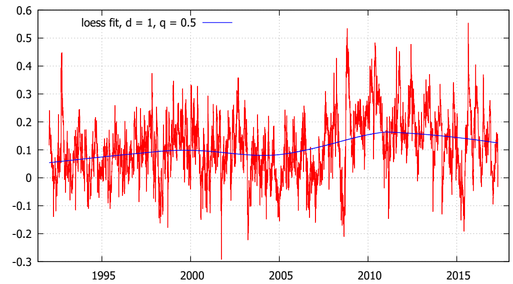


(h) Industrial goods and services

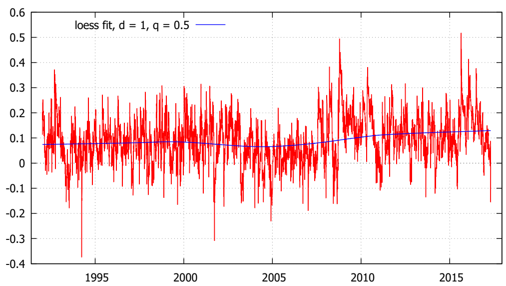
Figure 3: Conditional correlations between crude oil and stock sectors



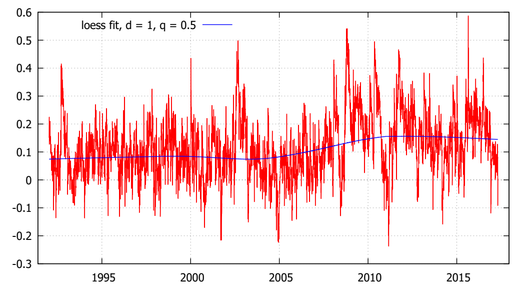
(i) Oil and gas energy



(j) Technology



(k) Telecommunications



(l) Utilities

Figure 3: Conditional correlations between crude oil and stock sectors (cont.)

4.3.1 Model evaluation

Results of standardized residual testing are presented in Table 4. We test both univariate and multivariate standardized residuals for residual autocorrelation and for residual ARCH effects.

For univariate testing we used Ljung-Box Q statistic with 10 lags and Ljung-Box test for squared residuals with 20 lags. There might be weak residual autocorrelation in some of the residuals, however in all sectors, at 1% significance level, we cannot reject the null hypothesis of no autocorrelation. There seems to be no significant ARCH effects at 5% significance level, which supports the choice of the model.

Regarding the multivariate testing, we used multivariate Q test with 10 lags and multivariate ARCH test with 20 lags. At 1% level, we can conclude that none of the model joint standardized residuals contain residual autocorrelation or ARCH effects.

Jarque Bera normality test was applied on univariate standardized residuals, with null hypothesis still being rejected. However the Jarque Bera statistic is greatly reduced compared to raw returns (in Table 1).

Overall, it seems from these tests that the model selected fits reasonably well to all sectors supporting the choice of model from GARCH family.

4.4 Optimal portfolio weights and hedge ratios

In this subsection we will present possible implications of our results (particularly of the estimated conditional covariance matrix) to portfolio management.

One of them is risk minimizing portfolio weight of holding two types of assets, oil and stock sector which can be computed as (Kroner and Ng, 1998):

$$\omega_t = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}} \tag{44}$$

the optimal portfolio holding of crude oil at time t is following:

$$\omega_t^* = \begin{cases} 0 & \text{if } \ \omega_t < 0 \\ \omega_t & \text{if } \ 0 \leq \omega_t \leq 1 \\ 1 & \text{if } \ \omega_t > 1 \end{cases} \tag{45}$$

and the optimal holding of the stock sector portfolio is $(1 - \omega_t^*)$. In this case the investor is limited to long time investment in two sectors and cannot use hedging strategies.

Second, we compute risk minimizing hedge ratios (Kroner and Sultan, 1993). To hedge against a long position \$1 in crude oil an investor should short \$$\beta$ of stocks, the optimal hedge ratio is following:

$$\beta_t = \frac{h_{12,t}}{h_{22,t}} \tag{46}$$

However, as noted by Kroner and Ng (1998), optimal portfolio weights and hedging ratios differ depending on the type of model chosen to estimate the conditional covariance matrix so cautiousness is advised when selecting the model.

Table 5: Portfolio weights and hedge ratios

	1992-2017		2004-2007		2008-2010		2011-2017	
	ω^*	β	ω^*	β	ω^*	β	ω^*	β
Euro Stoxx 50	0.263	0.204	0.188	0.114	0.343	0.178	0.320	0.253
Euro Stoxx broad	0.230	0.227	0.167	0.129	0.305	0.185	0.282	0.282
Basic materials	0.265	0.184	0.217	0.117	0.372	0.138	0.322	0.261
Consumer goods	0.235	0.182	0.185	0.094	0.303	0.181	0.275	0.234
Consumer services	0.208	0.190	0.156	0.082	0.227	0.242	0.231	0.245
Financials	0.313	0.125	0.208	0.046	0.504	0.128	0.440	0.179
Healthcare	0.267	0.109	0.222	0.029	0.261	0.167	0.289	0.161
Industrials	0.261	0.187	0.220	0.098	0.399	0.144	0.301	0.257
Oil and gas	0.256	0.380	0.197	0.373	0.318	0.164	0.317	0.441
Technology	0.372	0.139	0.314	0.072	0.404	0.153	0.341	0.197
Telecommunications	0.336	0.126	0.210	0.060	0.280	0.162	0.350	0.163
Utilities	0.239	0.179	0.186	0.085	0.275	0.170	0.314	0.223

Average portfolio weights and average hedge ratios are presented in Table 5. Portfolio weights reported are the ratio of crude oil that should an investor own in a portfolio, the rest of the portfolio will be a particular sector stocks. To better see the changes of these measures over time, the last 14 years of our sample were divided into three sub-samples (pre-crisis period of 2004-2007, the global financial crisis 2008-2010, after the crisis period of 2011-2017).

The average portfolio weight for oil ranges between 21% for consumer services to 37% for technology sector. This result suggests that investors should hold more stocks than oil in their portfolio to keep the risk minimized. These weights vary over time, weight of oil in oil-stock portfolio increases in all cases during the 2008 crisis and slightly decreases in the last sub-sample in most cases.

The average hedge ratios vary between 11% for healthcare and 38% for oil and gas sector. Ratios are higher during the crisis period (2008-2010) compared to 2004-2007 period with only one exception of oil and gas sector where the ratio went down from 37% to 16%. The last subsample has lower hedging effectiveness compared to two previous periods because the hedge ratios were higher. The least expensive hedges in the last subsample are in healthcare, telecommunications and financial sectors (16.1%, 16.3% and 18% respectively)

Conclusion

The main objective of this thesis was to find whether there are volatility transmissions between crude oil returns and stock sector returns from euro area. We presented theory needed for our analysis including tests for a proper model selection and hypothesis testing. An analysis was done using bivariate VAR BEKK-GARCH model on a daily data. Afterwards optimal portfolio weights and hedge ratios were calculated.

Regarding our regults, we found in the half of the cases that oil returns are Granger causing stock sector returns while the opposite relationship was found only in two sectors. Regarding volatility spillovers, we found statistically significant volatility transmissions from stocks to oil in most cases, while from oil to stocks some significant results were found but of a nominal effect. Optimal portfolio weights for crude oil are relatively low (mostly from 20% to 30%) suggesting that investors should have in their portfolio more particular sector stocks than oil. Hedge ratios were obtained as well, with results suggesting that in some stock sectors an inexpensive hedging possibilities can be found. The results give us an insight into the relationship between different markets and how shocks are transmitted between them.

As we did not consider underlying causes of these relationships it could be the topic for a further research. Our analysis assumed that the impact of a positive shock is the same as of a negative shock so it might be useful to consider asymmetric terms to get further information about the market behaviour.

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