The impact of oil prices on international financial markets

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Abstract
This paper investigates the impact of oil prices and the volatility of oil prices on the main stock market indices. Our analysis includes the returns on the DJIA, S&P500, NASDAQ, FTSE100, DAX, NIKKEI225 and the returns on the WTI crude price. We consider the oil price returns and volatility of oil prices as explanatory variables in the mean equation of the stock market indices. Using the multivariate GARCH model we check the links between volatilities of stock market returns and oil price returns. We detect different patterns of the relationship between these two variables. We observe the negative relationship between the returns on DJIA, S&P500 and DAX and the daily oil prices changes. The American stock markets react to the volatility of the oil prices. S&P500 and FTSE react to the significant increases in the oil prices and DJIA to significant decreases in the oil prices. The bi-variate Extended Constant Conditional Correlation GARCH model shows the contemporaneous links between volatilities of oil prices and volatilities of DJIA and DAX and the spillover effect between volatility of oil prices and volatilities of DJIA and S&P500.

JEL classification: F3, G1, C5, C14

Keywords: oil prices, volatility transmission, GARCH, stock markets

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1 Introduction

Oil is one of the important resources in the economy and plays the crucial role in setting the economic policies. The relation between oil price changes, economic activity and employment is an issue that has been studied during long time. In a pioneer work Hamilton (1983) shows that oil price increases are responsible for almost every post World War II US recession, except the one in 1960. Mork et al. (1994) survey the extensive literature on relationship between oil prices and macroeconomy and evidence a clear negative correlation between oil prices and measures of output or employment.

The oil prices affect economy through many channels. The initial impact of changes in oil prices is through the transfer of income from consumers to producers, and on the international level from oil-importing countries to oil-exporting countries. Higher oil prices increase production costs in almost all industries, particularly in such energy-intensive sectors like transport, and are likely to lead to an increase in inflation, which in turn will depend on the extent to which companies pass the higher oil prices on their final product, on the consequences for wages and on the effectiveness of the anti-inflationary policies. A tightening of macroeconomic policies in response to higher oil prices and increasing inflation would have an impact on global financial markets. This impact of higher oil prices on disposable income, business profits and inflation lowers the value of financial assets.

Stock prices can be regarded as the discounted values of expected future cash flows the company will generate. Oil prices can affect both the expected cash flows and discount rates. The increasing oil prices rise the cost of production and lower the benefits of the companies. The expected discount rate is the sum of the expected inflation rate and expected real interest rate, both of which may in turn depend on oil prices. Rising oil prices are often indicative of inflationary pressures which central banks can control by raising interest rates. Higher interest rates make bonds look more attractive than stocks leading to a fall in stock prices. The overall impact of rising oil prices on stock prices depends of course on whether a company is a consumer or producer of oil and oil related products.

Although a bulk of economic research has studied the relation between oil price changes and economic activity, there is little research on the relationship between oil price changes and financial markets.
In the related literature most of the authors (Jones and Kaul (1996), Huang et al. (1996), Sadorsky (1999)) focuses on the linear relationship between oil price returns and stock returns. Huang et al. (1996) conclude that oil futures returns do lead only individual oil companies and the petroleum index sector but do not have impact on S&P500 stock index or other sector indices; Sadorsky (1999) shows that oil prices and the volatility of oil prices do affect real stock returns and that the oil price increases have a greater impact on economic activities than oil price decreases. Nandha and Faff (2008) analyze monthly returns of 35 global industry indices and conclude that oil price rises have a negative impact on equity returns for all sectors except mining, and oil and gas industries and provide little evidence of any asymmetry in the oil price - stock market indices relationship.

Understanding of the relationship between stock markets and oil prices is of highest interest of stock market investors, especially in the period when the oil prices are more and more volatile and the levels of oil prices changes in the shorter period of time. Detection of impact of oil price returns on the stock market returns and spill-over effect from volatility of oil prices to volatility of stock markets will allow setting the best investment strategies. Our analysis will also permit to understand the nature of the relationship between oil prices and stock markets.

In this work we use the daily data for the period 1984 - 2005 to analyze and assess the relation between oil price returns, oil price volatility and returns of stock indices. We will consider the prices of WTI crude and six main world stock indices - DJIA, NASDAQ, S&P500, DAX, FTSE100 and NIKKEI225.

We investigate first the linear relationship between returns on oil prices and stock market returns taking the oil variables as the explanatory variable in the mean equation. In the second step we consider the non-linear transformations of oil prices. In the mid 1980s the economist observed the change in the oil prices – macroeconomy relationship that became non-linear. Hamilton (1996) and Lee et at. (1995) therefore redefine the measure of the oil price changes and propose the non-linear transformation of the oil price returns. Further we investigate the threshold effect in the relationship between oil prices and stock markets. Finally we analyze the links between the volatilities of the returns of oil prices and stock markets in the dynamic setting using the bi-variate multivariate GARCH model.
Our analysis shows different patterns of the relationship between oil prices and stock markets. We observe the negative relationship between the returns on DJIA, S&P500 and DAX and the daily oil prices changes. In line with the economic theory the increases in the oil prices lead to the negative returns of stock markets. At the same time the American stock markets react to the volatility of oil prices. S&P500 and FTSE react to the significant increases in the oil prices and DJIA to significant decreases in oil prices.

The bi-variate Extended Constant Conditional Correlation GARCH models show the contemporaneous links between volatilities of oil prices and volatilities of DJIA and DAX and the dynamic links between volatility of oil prices and volatilities of DJIA and S&P500.

The paper is organized as follows. Section 2 discusses the specification of the models we use in this paper. Section 3 presents the data. In Section 4 we discuss the statistic properties of the data and present the empirical results. Section 5 concludes and sketches further research possibilities. In the appendix we present the specifications tested in this paper, discuss the tests used and present the figures and detailed results of the estimation.

2 Methodology

This section presents the specification of the models estimated in the empirical part. As mentioned in the introduction we analyze the impact of oil prices on the stock markets on two levels - on the level of returns and the level of volatility. In the first part we investigate, using both the linear and non-linear specification the impact of changes in oil prices on the returns on stock prices. In the second part of the analysis we concentrate on the links between the volatilities and transmission of shocks between oil prices and stock markets.

The starting point is to determine the GARCH models for each series of returns. We define the best specification of the conditional mean by considering the Schwarz Information Criterion (BIC), that takes the lowest value for the best model.

To check the presence of GARCH effects in the conditional volatility equation we use the ARCH-LM test proposed by Engle (1982) and to detect
the leverage effects in conditional volatility (asymmetry) we consider the
Sign Bias, Negative and Positive Size Bias tests proposed by Engle and Ng
(1993). All the tests are discussed in the appendix.

For the conditional variance for each of the time series we consider
the linear GARCH (see Bollerslev (1986)) and non-linear GARCH mod-
el models. To account for observed asymmetry in the volatility of stock markets
we consider the GJRGARCH model of Glosten et al. (1993). The sim-
plest representation of these models is \( \text{GARCH}(1,1) \) in which the condi-
tional volatility evolves as \( h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \) and \( \text{GJRGARCH}(1,1) \)
- \( h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^\gamma - \varepsilon_{t-1}^2 + \beta h_{t-1} \), where \( \varepsilon_t \) are the residuals from
the mean equation and \( S_{t-1}^\gamma \) is the dummy variable that takes the value of 1
when the \( \varepsilon_{t-1} < 0 \) and 0 otherwise. The leverage effect is captured by the
use of this dummy variable - the positive news have an impact of \( \alpha \), while
the negative of \( \alpha + \gamma \).

2.1 Linear specification

The first analysis concentrates on the impact of returns on oil prices on each
stock market separately.

Specification 1 incorporates the returns on oil prices as the explanatory
variable in the mean equation. This specification tests if there is impact of
oil prices on each of the stock markets. We also take the lagged returns of
oil prices as the explanatory variable (Specification 2) to investigate if the
changes of oil prices in the past influence the stock markets contemporane-
ously.

Further we construct the dummy variable that accounts for the sign of
the returns on oil prices to see if there is an asymmetry in this relationship
(Specification 3). This specification coincides with the one proposed by

Specification 4 takes the estimated conditional volatility of returns on
oil prices (modelled by GARCH) as the explanatory variable in the mean
equation of the returns on stock markets. In this way we can analyze if the
returns of the stock markets depend on the volatility of oil prices. Sadorsky
(1999) and Lee et al. (1995) use the GARCH model for computation of oil
price volatility.
2.2 Non-linear specification

The first approach in investigating the impact of oil prices of the macro-economic variables was the linear specification. By the mid-1980s, this estimated linear relationship between oil prices and real activity began to lose significance. The declines in oil prices that occurred over the second part of the 1980s were found to have smaller positive effect on economic activity than the predictions made by the linear models. This motivated researchers to propose the non-linear transformations of the oil price variables. In this paper we use two of them - \textit{NOPI} (net oil price increases) proposed by Hamilton (1996) and \textit{SOPI} (scaled oil price increases) proposed by Lee \textit{et al.} (1995).

Hamilton (1996) claims that it seems more appropriate to compare the prevailing price of oil with what it was during the previous year, rather than during the previous quarter. He therefore defines a new measure, the NOPI - \textit{net oil price increase}. In our setting we define the NOPI$^t$ as the amount by which the return on oil prices on day \( t \), \( r_{oil t} \), exceeds the maximum value over the previous \( n \) days; and 0 otherwise. We will consider \( n = 5, 6, ..., 10 \) to account for the maximum in the period of one to two weeks.

We define the NOPI$^t$ variable as

\[
NOPI^t = \max \{0, r_{oil t} - \max \{r_{oil t-1}, r_{oil t-2}, ..., r_{oil t-n}\} \}
\]

The specification proposed by Lee \textit{et al.} (1995) \textit{SOPI} - scaled oil price increases focuses on volatility of returns on oil prices and argues that the oil price increases after a period of price stability have stronger macroeconomic consequences than those that are corrections to the greater oil price decreases. Lee \textit{et al.} (1995) propose to use the GARCH model with the appropriate mean specification and define SOPI$^t$ as the positive standardized residuals

\[
SOPI^t = \max \left(0, \frac{\hat{\varepsilon}_t}{\sqrt{\hat{h}_t}}\right)
\]

where \( \hat{\varepsilon} \) are the estimated residuals from the mean equation and \( \hat{h}_t \) is the estimated conditional variance of returns on oil prices.
Finally we will use the Hansen (2000) procedure to test for the threshold effect based on a threshold regression model where observations fall into classes or regimes that depend on the unknown value of the observed variable. In this setting $y$ is the dependent variable, $x$ is the explanatory variable for which we want to test the presence of the threshold effect, $z$ is the set of exogenous explanatory variables and $I(\cdot)$ is the indicator function

$$y_{it} = \beta_0 + \beta_{a1}x_{it}I(x_{it} \leq \gamma) + \beta_{a2}x_{it}I(x_{it} > \gamma) + \beta_zz_{it} + u_{it}$$

Hansen (2000) recommends obtaining the least square estimate $\hat{\gamma}$ as the value that minimizes the sum of squared errors $S_I(\gamma)$. We test the significance of the detected threshold using the following hypothesis

$$H_0 : \beta_{a1} = \beta_{a2}$$
$$H_1 : \beta_{a1} \neq \beta_{a2}$$

in which $H_0$ states that the linear model is appropriate whereas $H_1$ is in favour of the threshold model.

One complication is that $\gamma$ is not identified under the null so that the classical tests do not have standard distribution and critical values cannot be read off from the standard distribution tables. Hansen(1996) proposes the likelihood ratio test statistic and the bootstrapping method for finding the $p$-value. We present the details of the test in the appendix.

2.3 Volatility linkages

Following the success of the ARCH and GARCH models in describing the time-varying variances of economic data in the univariate case the extension to the multivariate case has been developed immediately. Bauwens et al. (2006) discuss the most important developments in multivariate ARCH-type modelling. Several applications of multivariate GARCH models (MV-GARCH, thereafter) can be found in the financial literature: Bollerslev (1990), Karolyi (1995), Tse and Tsui (2000), among others. The multivariate GARCH models offer a suitable framework to investigate the nature of the transmission of shocks among financial time series.

The extension from a univariate GARCH model to the $N$-variate model requires allowing the conditional variance-covariance matrix of the $N$ dimensional zero mean random variables $\varepsilon_t$ (errors from the mean equation)
to depend on the elements of the information set. Let \( \{z_t\} \) be a sequence of \((N \times 1)\) i.i.d vector such that

\[
z_t \sim F(0, I_N)
\]

with \( F \) continuous density function. Let \( \{\varepsilon_t\} \) be a sequence \((N \times 1)\) random vectors defined as

\[
\varepsilon_t = H_t^{1/2} z_t
\]

where

\[
E_{t-1}(\varepsilon_t) = 0, \quad E_{t-1}(\varepsilon_t \varepsilon_t') = H_t
\]

where \( H_t \) is a matrix \((N \times N)\) positive definite.

In our paper we estimate the Extended Constant Conditional Correlation GARCH model (ECCC-GARCH hereafter) which is the extension proposed by Jeantheau (1998) of the Constant Conditional Correlation GARCH model (CCC-GARCH) (see Bollerslev 1990). This model allows the interactions among volatilities of time series.

Engle and Sheppard (2002) propose a test for constant versus dynamic correlation structure. We apply this test for the bi-variate structure (stock market returns and oil returns). The test rejects the dynamic nature of the conditional correlation between these series therefore ECCC-GARCH best suit the nature of the constant correlation.

2.3.1 ECCC-MVGARCH model

Bollerslev (1990) introduces the Constant Conditional Correlation GARCH model. In this model, the conditional correlation matrix is time invariant. The assumption of constant correlation makes estimating a large model feasible and ensures that the estimator is positive definite, simply by requiring each univariate conditional variance to be non-zero and the correlation matrix to be full rank.

In this model the matrix of variances-covariances \( H_t \) is proposed to be

\[
\{H_t\}_{ii} = h_{it}
\]
\[ \{H_t\}_{ij} = \sqrt{h_{ijt}} = \rho_{ij}\sqrt{h_{it}}\sqrt{h_{jt}} \quad i \neq j \]

We can partition the matrix \( H_t \) as

\[ H_t = D_tRD_t \]

where \( D_t \) is the \((N \times N)\) diagonal matrix with the conditional standard deviations along the diagonal, \( \{D_t\}_{ii} = \sqrt{h_{iit}} \) and \( R \) denote the matrix of conditional correlations with \((i, j)^{th}\) element being \( \rho_{ij} \) and \( \rho_{ii} = 1 \). So it follows that the \((i, j)^{th}\) element of \( H_t \) is given as

\[ h_{ijt} = \rho_{ij}\sqrt{h_{iit}h_{jjt}} \]

\( H_t \) will be positive definite for all \( t \) if and only if each element of the \( N \) conditional variances are well defined and \( R \) is positive definite.

The diagonal structure implies that each variance behaves like a univariate GARCH model. The only interaction between volatilities is through contemporaneous constant correlation. The main drawback of this diagonal specification is that it rules out the possible interactions between volatilities.

For the bivariate cases we consider in this paper (stock market returns and oil returns) the CCC-GARCH model has following formulation

\[
\begin{bmatrix}
  h_{1t} \\
  h_{2t}
\end{bmatrix} =
\begin{bmatrix}
  \omega_1 \\
  \omega_2
\end{bmatrix} +
\begin{bmatrix}
  \alpha_{11} & 0 \\
  0 & \alpha_{22}
\end{bmatrix}
\begin{bmatrix}
  \varepsilon_{1t-1}^2 \\
  \varepsilon_{2t-1}^2
\end{bmatrix} +
\begin{bmatrix}
  \gamma \\
  0
\end{bmatrix}
\begin{bmatrix}
  S_{t-1}^{-1} \varepsilon_{1t-1}^2 \\
  \varepsilon_{2t-1}^2
\end{bmatrix} +
\begin{bmatrix}
  \beta_{11} & 0 \\
  0 & \beta_{22}
\end{bmatrix}
\begin{bmatrix}
  h_{1t-1} \\
  h_{2t-1}
\end{bmatrix}
\]

since we consider GJRGARCH for stock market returns and GARCH for oil price returns.

The positivity of each conditional variance in the CCC-GARCH model can simply be achieved by assuming that the parameters of each equation satisfy the conditions derived in Nelson and Cao (1992) and Glosten et al. (1993).

To account for the possible interactions between contemporaneous and past volatilities Jeantheau (1998) proposes the Extended Constant Conditional Correlation GARCH model (ECCC-GARCH) which relaxes the assumption about the diagonal matrixes and allows the past squared returns...
and variances of all series to enter the individual conditional variance equation. This in turn allows to account for possible volatility spillovers. Wong et al. (2000) apply the ECCC-GARCH for modelling the interactions between S&P500 index and the Sydney All Ordinaries one, and among three major exchange rates.

This model in turn requires the reformulation of the positivity constraints for the conditional volatility because now the conditional volatility equation includes the spillover effect and includes lagged squared innovations of other variables in the system. This problem is still not sufficiently explored in the academic literature.

Nakatani and Teräsvirta (2008) derive a set of necessary and sufficient conditions for positivity of the vector conditional variance equation in the CCC-GARCH model that allows the negative volatility spillovers in the model. They consider the simplest CCC-GARCH(1,1) model and derive the conditions for positivity of the conditional variances and what follows for conditional correlation and claim that the extension to more complicated models makes the task even more complicated. Conrad and Karanasos (2008) discuss the conditions to guarantee a positive definite variance-covariance matrix even if some parameters are negative.

Using the ECCC-GARCH model we investigate both the dynamic links between volatilities. In the bivariate setting we model each volatility of the series using the univariate GARCH model (GJRGARCH for the series of stock returns \((h_{1t})\) and linear GARCH for the oil prices \((h_{2t})\)). We have tried to impose the conditions for positive definiteness as discussed in Conrad and Karanasos (2008) but the off-diagonal elements in the matrix of responses to shocks \((\alpha)\) were converging to zero. Hence we allow for the dynamic relationship only between volatility of oil prices and the volatility of stock markets (we impose \(\alpha_{12} = \alpha_{21} = 0\)) and the model ECCC-GARCH is

\[
\begin{bmatrix}
  h_{1t} \\
  h_{2t}
\end{bmatrix} =
\begin{bmatrix}
  \omega_1 \\
  \omega_2
\end{bmatrix} + \begin{bmatrix}
  \alpha_{11} & 0 \\
  0 & \alpha_{22}
\end{bmatrix} \begin{bmatrix}
  \varepsilon^2_{1t-1} \\
  \varepsilon^2_{2t-1}
\end{bmatrix} + \begin{bmatrix}
  \gamma
\end{bmatrix} \begin{bmatrix}
  S_{t-1} \varepsilon^2_{1t-1} \\
  \varepsilon^2_{2t-1}
\end{bmatrix} + \begin{bmatrix}
  \beta_{11} & \beta_{12} \\
  \beta_{21} & \beta_{22}
\end{bmatrix} \begin{bmatrix}
  h_{1t-1} \\
  h_{2t-1}
\end{bmatrix}
\]

If \(\beta_{12}\) is statistically significant we have an impact of the past volatility of the oil prices on the current volatility of stock markets.
3 Data

In this paper we analyze the links between oil prices and main stock markets. We consider the DJIA, S&P500 and NASDAQ as the most important stock market indices in United States. The FTSE100 and DAX30 are the main European stock market indices from the UK and Germany respectively. Finally we include in the analysis NIKKEI225 as the main index on the Tokyo Stock Exchange. The appendix shows the plots of the stock market indexes versus the prices of oil crude. For the crude oil prices we use one of the two mostly watched spot prices - the price of the West Texas Intermediate (WTI) Cushing Crude Oil.

All the data we obtain from Bloomberg and are the closing prices. Using the historical exchange rates we convert the values of the stock market indices from local currency into dollar terms.

We remove all the non-trading days and obtain seven time series of 4949 observations. The data spans from 01/01/1984 (initiation of FTSE 100) to 30/06/2005. Finally to have stationary series we consider continuously compounded returns on the stock market indices and oil prices.

Figure 1 shows the evolution of DJIA and WTI over the period of interest. The plots for all the series are presented in the appendix.

Figure 1. Evolution of DJIA and WTI over the period 1984 - 2005. On the right hand side the scale for DJIA and on the left hand side for WTI.
4 Empirical evidence

This section discusses the empirical results of the estimation of both uni-
variate and multivariate GARCH models. In the appendix we present the
detailed results of the estimation.

4.1 Daily returns

The series of interest are the continuously compounded returns, that are
stationary as shown by the Augmented Dickey Fuller test. The results of
the Augmented Dickey Fuller test with intercept and the lag determined by
the SIC criterion available upon request.

Table 1 displays the summary statistics of the data.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St.Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJIA</td>
<td>0.0425</td>
<td>1.1301</td>
<td>-2.54</td>
<td>61.36</td>
<td>70.0920 (0.0000)</td>
</tr>
<tr>
<td>S&amp;P</td>
<td>0.0399</td>
<td>1.1044</td>
<td>-1.97</td>
<td>44.67</td>
<td>30.0920 (0.0000)</td>
</tr>
<tr>
<td>NASDAQ</td>
<td>0.0403</td>
<td>1.4239</td>
<td>-0.33</td>
<td>9.76</td>
<td>95.17 (0.0000)</td>
</tr>
<tr>
<td>FTSE</td>
<td>0.0326</td>
<td>1.0858</td>
<td>-0.78</td>
<td>12.81</td>
<td>20375 (0.0000)</td>
</tr>
<tr>
<td>DAX</td>
<td>0.0464</td>
<td>1.5159</td>
<td>-0.25</td>
<td>7.06</td>
<td>3448 (0.0000)</td>
</tr>
<tr>
<td>NIKKEI</td>
<td>0.0181</td>
<td>1.6170</td>
<td>-0.01</td>
<td>9.10</td>
<td>7678 (0.0000)</td>
</tr>
<tr>
<td>WTI</td>
<td>0.0134</td>
<td>2.5653</td>
<td>-1.09</td>
<td>20.75</td>
<td>65936 (0.0000)</td>
</tr>
</tbody>
</table>

Table 1. The main statistics of the data.

The returns on oil prices show the highest standard deviation - the high-
est volatility among all the series. The value of the skewness in all the cases
is negative showing the left-skewed series and the kurtosis indicates fat tails
in the distribution. Those are the common stylized facts observed in the
series of returns on stock markets.

For each of the series of returns we have performed the Jarque Bera test
for the null hypothesis about the normality of the series. In all the cases
we reject the hypothesis about the normality at 5% level of significance.
This fact influences the way of estimation of the model, determining the
underlying distribution of the errors. As Bollerslev and Wooldridge (1992)
show we can still assume conditional normality and will obtain consistent
quasi maximum likelihood estimators, even if the underlying distribution of the errors is not normal.

We take into account the differences in opening and closing time of the stock markets since the stock exchanges are located in the different time zones. When analyzing the impact of returns on oil prices on the European and Japanese markets we will take the first lag of the returns on oil prices since the data we consider (WTI) are from the New York Stock Exchange. Marten and Poon (2001) show that using non-synchronous data results in significant downward bias in correlation, as compared to pseudo-closed, which means simply constructed by sampling the data at the same time.

The European and Japanese stock markets are closed when the American markets open - at day \( t \) the FTSE, DAX and NIKKEI react to \( t - 1 \) returns of oil prices (WTI is quoted in New York).

Table 2 shows the correlations between the series on returns and the corresponding \( p \)-values for the statistical significance.

<table>
<thead>
<tr>
<th>( \hat{y} )</th>
<th>DJIA(_t) (-1)</th>
<th>S&amp;P(_t) (-1)</th>
<th>NASDAQ(_t) (-1)</th>
<th>FTSE(_t)</th>
<th>DAX(_t)</th>
<th>NIKKEI(_t)</th>
<th>WTI(_t) (-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJIA(_t) (-1)</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S&amp;P(_t) (-1)</td>
<td>0.9544 *</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>NASDAQ(_t) (-1)</td>
<td>0.0703</td>
<td>0.7820 *</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>FTSE(_t)</td>
<td>0.3122 *</td>
<td>0.3344 *</td>
<td>0.2471 *</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DAX(_t)</td>
<td>0.2376 *</td>
<td>0.2457 *</td>
<td>0.1727 *</td>
<td>0.5351</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>NIKKEI(_t)</td>
<td>0.2061 *</td>
<td>0.2500 *</td>
<td>0.2461 *</td>
<td>0.2097</td>
<td>0.2094 *</td>
<td>1.0000</td>
<td>-</td>
</tr>
<tr>
<td>WTI(_t) (-1)</td>
<td>-0.0470</td>
<td>-0.0380 *</td>
<td>-0.0183</td>
<td>0.0157</td>
<td>-0.0366 *</td>
<td>-0.0282 *</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Table 2. The correlations of the series and the corresponding \( p \)-values (* - statistically significant at 5%)

We see that the correlation between American stock markets, DAX and NIKKEI and oil prices is negative, small and statistically significant. In the case of NASDAQ and WTI and FTSE and WTI the correlation is not statistically significant.

We also observe high correlation between American markets but surprisingly low correlation between American and European stock markets,
which we could expect to be high, and very low correlation between changes in stock markets and changes in oil prices. Capiello et al. (2006) obtain similar results with the average correlation among the European markets of 0.5289 and the correlation between European and North American markets of 0.3386.

The correlation between stock markets and oil prices is a dynamic process. In the appendix we present the plots of the correlations between returns on stock markets and return on oil prices computed in the 3-month-windows. The correlation was changing over time - the American markets follow very similar pattern - high negative spikes at the beginning of 1990s, positive one around 1992 and significant changes around 1995 - 1996. There are similar, but lower, spikes in the case of European and Japanese market.

To show the dynamic behaviour of the correlation we compute the average monthly correlations across markets in a very similar manner as Campbell et al. (2001). First we have calculated monthly non-overlapping correlation coefficients for each pair of the stock returns and oil price returns. We then average the correlations between returns to compute a synthetic equally weighted index of the average correlation.

![Average monthly correlations between stock markets and oil prices](image)

Figure 2. Average monthly correlations.
Figure 2 shows average monthly correlation between returns on stock markets and oil prices. Once again we demonstrate that the correlation between stock markets and oil prices is a dynamic process.

4.2 Linear specification

In this section we present the results of the estimation of the linear specification. We start by discussing the models for the series of returns followed by analyzing the results of the linear specification.

4.2.1 Univariate models for oil price returns and stock market returns

We start by investigating the model for oil price returns. The estimated conditional correlation will be used as the explanatory variable in the further analysis.

First we determine the conditional mean equation defined as the mixture of the autoregressive part and lagged innovations. The lowest value of the BIC criterion we obtain for ARMA(1,2).

Engle (1982) develops a test for conditional heteroscedasticity in the context of ARCH models based on the Lagrange Multiplier principle. We present the details of the test in the appendix.

We apply the ARCH-LM test to residuals $\varepsilon_t$ from the mean equation and compute the ARCH-LM test statistics for the values of $q = 1, 5, 10$. Following we investigate the asymmetry in the conditional volatility. This idea was motivated by the empirical observation that the volatility of stock markets reacts differently to positive and negative shocks. We use Sign Bias, Negative Size Bias and Positive Size Bias tests proposed by Engle and Ng (1993), discussed in the appendix. For the Sign Bias we calculate the $t$-statistic for the parameter $\gamma_1$ and compute the statistics for Negative Size Bias and Positive Size Bias test.

Table 3 presents the results of these tests.

<table>
<thead>
<tr>
<th>ARCH(1)</th>
<th>ARCH(5)</th>
<th>ARCH(10)</th>
<th>Sign_bias</th>
<th>Negative_Size</th>
<th>Positive_Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>58.30(0.00)</td>
<td>145.07(0.00)</td>
<td>285.21(0.00)</td>
<td>0.0367(0.00)</td>
<td>-6.399(0.00)</td>
<td>5.883(0.00)</td>
</tr>
</tbody>
</table>

Table 3. ARCH-LM and Sign Bias, Positive and Negative Size Bias tests for the oil price returns.
The ARCH-LM test evidences the presence of ARCH effects, therefore we model the conditional volatility as the GARCH model. The results show the evidence of asymmetric ARCH effects.

Following we estimate the models for the returns on oil prices - ARMA(1,2) and consider the volatility specification as GARCH(1,1) and GJRGARCH(1,1) with normally distributed errors. Although the test proposed by Engle and Ng (1993) gives evidence of the asymmetric conditional volatility the parameter that governs this asymmetry is not significant in GJR-GARCH. The model we propose for oil price returns is therefore $ARMA(1, 2) - GARCH(1, 1)$.

We follow similar steps with the series of stock market returns. We define first the conditional mean equation, check the presence of volatility and its nature. As the asymmetric models for volatility we consider GJR-GARCH. The best model we choose are - for DJIA and DAX - $ARMA(0, 0) - GJR_{GARCH}(1, 1)$, for S&P500, NASDAQ, FTSE and NIKKEI - $ARMA(1, 0) - GJR_{GARCH}(1, 1)$. The advantage of using the $GJR_{GARCH}$ model for the conditional volatility is the straightforward understanding of the model that governs the dynamics of the conditional volatility. The parameter $\gamma$ in the conditional volatility stands for the dummy variable that takes the value of 1 when the shocks are negative. This parameter is expected to be positive to confirm the empirical fact that the negative shocks to the series increase the volatility stronger than the positive ones.

We check the adequacy of the variance model by examining the series $\{\tilde{z}_t\}$, the series of standardized residuals defined as $\tilde{\varepsilon}_t / \sqrt{\hat{h}_t}$, where $\tilde{\varepsilon}_t$ are the estimated residuals from the mean equation and $\sqrt{\hat{h}_t}$ is the estimated conditional volatility. The Ljung-Box test statistics of $\tilde{z}_t$ are used to check the adequacy of the mean equation and those of the $\tilde{z}_t^2$ of the volatility equation.

Lundberg and Teräsvirta (2002) discuss the framework for testing the adequacy of the estimated GARCH model. They propose the LM type tests of no ARCH in the standardized errors.

If the model for the series of returns is correctly specified we expect not to have any autocorrelation in the series of standardized and standardized residuals.
squared residuals. We compute the Ljung-Box test statistics for 5 and 10 lags. Table 4 shows the results for each of the series.

<table>
<thead>
<tr>
<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
<th>WTII</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>0.0405*</td>
<td>(3.11)</td>
<td>0.0320*</td>
<td>(2.33)</td>
<td>0.0446</td>
<td>(2.75)</td>
<td>0.0341*</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>0.0195*</td>
<td>(2.26)</td>
<td>0.1138*</td>
<td>(9.83)</td>
<td>0.0231**</td>
<td>(1.59)</td>
<td>0.0226</td>
</tr>
<tr>
<td>( \theta_1 )</td>
<td>0.0298*</td>
<td>(15.02)</td>
<td>0.0227*</td>
<td>(3.85)</td>
<td>0.0326**</td>
<td>(1.88)</td>
<td>0.0617*</td>
</tr>
<tr>
<td>( \omega )</td>
<td>0.0176*</td>
<td>(2.89)</td>
<td>0.0582*</td>
<td>(5.01)</td>
<td>0.0567*</td>
<td>(2.88)</td>
<td>0.0473*</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.1165*</td>
<td>(4.21)</td>
<td>0.1203*</td>
<td>(4.44)</td>
<td>0.0804*</td>
<td>(1.94)</td>
<td>0.0725*</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.8999*</td>
<td>(65.03)</td>
<td>0.8644*</td>
<td>(41.17)</td>
<td>0.8746</td>
<td>(19.72)</td>
<td>0.8801</td>
</tr>
<tr>
<td>( \beta )</td>
<td>9.72*</td>
<td>(0.08)</td>
<td>8.60*</td>
<td>(0.12)</td>
<td>3.31*</td>
<td>(0.62)</td>
<td>5.19*</td>
</tr>
<tr>
<td>( Q(5) )</td>
<td>13.9*</td>
<td>(0.17)</td>
<td>16.66*</td>
<td>(0.08)</td>
<td>9.99*</td>
<td>(0.44)</td>
<td>14.27*</td>
</tr>
<tr>
<td>( Q(10) )</td>
<td>1.72*</td>
<td>(0.88)</td>
<td>2.11*</td>
<td>(0.83)</td>
<td>1.55*</td>
<td>(0.90)</td>
<td>4.90*</td>
</tr>
<tr>
<td>( Q(5)^2 )</td>
<td>3.87*</td>
<td>(0.82)</td>
<td>3.22*</td>
<td>(0.93)</td>
<td>1.55*</td>
<td>(0.94)</td>
<td>4.06*</td>
</tr>
<tr>
<td>( Q(10)^2 )</td>
<td>1.191</td>
<td>(8.87)</td>
<td>0.0589*</td>
<td>(3.76)</td>
<td>0.0589*</td>
<td>(3.76)</td>
<td>0.0589*</td>
</tr>
</tbody>
</table>

Table 4. Empirical estimation of the series of returns. We present the conditional mean equation and conditional volatility equation defined either as linear GARCH model or GJRGARCH model. The model is defined as \( r_t = \text{ARMA} + \varepsilon_t, \varepsilon_t = \sqrt{h_t} \varepsilon_t, h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \) (GARCH) or \( h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^2 + \beta h_{t-1} \) (GJRGARCH). In parenthesis we report the t-Statistics for the parameters and p-values for the Ljung-Box test statistics \( Q(5) \) and \( Q(10) \) for standardized residuals and \( Q(5)^2 \) and \( Q(10)^2 \) for squared standardized residuals. * - statistically significant at 5% level, ** - at 10% level.

All the parameters (except for \( \phi_1 \) in the case of FTSE) are statistically significant at 5% level and few of them at 10%. The Ljung-Box test statistics for both standardized and squared standardized residuals do not show any remaining autocorrelation therefore we conclude that the mean and volatility equations are correctly specified.

Additionally (presented on request) we calculate the Lundberg and Teräsvirta test statistics for the remaining ARCH process in the conditional volatility equation. For each \( m = 1, \ldots, 5 \) we accept at 5% level of significance the null hypothesis about no remaining ARCH in the model.

The figures below show the estimated conditional volatilities for DJIA
(other stock markets show a very similar figures) and WTI (all the plots are presented in the appendix).

![Volatility DJIA](image1.png)

![Volatility WTI](image2.png)

Figure 3. Estimated conditional volatility of DJIA and WTI

Figure 3 shows the evolution of conditional volatility over the period of interest. In case of DJIA we observe a high peak around the end of 1987, which reflects the stock market turbulences in October 1987 when DJIA lost during the single day more than 20%, following in high volatile periods at the beginning of 1990 (Gulf war), Asian and Russian financial crises (1997-1998), dot com bubble (2000-2001).

The volatility of oil prices shows much higher levels of volatility and periods of turbulences are more frequent. Until 1986 Saudi Arabia acted as the swing producer cutting its production to stop the fall in prices. By early 1986 they linked their oil price to the spot market for crude and increased their production from 2 MMBPD (million barrels per day) to 5 MMBPD. Crude oil prices plummeted below $10 per barrel by mid-1986.
The price of oil spiked in 1990 with the cuts in the production caused by the Iraqi invasion on Kuwait (August 1990) and the following Gulf war. In 1998 due to the financial crises the Asian Pacific oil consumption declined for the first time since 1982, higher OPEC production sent the prices into the downward spiral. In the fears of the economic downturn after the terrorist attack in September 2001 the price of WTI was down by 35 percent by the middle of November. In March 2003 the US military action commenced in Iraq.

4.2.2 The univariate GARCH models with the oil price returns as the explanatory variable - Specification 1, 2 and 3

Specification 1 and 2 test if the stock market returns react to changes in the oil prices. We add the returns of the oil prices as the explanatory variable in the mean equation (see appendix, section specifications, Specification1). The results show that the changes in oil prices affect the American markets (DJIA and S&P500) and DAX. The remaining three stock markets are not affected by the daily changes in oil prices.

The impact of the oil prices on DJIA, S&P and DAX is similar in both the nature and magnitude. This impact is negative, as expected with the economic theory. The increase in oil prices (positive returns) lowers the return on the stock index.

Of course the impact of the oil price returns on the given stock market index depends on the composition of the index. The indices that incorporate many companies in their composition (like S&P, FTSE or NIKKEI) represent a portfolio of different sectors each of which reacts differently to the increases in the oil prices. These well diversified indices show the impact of oil prices on the economy as the whole and do not depend on the composition of the index. On the other hand we have indices composed of the smaller number of companies DJIA or DAX that could show the link with oil prices purely by incorporating many companies which profits depend directly on the level of oil prices (oil producers or oil refineries).

We have analyzed the composition of the DJIA during the period of interest. The data available on the web page of Dow Jones Indexes (Dow Jones Industrial Average Historical Component Lists) shows only the composition of the index without the percentage breakdown. During the years 1994-2008
three big American oil companies were the composites of the index - Exxon (and later Exxon Mobile), Chevron (until 1999) and Texaco (until 1997). The results of our analysis show that although we have these big oil companies in the index which could make this relationship positive we have a negative impact since the negative reaction of the rest of the constituents is stronger than the positive of the big oil companies.

We check if the lagged returns on the oil prices have any influence on the stock market returns and we do not detect any such relationship (Specification 2).

Finally we investigate the possible asymmetry in the relationship between oil prices and stock markets by computing a dummy variable for negative returns on oil and we consider this variable as the new explanatory variable in the mean equation (Specification 3). In none of the cases we obtain statistically significant results and conclude that there is no asymmetry in this relationship.

4.2.3 The univariate GARCH models with the volatility of returns on oil prices as the explanatory variable - Specification 4

The aim of this analysis is to investigate the impact of volatility of returns on oil on stock market returns.

As mentioned earlier we estimate the GARCH model for the returns on oil. We consider the estimated conditional volatility, as the explanatory variable in the mean equation for the returns on oil prices. We present the results of the estimation in appendix.

The results of the analysis show that the volatility of the returns on oil prices do affect all the American stock markets (DJIA, S&P, NASDAQ). The Japanese and European stock markets remain unaffected.

Comparing the impact of the oil price returns and of its volatility on stock market returns we observe that the volatility of oil returns has the positive impact on stock markets while the oil price returns have a negative one. The magnitude of the effect of volatility is higher than the impact of returns. One of possible explanation is that volatility of oil prices moves
investors to change their portfolio composition (they shift among sectors and companies - if they are risk averse they will overweight the oil nonsensitive companies and sectors and if they are risk takers they will overweight the oil sensitive sectors and companies) and the stock index that tracks the spectrum of companies rises.

4.3 Non-linear specification

We first analyze the results with the $SOPI_t$ variable as the explanatory variable in the mean equation. We construct the series of $SOPI_t$ variable in the way the Lee, Ni and Ratti (1995) discuss. In our case the model for the oil price returns is $ARMA(1,2) - GARCH(1,1)$. The variable of interest is defined as

$$SOPI_t = \max \left( 0, \frac{\hat{\varepsilon}}{\sqrt{\hat{h}_t}} \right)$$

where $\hat{\varepsilon}$ are the estimated residuals from the mean equation and $\hat{h}_t$ is the estimated conditional variance of returns on oil prices.

Table 5 presents the value of the estimated parameters and in parenthesis the t-statistic (we present detailed results in appendix).

<table>
<thead>
<tr>
<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SOPI_t$</td>
<td>$-0.1034$</td>
<td>$-0.1004$</td>
<td>$0.1009$</td>
<td>$0.1019$</td>
<td>$-0.1036$</td>
<td>$0.10495$</td>
</tr>
<tr>
<td></td>
<td>($-0.26$)</td>
<td>($-0.35$)</td>
<td>($0.37$)</td>
<td>($0.81$)</td>
<td>($-0.97$)</td>
<td>($0.71$)</td>
</tr>
</tbody>
</table>

Table 5. The results of the estimation of the models with $SOPI_t$ as the explanatory variable in the mean equation. In parenthesis the values of the t-statistic.

The results of the estimation show that for each of the stock market indices the explanatory variable $SOPI_t$ - proxy for positive shocks of returns on oil prices is not statistically significant at 5% level of significance. The positive shocks of oil prices do not directly affect the returns on stock market indices.

In the second part of the analysis we consider another nonlinear transformation of oil price variable $NOPI_t$ - the net oil price increases as discussed before. We take into account different length of the series starting from $n = 5$ (a week) to $n = 10$ (two weeks). This variable will account for "significant" oil price increases during the period of $n$ days.
We present all the results in appendix. Only in the case of S&P and FTSE we obtain statistically significant results. In the case of S&P only for \( n = 8 \) we get a statistically significant (at 10% level) parameter estimate of \(-0.0227\). The increase in oil prices bigger than any change in oil prices in the period of eight days lowers the S&P returns. On the other hand in the case of FTSE we have a statistically significant result for the period of five days (which corresponds to one week) and the stock market positively reacts to this increase (the estimated parameters has a value of 0.0264). This result is quite surprising because so far we have not observed any link between oil returns and this stock market. We can explain this by the fact that the UK is an oil importer and such a companies like British Petroleum or Royal Dutch Shell form a part of this index.

In the last part of the analysis we want to discuss the results of the Hansen test for the threshold effects in the relationship between returns on oil prices and returns on stock market indices. Below we present the result of the test

<table>
<thead>
<tr>
<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>-2.43</td>
<td>-2.43</td>
<td>6.52</td>
<td>-1.31</td>
<td>-1.48</td>
<td>4.94</td>
</tr>
<tr>
<td>statistic</td>
<td>9.63</td>
<td>5.82</td>
<td>3.98</td>
<td>3.48</td>
<td>4.78</td>
<td>6.62</td>
</tr>
<tr>
<td>p-value</td>
<td>0.03</td>
<td>0.19</td>
<td>0.62</td>
<td>0.51</td>
<td>0.30</td>
<td>0.22</td>
</tr>
</tbody>
</table>


We observe only in the case of the DJIA statistically significant threshold effect, with the estimated threshold level of \(-2.43\). Indeed when we estimate the mean equation we obtain the estimate of the parameter of the variable \( r_{oil}I(r_{oil} \leq -2.43) \) of \(-0.0431\) and statistically significant (t-statistic of -3.69). Considering the results of the specification 1 we notice that the DJIA reacts much stronger to the negative and higher than \(-2.43\) returns on oil prices. In case of the other market we have not detected the threshold effect.

4.4 Volatility linkages - ECCC-GARCH

In this section we discuss the links between volatilities of the stock market returns and oil price returns.
We consider the ECCC-MVGARCH model of Bollerslev (1990) as indicated by the Engle and Sheppard (2002) test for the constant versus dynamic correlation structure test. We work in the bi-variate framework - stock market index and returns on oil prices.

First we filter the series by removing the deterministic component for each of the series to obtain pure stochastic errors from the model.

Engle and Sheppard (2002) propose a test to determine the nature of the conditional correlation among time series. They point out that testing models for constant correlation has proven to be a difficult problem, as testing for dynamic correlation with data that has time-varying volatilities can result in misleading conclusions and rejection of constant correlation when it is true due to the misspecified volatility model. They propose a test that only requires consistent estimate of the constant conditional correlation, and can be implemented using a vector autoregression. We discuss the details of the test in the appendix.

The table below shows the results of the Engle and Sheppard test for constant versus dynamic correlation structure in the bivariate framework - returns on given stock market and returns on oil prices.

<table>
<thead>
<tr>
<th>lag</th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.26 (0.53)</td>
<td>1.92 (0.38)</td>
<td>0.66 (0.71)</td>
<td>0.49 (0.77)</td>
<td>0.36 (0.64)</td>
<td>1.18 (0.553)</td>
</tr>
<tr>
<td>2</td>
<td>4.70 (0.19)</td>
<td>6.60 (0.08)</td>
<td>1.51 (0.67)</td>
<td>3.16 (0.36)</td>
<td>2.59 (0.45)</td>
<td>6.56 (0.087)</td>
</tr>
<tr>
<td>3</td>
<td>5.89 (0.22)</td>
<td>6.71 (0.15)</td>
<td>1.51 (0.82)</td>
<td>4.69 (0.31)</td>
<td>2.61 (0.62)</td>
<td>9.07 (0.509)</td>
</tr>
<tr>
<td>4</td>
<td>7.21 (0.20)</td>
<td>8.17 (0.14)</td>
<td>1.29 (0.90)</td>
<td>4.73 (0.44)</td>
<td>3.98 (0.61)</td>
<td>9.076 (0.106)</td>
</tr>
<tr>
<td>5</td>
<td>9.07 (0.16)</td>
<td>8.38 (0.20)</td>
<td>2.37 (0.88)</td>
<td>4.98 (0.54)</td>
<td>4.19 (0.64)</td>
<td>10.05 (0.122)</td>
</tr>
</tbody>
</table>

Table 7. Results of the test for constant correlation structure.

For each bivariate model we accept the hypothesis about the constant correlation structure at 5% level of significance. Following the results of the test we consider the ECCC-MVGARCH model for the bivariate case.

The estimated constant conditional correlation between the stock market returns and returns on oil prices are presented below.
Table 8. The results of the estimation of the constant conditional correlation, t-statistics in parenthesis.

The results of the estimation of the constant conditional correlation parameter show that only conditional volatilities between DJIA and oil prices and DAX and oil prices are contemporaneously interconnected. This correlation is negative and small.

The table below shows the estimated parameter $\beta_{12}$, that described the spillover effect between volatilities of oil prices and stock markets.

Table 9. The results of the estimation of the spillover effect from oil prices to stock markets, t-statistics in parenthesis.

Looking at estimated parameter $\beta_{12}$ - the relationship between lagged volatility of oil prices and volatility of stock markets we observe statistically significant spillover from oil prices to stock markets for DJIA and S&P. This effect is positive which means that the higher volatility of oil prices translated into higher volatility of oil prices on the next day.

5 Conclusions

In this work we analyze and assess the relation between oil prices and oil price volatility and main stock market indices. We consider the prices of WTI crude and six main world stock indexes - DJIA, NASDAQ, S&P500, DAX, FTSE100 and NIKKEI225.

The results show different channels the oil prices impact stock markets. The two main American stock markets - DJIA and S&P appear to react strongest to changes in oil prices. We detect some reaction from two European stock market indices we consider - DAX and FTSE. The Japanese NIKKEI225 seams not to react at all.

Our results show that DJIA, S&P500 and DAX react to daily changes in oil prices. This impact is negative and goes with the economic theory.
since the increases in oil prices cause the negative returns on stock markets. We do not detect any lagged or asymmetric nature of this relationship. The return on American stock markets (DJIA, S&P, NASDAQ) are influenced by the volatility of oil prices and this effect is positive.

The higher volatility of oil prices causes changes in the investors’ portfolios and can have a positive effect on the stock market index.

In the non-linear framework we observe that S&P and FTSE react to the significant increases of oil prices. DJIA especially strongly react to the high decreases in the oil prices which causes an increase in stock market returns. The decreases of more than 2.43% significantly increases the returns on that index.

Investigating the links between volatilities we detect the small negative correlation between volatilities of DJIA and oil prices and DAX and oil prices. In the case of DJIA and S&P we observe a spillover effect from volatility of oil prices to volatilities of those indices. The lagged volatility of oil prices has a significant positive effect on the current volatility of these two indices.

The straightforward extension of this analysis is the sector analysis. Analyzing the sector indices (e.g. transportation, energy, banks) we may detect the reaction of different groups of companies on the changes in the oil prices and this could be a good tool when optimizing the portfolio composition since we could give hints which portfolio management strategies to consider when there are changes in oil prices.
References


[14] Hansen, B. (1996), "Inference when the Nuisance Parameter is not Identified under the Null Hypothesis", *Econometrica*, 64, 413-430.


6 Appendix

6.1 Specifications

In this section we want to present the specification

Let us denote \( r_{stock_t} \) as the return on given stock market at time \( t \), \( ARMA \) - autoregressive - moving average specification of the conditional mean equation, specific for every stock markets. The \( ARMA \) specification is given as

\[
r_{stock_t} = c + \alpha_1 r_{stock_{t-1}} + \ldots + \alpha_n r_{stock_{t-n}} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \ldots + \beta_m \varepsilon_{t-m}
\]

where \( m, n \) are specific for every stock markets.

\( r_{oil_t} \) is the return on oil prices at time \( t \), \( vol_t \) a series of conditional volatility of stock prices.

We will test different specifications for the mean equation and taking an appropriate GARCH model as the model for conditional volatility.

Specification 1 tests if there is any impact of the oil prices on each of the stock markets. The relevant equation is given as

\[
r_{stock_t} = ARMA + r_{oil_t} + \varepsilon_t
\]

where the dynamics of the shocks is modelled by appropriate (symmetric or asymmetric GARCH model).

We also analyze the lagged returns of oil prices as the explanatory variable (Specification 2) to investigate if the changes of oil prices in the past influence the stock markets contemporaneously. This specification takes into account the lagged oil prices and is given by

\[
r_{stock_t} = ARMA + r_{oil_{t-1}} + \varepsilon_t
\]

Further to analyze the way the oil prices influence stock market we construct the dummy variable that accounts for the sign of the returns on oil prices to investigate if there is any asymmetry in the relationship between returns on stock markets and returns on oil prices (Specification 3). Let us
define the dummy variable \( d_t \) that takes the value of 1 when \( r_{oil_t} < 0 \) and zero otherwise.

\[
r_{stock_t} = ARMA + d_t + \varepsilon_t
\]

Another specification we will test takes the estimated conditional volatility of returns on oil prices as the explanatory variable in the mean equation of the returns on stock markets Specification 3), here we can analyze if the returns of the stock markets depend on the volatility of oil prices.

\[
r_{stock_t} = ARMA + vol_t + \varepsilon_t
\]

6.2 Tests


Engle(1982) developed a test for conditional heteroscedasticity in the context of ARCH models based on the Lagrange Multiplier principle. The LM test can be computed as \( nR^2 \), where \( n \) is the sample size and \( R^2 \) is obtained from a regression of the squared residuals on the constant and \( q \) of its lags. The LM test statistic has an asymptotic \( \chi^2(q) \) distribution.

6.2.2 Sign Bias, Positive Size Bias and Negative Size Bias tests - Engle and Ng (1993)

Engle and Ng (1993) propose tests to check whether positive and negative shocks have a different impact on the conditional variance. Let \( S^-_{t-1} \) denote a dummy variable which takes the value of 1 when \( \hat{\varepsilon}_{t-1} \) is negative and 0 otherwise, where \( \hat{\varepsilon} \) are residuals from estimating a model for the conditional mean of the series under the assumption of conditional homoscedasticity. The tests examine whether the squared residuals can be predicted by \( S^-_{t-1}, S^-_{t-1}\hat{\varepsilon}_{t-1}, \) and or \( S^+_{t-1}\hat{\varepsilon}_{t-1} \), where \( S^+_{t-1} = 1 - S^-_{t-1} \).

The test statistics are computed as the \( t \)-ratio of the parameter \( \gamma_1 \) in the regression

\[
\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 \hat{w}_t + \xi_t
\]

where \( \hat{w}_t \) is one of the three measures of asymmetry defined above and \( \xi_t \) the residual.
When \( \hat{w}_t = S_{t-1} \) in the regression the test is called Sign Bias (SB) as it tests whether the magnitude of the square of the current shock \( \varepsilon_t \) (and as the consequence the conditional variance \( h_t \)) depends on the sign of the lagged shock \( \varepsilon_{t-1} \). In the case when \( \hat{w}_t = S_{t-1} \hat{\varepsilon}_{t-1} \) or \( \hat{w}_t = S_{t-1}^+ \hat{\varepsilon}_{t-1} \) the tests are called Negative Size Bias (NSB) and Positive Size Bias (PSB), respectively, and these tests examine whether the effect of positive or negative shocks on the conditional variance also depends on their size.

### 6.2.3 Test for remaining ARCH - Lundberg and Teräsvirta (2002)

They propose the LM test for remaining ARCH\((m)\) in \( \hat{\varepsilon}_t \), which is computed as \( nR^2 \), where \( R^2 \) is obtained from the auxiliary regression

\[
\hat{\varepsilon}_t^2 = \phi_0 + \phi_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \phi_m \hat{\varepsilon}_{t-m}^2 + \lambda' \hat{x}_t + u_t
\]

where the vector \( \hat{x}_t \) consists of the partial derivatives of the conditional variance \( h_t \) with respect to the parameters in the GARCH model, evaluated at the estimates - \( \hat{x}_t = \hat{h}_t^{-1} \partial \hat{h}_t / \partial \theta \) where \( \theta \) is the vector of parameters in the conditional variance equation. The test statistic based on this regression, which tests the hypothesis \( H_0 : \phi_1 = \cdots = \phi_m = 0 \) is asymptotically \( \chi^2 \) distributed with \( m \) degrees of freedom.

### 6.2.4 Hansen (1996,2000) test for threshold effects

Hansen(2000) - proposed the method based on a threshold regression model where observations fall into classes or regimes that depend on the unknown value of the observed variable

\[
y_{it} = \beta_0 + \beta_{a1} A_{it} I(A_{it} \leq \gamma) + \beta_{a2} A_{it} I(A_{it} > \gamma) + \beta_z z_{it} + u_{it}
\]

where \( I(\cdot) \) is the indicator function and \( z_{it} \) are other regressions.

Hansen(2000) recommends obtaining the least square estimate \( \hat{\gamma} \) as the value that minimizes the sum of squared errors \( S_t(\gamma) \). The sum of the squared errors in turn depends on \( \gamma \) through the indicator function. Minimization problem here is the step procedure where each step occurs at the distinct values of the observed threshold value \( A_{it} \). For each of these values the threshold regression model is estimated and the sum of squared residuals obtained. The value \( \hat{\gamma} \) is the one that minimizes the function.
Hansen (2000) suggests bootstrapping to obtain the p-value of this test. First estimate the model under the null and alternative, this gives the actual values of the likelihood ratio test $F_1$

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2} \quad \hat{\sigma}^2 = \frac{1}{n(t-1)}S_1(\hat{\gamma})$$

A bootstrap sample is created by drawing from the normal distribution of the residuals of the estimated threshold model. Regressors are held fixed in the repeated bootstrap sample using the generated sample the model is estimated under the null (of no threshold) and alternative ($\hat{\gamma}$) to obtain a new $F_1$. Repeat this procedure large number of times. The bootstrap estimate of the p-values for $F_1$ under the null is given by the percentage of draws for which the simulated statistic $F_1$ exceeds the actual one.

### 6.2.5 Test for dynamic correlation model - Engle and Sheppard (2001)

The null hypothesis is of the constant correlation against the alternative of dynamic conditional correlation

$$H_0 : R_t = \overline{R} \quad t \epsilon T$$

$$H_A : vech(R_t) = vech(\overline{R}) + \beta_1 vech(R_{t-1}) + ... + \beta_p vech(R_{t-p})$$

The testing procedure is as follows. Estimate the univariate GARCH processes and standardized the residuals for each series. Then estimate the correlation of the standardized residuals, and jointly standardized the vector of univariate standardized residuals by the symmetric square root decomposition of $\overline{R}$. Under the null of constant correlation, these residuals should be IID with the variance covariance matrix unit diagonal $I_k$ (we consider $k$ series). The artificial regression will be a regression of the outer products of the residuals on a constant and lagged outer products. Let

$$Y_t = vech^u[(\overline{R}^{-1/2}D_t^{-1}\varepsilon_t)(\overline{R}^{-1/2}D_t^{-1}\varepsilon_t)' - I]$$

where $(\overline{R}^{-1/2}D_t^{-1}\varepsilon_t)$ is a $k$ by 1 vector of residuals jointly standardized under the null, and $vech^u$ is a modified $vech$ which only selects elements above the diagonal. The vector autoregression is
\[ Y_t = \alpha + \beta_1 Y_{t-1} + \ldots + \beta_s Y_{t-s} + \eta_t \]

Under the null the constant and all the lagged parameters in the model should be zero. The test statistics is \( \chi^2_{s+1} \) distributed.
6.3 Figures

6.3.1 The stock markets versus oil price

- DJIA versus WTI
- S&P 500 versus WTI
- NASDAQ versus WTI
- FTSE100 versus WTI
- DAX versus WTI
- NIKKEI versus WTI
6.3.2 The correlation between returns on stock markets and returns on oil prices in 3-month-window
6.4 Estimated conditional variances

![Graphs of estimated conditional variances for different indices and commodities from 1984 to 2005. The graphs show volatility over time with axes labeled.]
6.5 Results

6.5.1 The univariate GARCH models with the oil price returns as the explanatory variable - Specification 1

Table 9. Estimation results for each series of stock market returns for Specification 1. Specification 1 takes the oil price returns as the explanatory variable in the mean equation.

<table>
<thead>
<tr>
<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>0.0405*</td>
<td>0.0323*</td>
<td>0.0447*</td>
<td>0.3394*</td>
<td>0.0432*</td>
<td>0.0327**</td>
</tr>
<tr>
<td></td>
<td>(3.11)</td>
<td>(2.34)</td>
<td>(3.48)</td>
<td>(2.71)</td>
<td>(2.21)</td>
<td>(1.87)</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.0371*</td>
<td>0.1733*</td>
<td>0.0250*</td>
<td>0.0225</td>
<td>0.0371*</td>
<td>0.0633*</td>
</tr>
<tr>
<td></td>
<td>(2.22)</td>
<td>(10.03)</td>
<td>(1.59)</td>
<td>(1.37)</td>
<td>(3.24)</td>
<td>(2.63)</td>
</tr>
<tr>
<td>$r_{oil}$</td>
<td>-0.0131*</td>
<td>-0.0098*</td>
<td>-0.0037*</td>
<td>0.0053</td>
<td>-0.0135**</td>
<td>-0.0033</td>
</tr>
<tr>
<td></td>
<td>(-3.12)</td>
<td>(-2.27)</td>
<td>(-0.59)</td>
<td>(0.90)</td>
<td>(-1.70)</td>
<td>(-0.33)</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.0294*</td>
<td>0.0235*</td>
<td>0.0227*</td>
<td>0.0327**</td>
<td>0.0630*</td>
<td>0.0658*</td>
</tr>
<tr>
<td></td>
<td>(6.28)</td>
<td>(2.30)</td>
<td>(3.39)</td>
<td>(1.86)</td>
<td>(1.87)</td>
<td>(2.13)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0177*</td>
<td>0.0106*</td>
<td>0.0582*</td>
<td>0.0564*</td>
<td>0.0471*</td>
<td>0.0455*</td>
</tr>
<tr>
<td></td>
<td>(2.98)</td>
<td>(1.88)</td>
<td>(5.01)</td>
<td>(2.85)</td>
<td>(3.24)</td>
<td>(2.63)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.1143*</td>
<td>0.1227*</td>
<td>0.1289*</td>
<td>0.0809*</td>
<td>0.0734*</td>
<td>0.1117*</td>
</tr>
<tr>
<td></td>
<td>(8.90)</td>
<td>(4.20)</td>
<td>(4.44)</td>
<td>(1.93)</td>
<td>(2.34)</td>
<td>(3.22)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.9003*</td>
<td>0.9012*</td>
<td>0.8044*</td>
<td>0.8740*</td>
<td>0.8883*</td>
<td>0.5778*</td>
</tr>
<tr>
<td></td>
<td>(173.33)</td>
<td>(47.37)</td>
<td>(41.17)</td>
<td>(19.47)</td>
<td>(25.36)</td>
<td>(24.67)</td>
</tr>
<tr>
<td>$Q(5)$</td>
<td>1.72*</td>
<td>8.30*</td>
<td>3.51*</td>
<td>3.10*</td>
<td>1.95*</td>
<td>2.91*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.11)</td>
<td>(0.62)</td>
<td>(0.62)</td>
<td>(0.85)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>$Q(10)$</td>
<td>13.97*</td>
<td>17.06*</td>
<td>9.99*</td>
<td>9.92*</td>
<td>7.61*</td>
<td>15.58*</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.07)</td>
<td>(0.44)</td>
<td>(0.44)</td>
<td>(0.66)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$Q(5)^2$</td>
<td>1.72*</td>
<td>2.04*</td>
<td>1.55*</td>
<td>1.50*</td>
<td>7.98*</td>
<td>0.57*</td>
</tr>
<tr>
<td></td>
<td>(0.88)</td>
<td>(0.84)</td>
<td>(0.90)</td>
<td>(0.91)</td>
<td>(0.15)</td>
<td>(0.98)</td>
</tr>
<tr>
<td>$Q(10)^2$</td>
<td>5.81*</td>
<td>4.19*</td>
<td>4.15*</td>
<td>4.09*</td>
<td>10.88*</td>
<td>1.29*</td>
</tr>
<tr>
<td></td>
<td>(0.82)</td>
<td>(0.93)</td>
<td>(0.94)</td>
<td>(0.94)</td>
<td>(0.36)</td>
<td>(0.99)</td>
</tr>
</tbody>
</table>

Table 9. Empirical estimation of the series of returns. We present the conditional mean equation and conditional volatility equation defined either as linear GARCH model or GJRGARCH model. The model is defined as $r_t = ARMA + r_{oil}t + \varepsilon_t$, $\varepsilon_t = \sqrt{h_t}\varepsilon_t$, $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$ (GARCH) or $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}$ (GJRGARCH). In parenthesis we report the t-Statistics for the parameters and p-values for the Ljung-Box test statistics ($Q(5)$ and $Q(10)$ for standardized residuals and $Q(5)^2$ and $Q(10)^2$ for squared standardized residuals. * - statistically significant at 5% level, ** - at 10% level.
6.5.2 The univariate GARCH models with the oil price returns as the explanatory variable - Specification 2

Table 10. Estimation results for each series of stock market returns for Specification 2. Specification 2 takes the lagged oil price returns as the explanatory variables.

<table>
<thead>
<tr>
<th>Specification 2</th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0407*</td>
<td>0.0520*</td>
<td>0.0446*</td>
<td>0.0641*</td>
<td>0.0427*</td>
<td>0.0624**</td>
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</tr>
<tr>
<td>(3.07)</td>
<td>(2.55)</td>
<td>(3.30)</td>
<td>(2.72)</td>
<td>(2.16)</td>
<td>(1.77)</td>
<td></td>
</tr>
<tr>
<td>0.0047</td>
<td>0.0047</td>
<td>0.0053</td>
<td>0.0024</td>
<td>0.0052</td>
<td>0.0059</td>
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</tr>
<tr>
<td>(0.90)</td>
<td>(0.90)</td>
<td>(1.05)</td>
<td>(0.43)</td>
<td>(0.65)</td>
<td>(0.66)</td>
<td></td>
</tr>
<tr>
<td>0.01209</td>
<td>0.01209</td>
<td>0.01260</td>
<td>0.01260</td>
<td>0.01615</td>
<td>0.01636</td>
<td></td>
</tr>
<tr>
<td>(4.51)</td>
<td>(2.32)</td>
<td>(3.33)</td>
<td>(1.85)</td>
<td>(1.96)</td>
<td>(2.22)</td>
<td></td>
</tr>
<tr>
<td>0.0176*</td>
<td>0.0104**</td>
<td>0.0580*</td>
<td>0.0568*</td>
<td>0.0472*</td>
<td>0.0455*</td>
<td></td>
</tr>
<tr>
<td>(3.00)</td>
<td>(1.86)</td>
<td>(4.82)</td>
<td>(2.85)</td>
<td>(3.13)</td>
<td>(2.67)</td>
<td></td>
</tr>
<tr>
<td>0.1134*</td>
<td>0.1237</td>
<td>0.1290</td>
<td>0.0802</td>
<td>0.0725</td>
<td>0.1112</td>
<td></td>
</tr>
<tr>
<td>(19.34)</td>
<td>(4.32)</td>
<td>(4.24)</td>
<td>(1.92)</td>
<td>(2.28)</td>
<td>(3.24)</td>
<td></td>
</tr>
<tr>
<td>0.8995*</td>
<td>0.9009*</td>
<td>0.8645*</td>
<td>0.8737*</td>
<td>0.8895*</td>
<td>0.8784*</td>
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<td>(185.0)</td>
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<td>(39.78)</td>
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<td>(25.36)</td>
<td>(24.81)</td>
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</tr>
<tr>
<td>9.60*</td>
<td>8.60*</td>
<td>3.67*</td>
<td>5.40*</td>
<td>2.00*</td>
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</tr>
<tr>
<td>(0.08)</td>
<td>(0.12)</td>
<td>(0.59)</td>
<td>(0.36)</td>
<td>(0.84)</td>
<td>(0.71)</td>
<td></td>
</tr>
<tr>
<td>14.90*</td>
<td>16.06*</td>
<td>10.26*</td>
<td>14.43*</td>
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<td></td>
</tr>
<tr>
<td>(0.17)</td>
<td>(0.08)</td>
<td>(0.41)</td>
<td>(0.15)</td>
<td>(0.63)</td>
<td>(0.11)</td>
<td></td>
</tr>
<tr>
<td>1.71*</td>
<td>2.11*</td>
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<td>0.56*</td>
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<tr>
<td>(0.88)</td>
<td>(0.83)</td>
<td>(0.90)</td>
<td>(0.42)</td>
<td>(0.16)</td>
<td>(0.98)</td>
<td></td>
</tr>
<tr>
<td>5.91*</td>
<td>4.22*</td>
<td>4.17*</td>
<td>6.08*</td>
<td>10.55*</td>
<td>1.27*</td>
<td></td>
</tr>
<tr>
<td>(0.82)</td>
<td>(0.93)</td>
<td>(0.93)</td>
<td>(0.80)</td>
<td>(0.39)</td>
<td>(0.99)</td>
<td></td>
</tr>
</tbody>
</table>

Table 10. Empirical estimation of the series of returns. We present the conditional mean equation and conditional volatility equation defined either as linear GARCH model or GJR-GARCH model. The model is defined as $r_t = ARMA + r_oil_t + \varepsilon_t$, $\varepsilon_t = \sqrt{h_t}z_t$, $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$ (GARCH) or $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^2 \varepsilon_{t-1}^2 + \beta h_{t-1}$ (GJR-GARCH). In parenthesis we report the t-Statistics for the parameters and p-values for the Ljung-Box test statistics (Q(5) and Q(10) for standardized residuals and Q(5)^2 and Q(10)^2) for squared standardized residuals. * - statistically significant at 5% level, ** - at 10% level.

6.5.3 The univariate GARCH models with the dummy variable and the volatility of oil prices as the explanatory variable - Specification 3

Table 11. Estimation results for each series of stock market returns for Specification 3. Specification 3 takes dummy variable of the negative oil price returns as the explanatory variable in the mean equation.
Table 11. Empirical estimation of the series of returns. We present the conditional mean equation and conditional volatility equation defined either as linear GARCH model or GJRGARCH model. The model is defined as

\[ r_t = \text{ARMA} + r_{oil} t + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t} \varepsilon_t, \quad h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \]  

(GARCH) or 

\[ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^2 \varepsilon_{t-1}^2 + \beta h_{t-1} \]  

(GJRGARCH). In parenthesis we report the t-Statistics for the parameters and p-values for the Ljung-Box test statistics (Q(5) and Q(10) for standardized residuals and Q(5)^2 and Q(10)^2 for squared standardized residuals. * - statistically significant at 5% level, ** - at 10% level.

### 6.5.4 The univariate GARCH models with the dummy variable and the volatility of oil prices as the explanatory variable - Specification 4

Table 12. Estimation results for each series of stock market returns for Specification 4. Specification 4 takes the volatility of oil price returns as the explanatory variables.
The model is defined as a mean equation and conditional volatility equation defined either as linear GARCH model (scaled oil prices increases and NOPI (net oil price increases)

Table 13. Estimation results for each series of stock market returns with nonlinear transformation of oil prices as the explanatory variables - SOPI (scaled oil prices increases and NOPI (net oil price increases)
The model is defined as $r_t = AR MA + r_{-oil} + \varepsilon_t$, $\varepsilon_t = \sqrt{h_t} z_t$, $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$ (GARCH) or $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \gamma S_{t-1}^- \varepsilon_{t-1} + \beta h_{t-1}$ (GJRGARCH). In parenthesis we report the t-statistics for the parameters and p-values for the Ljung-Box test statistics (Q(5) and Q(10) for standardized residuals and Q(5)$^2$ and Q(10)$^2$ for squared standardized residuals. * - statistically significant at 5% level, ** - at 10% level. For NOPI we present only the estimated parameters and the corresponding t-statistics. The rest of the results available upon request.

<table>
<thead>
<tr>
<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>0.0421*</td>
<td>0.0344*</td>
<td>0.0409*</td>
<td>0.0269*</td>
<td>0.0567*</td>
<td>0.0137</td>
</tr>
<tr>
<td>$\phi_1$</td>
<td>0.0378*</td>
<td>0.1739*</td>
<td>0.0230</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_{-oil}$</td>
<td>-0.0041*</td>
<td>-0.0065*</td>
<td>0.0097*</td>
<td>0.0190</td>
<td>-0.0863*</td>
<td></td>
</tr>
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<td>$\omega$</td>
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<td>0.0227*</td>
<td>0.0058*</td>
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<td>0.0016*</td>
<td>0.0016*</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.0116*</td>
<td>0.0104*</td>
<td>0.0038*</td>
<td>0.0056*</td>
<td>0.0016*</td>
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<tr>
<td>$\gamma$</td>
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<td>0.1201*</td>
<td>0.0809*</td>
<td>0.0726*</td>
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</tr>
<tr>
<td>$\beta$</td>
<td>0.8997*</td>
<td>0.9069*</td>
<td>0.8642*</td>
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<td>0.8896*</td>
<td>0.8752*</td>
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<td>Q(5)</td>
<td>1.74*</td>
<td>8.65*</td>
<td>3.60*</td>
<td>5.32*</td>
<td>7.83*</td>
<td>6.22*</td>
</tr>
<tr>
<td>Q(10)</td>
<td>1.35*</td>
<td>4.71*</td>
<td>2.10*</td>
<td>4.71*</td>
<td>7.83*</td>
<td>6.22*</td>
</tr>
</tbody>
</table>

Table 13. Empirical estimation of the series of returns. We present the conditional mean equation and conditional volatility equation defined either as linear GARCH model or GJRGARCH model. For NOPI we present only the estimated parameters and the corresponding t-statistics. The rest of the results available upon request.
6.5.6 ECCC-GARCH model

Extended Constant Conditional Correlation GARCH model given as

$$
\begin{bmatrix}
  h_{1t} \\
  h_{2t}
\end{bmatrix} = \begin{bmatrix}
  \omega_1 & 0 & 0 \\
  \alpha_{11} & \omega_2 & \text{std dev of } \varepsilon_{1t-1} \\
  0 & \alpha_{22} & \text{std dev of } \varepsilon_{2t-1}
\end{bmatrix} \begin{bmatrix}
  \varepsilon_{1t-1}^2 \\
  \varepsilon_{2t-1}^2
\end{bmatrix} + \begin{bmatrix}
  \gamma \\
  0
\end{bmatrix} \begin{bmatrix}
  S_{t-1}^2 \\
  \varepsilon_{2t-1}^2
\end{bmatrix} + \begin{bmatrix}
  \beta_{11} & \beta_{12} \\
  \beta_{21} & \beta_{22}
\end{bmatrix} \begin{bmatrix}
  h_{1t-1} \\
  h_{2t-1}
\end{bmatrix}
$$

We present the t-statistics of the parameter estimates in parenthesis calculated with the robust errors. We present the values of the LjungBox statistics at lags 5 and 10 for standardized and squares standardized residuals for stock markets returns and oil returns with p-values in parenthesis * and ** statistically significant at 5% and 10% level respectively.

<table>
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<th></th>
<th>DJIA</th>
<th>S&amp;P</th>
<th>NASDAQ</th>
<th>FTSE</th>
<th>DAX</th>
<th>NIKKEI</th>
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<td>0.0227*</td>
<td>0.0222*</td>
<td>0.0344*</td>
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<td>0.0132</td>
<td>0.0058</td>
<td>0.0566*</td>
<td>0.0582*</td>
<td>0.0488</td>
<td>0.0421*</td>
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<td></td>
<td>(2.62)</td>
<td>(1.15)</td>
<td>(6.22)</td>
<td>(7.00)</td>
<td>(6.47)</td>
<td>(6.89)</td>
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<tr>
<td>$\gamma$</td>
<td>0.1224</td>
<td>0.1394*</td>
<td>0.1329*</td>
<td>0.0878*</td>
<td>0.0722</td>
<td>0.1115*</td>
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<tr>
<td></td>
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<td>(22.27)</td>
<td>(13.14)</td>
<td>(11.53)</td>
<td>(9.70)</td>
<td>(10.82)</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
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<td>0.9039*</td>
<td>0.8665*</td>
<td>0.8660*</td>
<td>0.8812*</td>
<td>0.8817*</td>
</tr>
<tr>
<td></td>
<td>(213.19)</td>
<td>(224.91)</td>
<td>(122.67)</td>
<td>(100.27)</td>
<td>(105.85)</td>
<td>(142.94)</td>
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<td>0.0006*</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.0004</td>
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<td>(3.61)</td>
<td>(1.04)</td>
<td>(1.02)</td>
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<tr>
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<td>(4.82)</td>
<td>(4.80)</td>
<td>(4.35)</td>
<td>(3.88)</td>
<td>(2.50)</td>
<td>(3.24)</td>
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<tr>
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<td>0.0927*</td>
<td>0.0930*</td>
<td>0.0939*</td>
<td>0.0943*</td>
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<td>0.0027</td>
<td>0.0092*</td>
<td>0.0032</td>
<td>0.0053*</td>
<td>0.0041*</td>
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<tr>
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<td>(1.24)</td>
<td>(1.32)</td>
<td>(3.25)</td>
<td>(1.23)</td>
<td>(2.10)</td>
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<td>$\beta_{22}$</td>
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<td>0.9132*</td>
<td>0.9103*</td>
<td>0.9125*</td>
<td>0.9112*</td>
<td>0.9111*</td>
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<tr>
<td></td>
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<td>(229.99)</td>
<td>(220.23)</td>
<td>(229.37)</td>
<td>(226.48)</td>
<td>(224.93)</td>
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<tr>
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<td>-0.0185</td>
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<tr>
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<td>(-1.93)</td>
<td>(-1.44)</td>
<td>(-1.08)</td>
<td>(1.26)</td>
<td>(-1.95)</td>
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<tr>
<td>$Q(5)_{stock}$</td>
<td>6.60*</td>
<td>8.72*</td>
<td>4.97*</td>
<td>3.00*</td>
<td>4.52*</td>
<td>2.92*</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.12)</td>
<td>(0.53)</td>
<td>(0.41)</td>
<td>(0.85)</td>
<td>(0.71)</td>
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<tr>
<td>$Q(10)_{stock}$</td>
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<td>16.74*</td>
<td>10.30*</td>
<td>14.13*</td>
<td>8.11*</td>
<td>16.16*</td>
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<td>(0.08)</td>
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<tr>
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<td>1.56*</td>
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<td></td>
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<td>(0.80)</td>
<td>(0.42)</td>
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<tr>
<td>$Q(10)_{stock}^2$</td>
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<td>4.84*</td>
<td>4.84*</td>
<td>6.00*</td>
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<tr>
<td></td>
<td>(0.77)</td>
<td>(0.91)</td>
<td>(0.96)</td>
<td>(0.81)</td>
<td>(0.41)</td>
<td>(0.99)</td>
</tr>
<tr>
<td>$Q(5)_{oil}$</td>
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<td>7.93*</td>
<td>6.97*</td>
<td>8.23*</td>
<td>6.95*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.21)</td>
<td>(0.21)</td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.22)</td>
</tr>
<tr>
<td>$Q(10)_{oil}$</td>
<td>13.97*</td>
<td>13.97*</td>
<td>14.21*</td>
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<td>13.91*</td>
<td>13.83*</td>
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<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.16)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>$Q(5)_{oil}^2$</td>
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<td>3.84*</td>
<td>3.64*</td>
<td>4.19*</td>
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<td>(0.58)</td>
<td>(0.57)</td>
<td>(0.59)</td>
<td>(0.52)</td>
<td>(0.58)</td>
<td></td>
</tr>
<tr>
<td>$Q(10)_{oil}^2$</td>
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<td>12.03*</td>
<td>11.49*</td>
<td>11.99*</td>
<td>11.28*</td>
<td>10.99*</td>
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<td>(0.28)</td>
<td>(0.28)</td>
<td>(0.32)</td>
<td>(0.28)</td>
<td>(0.33)</td>
<td>(0.35)</td>
</tr>
</tbody>
</table>

Table 14: Estimated Extended Constant Conditional Correlation Model.