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Realized volatility transmission between crude oil and equity futures markets: A multivariate HAR approach

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ABSTRACT

This paper differs from extant literature because it studies volatility co-movements with a multivariate orthogonalized HAR model, a flexible specification for the time series of realized volatility, which is able to identify short-, mid- and long-term spillover effects. We examine volatility transmission mechanisms using high-frequency data of the stock index futures on S&P 500, Nikkei 225, FTSE 100 and the futures on the West Texas Intermediate crude oil during the period from September 2002 to September 2012. Considering the full sample, the short-term volatility of the equity futures contains information about future oil volatility incremental to the information inherent in the time series of oil volatility. On the other hand, weekly and monthly volatilities do not exhibit a significant spillover effect. Breaking the whole sample into three subsamples, no significant Granger causalities are observed in the pre-crisis period while in the crisis time and its aftermath, we document that the US and UK equity market volatilities to Granger cause the oil futures volatility which itself leads the Japanese market. In terms of magnitude, we observe an increase in the short-term volatility spillover over time. Studying the residuals of the HAR transmission models within a CCC/DCC-GARCH framework reveals increasing instantaneous correlation between the energy and equity volatilities in the course of time.

1. Introduction

Due to the rising amount of cross-asset acting investors and increasingly interlocking markets, financial market linkages are subject of rigorous research interest. Over the last decade, the number of contributions on cross asset price interrelationships has increased enormously and the question on how volatility is transmitted across major markets has triggered an outburst of studies based mostly on a multivariate GARCH framework.[1]

Oil is one of the key inputs for all major economies, which makes its relationship to various macroeconomic factors and stock market movements a topic of high practical importance. Many studies provide statistical proof of a significant link between oil price changes and returns on various equity markets. The literature on volatility interrelationships usually deducts either a spillover from oil price series to equity markets or a relationship of bidirectional nature (see Section 2). However, the various MGARCH specifications employed by most of the studies utilize returns sampled at a daily or lower frequency. Daily returns are known to provide noisy volatility estimates. In this study, we draw inferences about the volatility spillover mechanisms between the equity futures on S&P 500, Nikkei 225, FTSE 100 and the futures contracts on the light sweet crude oil West Texas Intermediate (WTI) using intraday data. These equity indices are chosen as established proxies of the US, UK and developed Asian equity markets. As these equity markets are highly liquid, numerous studies have already discussed the link between their returns and crude oil price movements. This fact allows us to compare our unique results for realized volatility series with the broad body of recent literature.

The contribution of this study is fourfold. First, it is the first to use a multivariate extension of the heterogeneous autoregressive (HAR) model of Corsi (2009) for realized volatility to explore the relationship between equity and oil market volatility. The HAR model is a powerful and flexible tool that is broadly acknowledged in the econometric literature mostly in its univariate version. The HAR model is a simple autoregressive-type model of realized volatility, considering volatilities realized over different interval sizes. It is very easy to use in practice and is shown to capture successfully the persistence of realized volatility for various forecasting horizons, and can be easily augmented by external variables. While the HAR model is an acknowledged volatility model in its univariate version, its application in multivariate settings is still rather scarce (see Section 2). Our analysis is based on the multivariate version of the HAR model as used by Bubák et al. (2011), who uncover volatility transmission between Central European currencies and the EUR/USD foreign exchange rate. The main advantage of the vector HAR (VHAR) model is its ability to split spillover effects in daily, weekly

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[1] For a review, see Soriano and Climent (2006).

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and monthly horizons, which cannot be done by means of the widely established multivariate GARCH framework.

Second, our methodological contribution is to extend the approach of Bubák et al. (2011) by using an orthogonalized version of the model. In particular, the equation of an asset's volatility contains the own volatility components as in the model's default univariate form whereas we employ an orthogonalized specification to capture the incremental information inherent in the realized volatility time series of a second asset. This approach aims to avoid ambiguous results caused by potential multicollinearity which may be emerging from a model setting within which realized volatilities of multiple assets are considered simultaneously. We focus on the volatility linkages of oil with the three equity markets in three separate bivariate models. To study the second moments of the volatility series, the residuals are considered within a CCC/DCC-GARCH(1,1) model by Bollerslev (1990) resp. Engle (2002). Hence, this study is unique in its investigation of the pattern of dynamic correlation between the second moments of equity and energy markets.

Third, the multivariate HAR model is fitted to the series of realized volatility of the assets under consideration. Realized volatility is a high-frequency data based volatility estimator and high-frequency data, which are known to improve volatility estimation substantially, are likely to allow for a far more precise analysis of the potential transmission patterns. In the case of S&P 500 and crude oil, the futures contracts are traded 24 h a day at the CME, so we do not need to cope with issues of overlapping trading and non-trading times between these assets. For Nikkei 225 and FTSE 100 index futures, the daily trading times are shorter in earlier years of the sample. However, since we are interested in lead–lag relationships of daily volatilities, the data allows for creating non-overlapping measures.

Last, our analysis covers the recent period from September 2002 to September 2012. Moreover, we discuss the volatility spillover effects between the equity futures and the crude oil futures markets for the full sample and due to the significant events influencing the markets over the last decade, we also split the volatility series into three subsamples. Results of the Granger causality tests, bivariate transmission models and correlation analysis are reported and discussed for the pre-crisis, crisis and after-crisis subperiods separately. This approach allows us to identify the source of the spillover effects found for the whole sample and to interpret their nature against the backdrop of major financial market events.

Focusing first on the whole sample period, we identify several causality relationships indicating that the equity markets are leading the volatility of crude oil. The interrelation between the realized volatilities in the full sample is mostly driven by the short-term shocks. The source of the volatility transmission appears to be the period starting with the financial crisis. Up until 2008, we find no evidence for significant Granger causalities. During the crisis, we can observe significant Granger causality going from the US and UK market to the oil futures volatility. The explanation is sought in the nature of the crisis which emerged from the markets for financial assets rather than from the overall shape of the economy. When the sub-prime market collapsed in 2008, the world economy followed these developments from the mid 2008. As broadly discussed in the literature (see Section 2), WTI can act as a gauge of the prevailing uncertainty of the overall macroeconomic environment and seems to lead the Japanese market in the short-term in our sample. The spillover effects persist in the period after 2009 with a strong relative impact of FTSE 100 on the oil market possibly due to the European sovereign debt crisis.

The analysis of the pattern of the conditional correlations shows additionally that there is a vast increase in the correlation during the recent capital market turmoil. The correlation observable after the global financial crisis is way higher than after the burst of the dot com bubble in 2001 and 2002. With appropriate caution, this might be interpreted as an additional evidence for the increasing integration of the equity and oil futures markets. Especially in the after-crisis period, we observe a decreasing strength of causality relationships on the one hand, and on the other hand, increasing instantaneous correlation indicating more pronounced simultaneous co-movements.

The rest of the paper is organized as follows: Section 2 reviews the literature on equity–oil market linkages and the HAR model. Sections 3 and 4 present the data and methodology. Section 5 discusses the empirical results and compares them with existing studies. Section 6 concludes the paper.

2. Literature review

Many scholars have discussed the relationships between oil prices and macroeconomic variables in detail. The pioneer papers of Hamilton (1983) and Gisser and Goodwin (1986) argue that oil price shocks might impact the future economic development and their findings are confirmed by many other studies, including Mork (1989), Lee et al. (1995) and Hooker (1996). As one of first, Jones and Kaul (1996) test the impact of oil prices on four developed markets using the cash-flow dividend model and find a significant negative correlation with the US stock market while the results for the Japanese and UK markets were inconclusive. However, more recent studies generally support the hypothesis that a significant link is present between numerous national stock indices and oil price time series (e.g. Basher and Sadorsky, 2006; Hammoudeh and Li, 2005; Park and Ratti, 2008; Sadorsky, 1999). Furthermore, some studies discuss the potential economic exploitability of such relationships (e.g. Arouri and Nquyen, 2010; Driesprong et al., 2008; Souček and Todorova, 2013).

Much attention has been paid to studying volatility transmission patterns, especially in equity markets (Soriano and Climent, 2006) whereas studies on oil markets are not so frequent. For instance, Malik and Hammoudeh (2007) show evidence for spillovers between oil prices, US, and the Gulf markets. Based on a multivariate GARCH analysis, Aloui et al. (2008) find oil volatility to have in general a negative impact on stock market development. Aloui and Jammazi (2009) use a Markov regime switching model to describe the course of volatility and show that oil price increases play a significant role in determining both the volatility of returns and the probability of transition across regimes. Chang et al. (2010), on the other hand, find only a little evidence for oil spillover in equity markets. Arouri et al. (2011) document a unidirectional spillover effect from oil to European stocks and a bidirectional relationship for US equities at sector level. Filis et al. (2011) support the results by, for instance, Choi and Hammoudeh (2010) and Chang et al. (2010) and show that the dynamic correlation between stock and oil markets exhibits time-varying patterns which are influenced by external information shocks. Malik and Ewing (2009) use bivariate GARCH models to simultaneously estimate the mean and conditional variance among five different US sector indexes and oil prices finding significant spillover effects. As previously mentioned, all contributions use return data sampled at a daily or lower frequency to examine volatility transmission mechanisms.

Since first discussed, numerous studies on financial market volatility have adopted the HAR model for realized volatility of Corsi (2009) (e.g. Ait-Sahalia and Mancini, 2008; Andersen et al., 2007; Bubák and Žikeš, 2009; Maheu and McCurdy, 2011) and a variety of model extensions has emerged. Giot and Laurent (2007) and Busch et al. (2011) examine the incremental content of implied volatility in the setting of a decomposition of realized volatility in jump and continuous elements. Corsi and Renó (2012) discuss the significance of leverage effects within the model and Corsi et al. (2012) address general nonlinear effects in volatility. In contrast, the literature using a multivariate HAR framework is rather scarce. Bauer and Vorkink (2011) propose a matrix-logarithm model of the realized covariance matrix of US stock returns. Bubák et al. (2011) use a vector HAR, to analyze volatility transmission between Central European currencies and the EUR/USD foreign exchange from 2003 to 2009. Against this backdrop, the current paper is clearly placed in the literature. It extends the empirical model of Bubák et al. (2011) by orthogonalized parameters, and is the first applying this advanced methodology for analyzing spillovers between equity and energy markets.

3. Methodology

3.1. Multivariate HAR model

The long-memory feature of volatility is often modeled by FIGARCH models of returns or ARFIMA models of realized volatility. However, fractionally integrated models are nontrivial to estimate and not easily extendable to multivariate settings (Corsi, 2009). To analyze interrelationships among volatility time series, we use a multivariate version of the HAR model of Corsi (2009), similar to the one used by Bubák et al. (2011). In spite of the fact that the HAR model does not formally possess long memory, it is well known to be capable of capturing a pronounced slow volatility autocorrelation decay that is almost indistinguishable from that reproduced by a hyperbolic (long memory) pattern (Andersen et al., 2007). The construction of the HAR model is motivated by the heterogeneous market hypothesis presented by Müller et al. (1997) and Dacorogna et al. (1998) which assumes the presence of heterogeneity across traders. Corsi (2009) proposes a simple autoregressive-type model for realized volatility considering volatilities realized over different time periods. This specification is based upon the idea that traders with different time horizons cause different types of volatility components. The notion of an asymmetric volatility propagation is supported by the observation that volatility over longer time intervals has a stronger influence on volatility over shorter time intervals than vice versa. In the default univariate version of the HAR model, volatility forecasts are linear functions of the daily, weekly, and monthly realized volatilities. The HAR model is very easy to use in practice and is shown to capture successfully the persistence of realized volatility for various forecasting horizons and can be easily augmented by external variables. In contrast to MGARCH models, the multivariate HAR framework is able to uncover the role of various time period volatility components (daily, weekly, monthly) in the interrelations between equity and energy markets.

To study the potential volatility transmission patterns between equity and oil markets, we modify slightly the multivariate framework of Bubák et al. (2011). Their VHAR specification is given by

$$\nu_t = \beta_0 + \beta_1 \nu_{t-1|t-1} + \beta_5 \nu_{t-1|t-5} + \beta_{22} \nu_{t-1|t-22+\epsilon_t}, \tag{1}$$

where v_t is a logarithmic volatility vector and $\nu_{t-1\,t-}k$, $k = 1, 5, 22$ represents the vectors containing the normalized volatility sums over the last 1, 5 and 22 days, respectively.

Realized volatilities of financial assets are often highly correlated. To ensure that we consider solely new information from the other assets' volatility related to the corresponding time component, we introduce an orthogonalized version of the above model. In particular, we run the following time series regression for every asset in the transmission model:

$$\nu_{i,t-1|t-k} = c_i + \alpha_{i,j} \nu_{j,t-1|t-k} + \omega_{i,t-k}, \quad k = 1, 5, 22. \tag{2}$$

If for example $\nu_{i,t-1|t-5}$ is the weekly volatility component of asset i, the residual $\omega_{i,t-5}$ describes the variation of $v_{i,t-1|t-5}$ which is not explained by the time series of the weekly realized volatility of asset j.

We examine the volatility linkages of oil with the three considered equity markets in three separate bivariate models. In the bivariate case of assets i and j, the estimated orthogonalized VHAR equation for the asset i is then:

$$\begin{aligned}\nu_{i,t} = \beta_{i,0} + \beta_{i,1}\nu_{i,t-1|t-1} + \beta_{i,5}\nu_{i,t-1|t-5} + \beta_{i,22}\nu_{i,t-1|t-22} \\ + \beta_{j,1}\omega_{j,t-1|t-1} + \beta_{j,5}\omega_{j,t-1|t-5} + \beta_{j,22}\omega_{j,t-1|t-22} + \epsilon_{i,t}.\end{aligned} \tag{3}$$

3.2. Second moments and time-varying correlation of realized volatilities

In the univariate case, Corsi et al. (2008) explicitly model the volatility of realized volatility for the HAR model by taking GARCH-type innovations into account. To capture the second moments of volatility and investigate the time-varying correlation of the volatilities in the multivariate case, the CCC- and DCC-GARCH model of Bollerslev (1990) resp. Engle (2002) is employed. A similar approach for multivariate modeling of HAR residuals can be found in Bubák et al. (2011).

The DCC correlation model is based on the decomposition of the conditional covariance matrix into conditional standard deviation and time varying conditional correlation. For the vector of innovation term ϵ_t from the VHAR model, a basic multivariate GARCH model is used, with

$$\epsilon_t = \mathbf{D}_t \boldsymbol{\eta}_t \quad \text{and} \quad \mathbf{V}_t = \mathbf{D}_t \Gamma_t \mathbf{D}_t \tag{4}$$

where $\boldsymbol{\eta}_t$ is a $n \times 1$ vector with $E(\boldsymbol{\eta}_t) = 0$ and $E(\boldsymbol{\eta}_t\boldsymbol{\eta}_t') = \mathbf{I}_n \cdot \mathbf{V}_t$ is the conditional covariance matrix and $\mathbf{D}_t = diag(h_1^{1/2}, \ldots, h_n^{1/2})$ is a diagonal matrix of conditional standard deviations. In some situations, the assumption of time varying conditional correlation matrix $\boldsymbol{\Gamma}_t$ is unnecessary. In such cases, the Constant Conditional Correlation (CCC) GARCH model by Bollerslev (1990) can be used, where Eq. (4) becomes $\mathbf{V}_t = \mathbf{D}_t \boldsymbol{\Gamma} \mathbf{D}_t$. In our subsample analysis, we employ the test of Engle and Sheppard (2001) for the time varying conditional correlation matrix to decide whether to use a DCC- or CCC-GARCH specification, testing the null hypothesis $H_0: \boldsymbol{\Gamma}_t = \boldsymbol{\Gamma}$.[2]

Looking more closely at the DCC specification, the conditional variance h_{it} is defined as a univariate GARCH(1,1) process,

$$h_{it} = \omega_i + \alpha_{i1} \varepsilon^2_{i,t-1} + \gamma_{i1} h_{i,t-1}. \tag{5}$$

If the $\boldsymbol{\eta}_t$ is a i.i.d. vector of random variables, with zero mean and unit variance, $\boldsymbol{\Gamma}_t$ is the conditional correlation matrix of the standardized residuals, $\eta_{it} = \varepsilon_{it}/\sqrt{h_{it}}$. The dynamic conditional correlation can be estimated as

$$\Gamma_t = \left\{diag(\mathbf{Q}_t)^{-1/2}\right\}\mathbf{Q}_t\left\{diag(\mathbf{Q}_t)^{-1/2}\right\}, \tag{6}$$

where $\mathbf{Q}_t$ is a $k \times k$ symmetric positive definite matrix given by

$$\mathbf{Q}_t = (1 - d_1 - d_2)\overline{\mathbf{Q}} + d_1 \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}'_{t-1} + d_2 \mathbf{Q}_{t-1}. \tag{7}$$

$\overline{\mathbf{Q}}$ stands for unconditional covariance matrix of the standardized residuals $\boldsymbol{\eta}_t$. The parameters d_1 and d_1 are scalars which capture the effect of previous shocks and previous dynamic correlation on the current conditional correlation. They have non-negative values and should satisfy $d_1 + d_2 < 1$.

CCC and DCC are not linear but can be estimated using a two-step method based on the classical maximum likelihood function. A first step is to estimate the univariate GARCH from Eq. (5) and in a second step, the correlation coefficients are estimated. For the discussion of statistical properties of the CCC/DCC models, the reader is referred to Bauwens et al. (2006), Silvennoinen and Teräsvirta (2009) and Martin et al. (2013) and for technical details about the estimation, to Silvennoinen and Teräsvirta (2009).

3.3. Realized volatility

To measure the daily quadratic variation using intraday data we employ the realized variance as proposed by Andersen and Bollerslev (1998). This broadly acknowledged estimator is calculated on the

[2] Even though this testing procedure is used in academic research, the original paper remains unpublished, due to the missing proof of the statistical properties of the parameter estimates. The results obtained for the three subsamples using the CCC model, however, support our test results showing a clear time-varying structure of the correlation throughout the subsamples.

basis of the intraday futures' quotations $P_{t,i}$. The resultant continuous intraday returns are calculated as follows:

$$r_{t,i} = \ln\left(\frac{P_{t,i}}{P_{t,i-1}}\right) \quad \text{for } i>0, \tag{8}$$

with the first index t denoting the day of observation $t = 0, 1, 2,\ldots,T$. The index i denotes the time of observation on a particular day $i = 0, 1, 2,\ldots,I$. For assets which are not traded 24 h a day, overnight returns

$$r_{t,0} = \ln\left(\frac{P_{t,0}}{P_{t-1,I}}\right) \quad \text{for } t>0 \tag{9}$$

are established as well. The realized variance of a trading day t is estimated by finding the total of squared 5-minute returns, and adding the sum to the last squared overnight return (if not traded 24 h a day). Furthermore, to give a sense of the magnitude of the attained estimates, we utilize the annualized form of realized variance,

$$RV_t = 252 \cdot \left(r_{t,0}^2 + \sum_{i=1}^{I} r_{t,i}^2\right). \tag{10}$$

We report results obtained using a logarithmic specification of the realized variance $v_t = \log(RV_t)$ rather than with volatility $\sqrt{RV_t}$ itself, because the distribution of logarithmic variance is closer to normal, as shown in the following section, which is beneficial for statistical purposes. Moreover, using variance in its log form does not impose non-negativity constraints for estimation purposes.

The theory of realized variation suggests that the sampling frequency goes to infinity. However, volatility based on sampling at a very high-frequency is likely to suffer from microstructure noise factors like bid–ask spreads and nonsynchronous trading to a great extent. In practice, it is necessary to find a point of tradeoff between the benefit of using very frequently sampled data and the attempt to minimize estimation errors caused by noise. The bias caused by microstructure noise is the subject of active research interest (e.g., Bandi and Russell, 2006; Hansen and Lunde, 2006, among others).[3] Various ways of dealing with the distortion due to microstructure noise other than sampling at lower frequencies are possible. Several bias correction procedures have been proposed, like for example subsampling and kernel-based approaches. However, as indicated by Bollerslev et al. (2011), the easily implemented estimator based on the sum of not very finely sampled high-frequency squared returns "remains the dominant method in practical applications" and sampling at a frequency of 5 min should be a reasonable choice for highly liquid assets like the futures considered in this study.

To obtain multi-period volatility measures, necessary for estimating the volatility transmission models, we calculate a simple mean over N trading days, conform to Corsi (2009),

$$v_{t-1|t-k} = \frac{1}{N}\sum_{n=1}^{N} \log(RV_{t-n}), \quad k = 1, 5, 22. \tag{11}$$

4. Data

Our analysis is based on 5-minute prices (in US$) of the one month futures contracts on Light Sweet Crude Oil (WTI), FTSE 100, the S&P 500 (e-mini futures, in the following referred to as S&P 500) and Nikkei 225. The futures on WTI, S&P 500 und Nikkei 225 are traded at the CME and the futures contracts on FTSE 100 are traded at the NYSE LIFFE. While the CME futures on S&P 500 and WTI are traded 24 h a day during the whole sample period, the remaining futures contracts were traded over shorter time slots before 2010.[4] Since we aim at gaining insights into volatility spillover effects in a context which is as close to real world setting as possible, we establish the daily realized volatilities over the longest available trading time of the corresponding day. Conform to Bubák et al. (2011), we define a trading day as the interval from 21:00 GMT to 20:59 GMT of the following day.

Regarding the deviating trading times of the considered assets, one should note that the VHAR model examines lead–lag relationships of daily volatilities which do not represent a concern of non-synchronicity. Let us consider for example the case of WTI and FTSE (traded for instance till 20:00 GMT). The equation for v_{WTI} presents oil volatility as a function of previous days' oil volatilities and previous equity volatilities where the information set for the equity futures ends 2 h before the oil futures' information set. The equation for v_{FTSE} presents the equity volatility as a function of previous days' equity volatilities and previous oil volatilities where the information set for the oil futures ends 2 h after the equity futures' information set but still before the next trading day for the equity index has started. Discarding WTI trading time at the evening for instance, when futures on FTSE are not traded, would lead to informational loss in our volatility transmission model which does not exist in this form for the market participants.

The data cover a period of 10 years and one month from September 2002 to September 2012 and are obtained from the Thomson Reuters Tick History database of the Securities Industries Research Centre of Asia Pacific (SIRCA). We do not consider weekend periods and take only trading days into account on which all future contracts are traded. This leads to a total of 2580 trading days. Table 1 shows the descriptive statistics for daily realized volatilities and logarithmic realized variances of all four considered futures contracts. The crude oil futures seem to have the highest level of fluctuation, which is what one might expect looking at Figs. 1 and 2. Fig. 1 describes the evolution of futures prices between September 2002 and September 2012, showing extreme percentage increases of crude oil prices before 2008, and its subsequent decline. Fig. 2 presents the development of realized volatilities. Around 2008, a huge decline in prices, as well as a corresponding increase in volatility are observable. Another, however, not so strong structural volatility increase is observable in 2002 and 2003, during the financial crisis which followed the burst of dot com bubble. Considering the skewness and kurtosis of the volatility series, the logarithmic specification appears to way closer to normal distribution, compared to the daily realized volatilities. Conform to previous literature, realized volatility and its logarithmic transformation exhibit strong autocorrelation.

As described in the previous section, the estimation is generally based on a version of a restricted $VAR(22)$ model. One of the key assumptions of such framework is the stationarity of the underlying time series. To test for the presence of unit roots, we employed the Augmented Dickey–Fuller (ADF) test for unit roots, Phillips and Perron (1988) (PP) test and Elliot et al. (1996) (ERS). All three tests are defined under the null hypothesis that the unit root is present. The results are summarized in Table 2. The t-values of the ADF and PP tests are compared with the Dickey–Fuller (DF) critical values. The critical values tabulated in Elliot et al. (1996) are used to evaluate the ERS test. The test results support the hypothesis of stationary logarithmic realized variances. It is worth to mention, that these tests are frequently omitted in other studies on volatility spillovers. Few studies on realized volatility (e.g. Areal and Taylor, 2002; Chiang et al., 2010) employ ADF tests to prove the presence of unit roots in the time series. We are aware of some drawbacks in the ADF methodology and verify the results using more advanced approaches.

[3] A summary of basic assumptions about microstructure noise and their implications for realized volatility can be found in McAleer and Medeiros (2008).

[4] Discarding data from the additional trading hours after 2010 would be in opposition to the spirit of realized volatility approach of using all the available information. We are thankful to Fulvio Corsi for this comment.

Table 1
Descriptive statistics.

	Realized volatility				Log of realized variance			
	S&P	Nikkei	FTSE	WTI	S&P	Nikkei	FTSE	WTI
Mean	0.17	0.25	0.28	0.33	−3.83	−3.10	−2.81	−2.41
Median	0.14	0.19	0.25	0.29	−3.97	−3.27	−2.79	−2.47
SD	0.12	0.19	0.15	0.17	1.03	1.06	1.00	0.83
Kurtosis	19.48	17.89	7.71	16.95	0.88	1.41	0.08	1.97
Skewness	3.44	3.58	2.01	3.02	0.64	0.98	0.06	0.45
AR(1)	0.86	0.70	0.72	0.66	0.84	0.66	0.67	0.57
Q(6)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JB	0.00	0.00	0.00	0.00	0.00	0.00	0.35	0.00

Note: Descriptive statistics is given for daily realized volatilities and daily logarithmic realized variances. Q(6) is the *p*-value of the χ^2 distributed Box–Ljung test statistics on autocorrelation of order 6. JB stands for the *p*-values of the Jarque–Bera test statistics with the null hypothesis that the variable is normally distributed.

5. Results

In the following section, we discuss the results of the multivariate extension of the HAR model. We employ orthogonalized realized volatility components and OLS estimates to analyze Granger causalities and regression coefficients as applied to the whole sample period and subsamples covering the pre-crisis, crisis and post-crisis period. Finally, we estimate CCC/DCC-GARCH models to capture the correlation between the logarithmic realized variances with the maximum likelihood method.

5.1. Whole sample

5.1.1. Granger causality

The Granger causality tests are based on the three bivariate HAR models and verify whether the inclusion of orthogonalized realized volatility of one asset increases the explanatory power of the volatility equation of the other asset. The estimation procedure was described by Granger (1969). First, in every bivariate model, we estimate Eq. (3). In the second step, we re-estimate Eq. (3) with the restriction $\beta_{j,1} = \beta_{j,5} = \beta_{j,22} = 0$. Third, Wald statistics are used to compare the explanatory power of both models. When we consider an impact of the orthogonalized volatility of the future i on the volatility of j, it holds that if ω_i does not cause v_j, the corresponding coefficients of ω_i are co-instantaneously zero and do not increase the explanatory power of the regression for v_j. Because the relationship is not symmetric, Granger causality in one direction does not imply the causality in the other direction.

Table 3 summarizes the *F*-values for the three bivariate models. The row labeled "Equity Future" represents the test of equity futures realized volatility Granger causing the volatility of crude oil futures. The row labeled "WTI" shows the results of the tests whether crude oil volatility causes the volatility of equity futures in the US, Japanese and the UK markets. The corresponding *p*-values of the *F*-statistics are shown in parentheses.

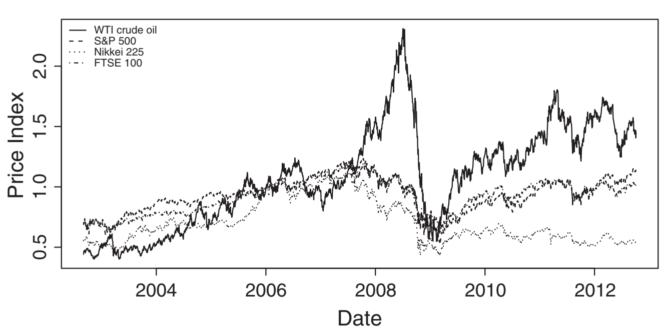

Fig. 1. Closing prices of one month futures on S&P 500, Nikkei 225, FTSE 100 and WTI crude oil indexed on 01.01.2006.

The lagged realized variance components of all the three equity index futures on S&P 500, Nikkei 225 and FTSE 100 seem to contain information for determining future crude oil volatility. A bidirectional causality could be stated in the case of Nikkei225. This result is at odds with existent studies suggesting the existence of spillover from oil to equity or bidirectional interrelationships between the two markets (see Section 2). In Section 5.2, we will interpret our result in light of the recent financial crisis.

5.1.2. Transmission models

In the following, we discuss the coefficients estimated using the VHAR model designed in Section 3. Most of the studies using a VAR framework focus in their interpretation solely on Granger causalities or other tests on joint significance of the regression coefficients answering the question whether additional independent variables increase the forecasting power of the equation system (e.g. Henriques and Sadorsky, 2008; Jones and Kaul, 1996). A greater number of lags in the independent variable might create a multiple testing problem while looking at individual test values for the coefficients. For this reason, the incremental information of our analysis is uncovered using Granger analysis. Nevertheless, under consideration of the results in Section 5.1.1, the analysis of the coefficients in models exhibiting significant causalities reveals additional information about the nature of the relationships. The estimation results are reported in Table 4.[5] Due to the high instantaneous correlation between the realized volatility components of equity and crude oil, we consider solely the variation in the realized volatility of equity (crude oil) futures which is not covered by the corresponding realized volatility component of crude oil (equity). $\beta_{E,i}(i = 1, 5, 22)$ denotes the coefficient of previous daily, weekly and monthly logarithmic volatility for equity futures. $\beta_{O,i}$ labels the corresponding impact of crude oil futures realized volatility. If the stock futures volatility is the endogenous variable of the estimated equation, the coefficients are responses to the orthogonalized volatility of crude oil as calculated in Eq. (2) and vice versa.[6]

Starting with Model 1 (S&P 500 and WTI), it appears that both are mostly affected by its own volatility components, as expected. Additionally, we find that the volatility of S&P 500 is affected positively by the long-term and negatively by mid-term volatility component of the crude oil. However, considering the results for Granger causality tests presented above, both effects rescind each other and do not improve the explanatory power of the equation to a notable extent. For the S&P 500 futures, the own mid-term volatility component appears to be the strongest in terms of magnitude ($\beta_{E,5} = 0.43$). On the other hand, in the equation for crude oil, besides own volatility components, the short-term shock in S&P 500 seems to have additional explanatory power for the future volatility of crude oil ($\beta_{E,1} = 0.12$). This is highly significant and only slightly lower than the impact of crude oil's own short-term volatility ($\beta_{O,1} = 0.16$). The strongest impact on the futures volatility can be observed from its own long-term volatility component ($\beta_{O,22} = 0.37$), which is however only marginally higher than the coefficient of the weekly volatility ($\beta_{O,5} = 0.36$).

Looking at the results for Nikkei 225 (Model 2), we observe no significant coefficients for the orthogonalized volatility terms of crude oil. On the other hand, we find a positive, low coefficient of 0.04, significant at the 10% level for the short-term volatility of Nikkei 225 in the equation for crude oil. Qualitatively very similar results can be seen in the

[5] The panel labeled "DCC estimation" is addressed in Section 5.3.1.

[6] To verify the robustness of our results, we also estimated all models using non-orthogonalized data. Not surprisingly, the estimated coefficients for the lagged endogenous realized volatilities and the standard deviations of the estimates differ in some cases due to the moderate correlation between the independent variables in the regression. Nevertheless, the Granger causality tests exhibit qualitatively very similar results and the parameter estimates do not allow for substantially different conclusions. The results for non-orthogonalized estimates are not reported in order to save space.

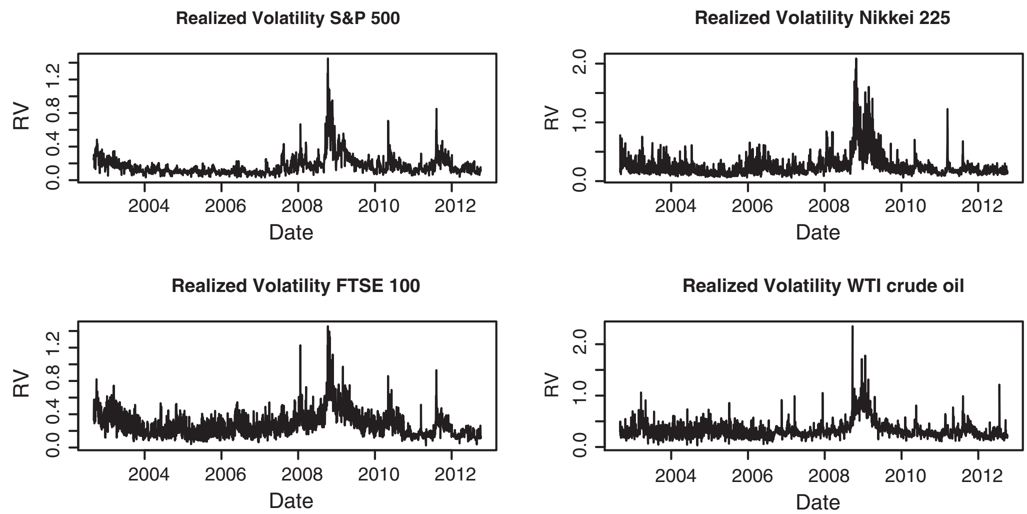

Fig. 2. Realized volatility of S&P 500, Nikkei 225, FTSE 100 and WTI crude oil futures.

case of FTSE 100 (Model 3). Additionally, we find significant (10% level) short-term impact of oil on the realized volatility of FTSE 100, however this is less than half of the impact of S&P 500 in terms of magnitude and the Granger causality is insignificant in this direction. For both models 2 and 3, the highest impact in terms of magnitude is the time series own weekly realized volatility ($\beta_{E,5}$ equal to 0.44 and 0.40, and $\beta_{O,5}$ equal to 0.46 and 0.46, respectively).

5.2. Subsample analysis

In the following, we seek to gain further insights into the source of the observed volatility transmission effects. To this end, we split the 10 year sample period into three subsamples covering the period between 2002 to June 2008 (pre-crisis), the most turbulent months of the global financial crisis (July 2008–Dec 2009) as well the post-crisis period thereafter.

The reason for considering mid 2008 as a start of the global financial crisis is the tremendous decrease in crude oil price starting at this time. If we look more closely at the development of equity and crude oil prices during the financial crisis, surprisingly, the decline of crude oil prices was not a reaction to the bankruptcy of Lehman Brothers, which is usually considered to be *officially* the beginning of the financial crash, but have already occurred earlier. In other studies, the period of financial crisis is often assumed to start from the beginning of 2007 or 2008 (e.g. Bubák et al., 2011; Thuraisamy et al., in press). Even though between mid 2007 and mid 2008, first contours of the upcoming financial crisis were noticeable, the crude oil prices remained going upward. The impact of the US sub-prime crisis was spreading over the banking sector and first banks were suffering from liquidity problems; for instance, Northern Rock plc. or Bear Stearns. While the Dow Jones Industrial Average reached its two year minimum in July 2008, oil prices continued to rise until July 2008. The markets were worried about the health of the banking sector but obviously less about the health of economic growth. This changed in July 2008 when the crude oil prices started to decrease dramatically (see Fig. 1). From this moment on, the turmoil on the financial markets spread over the whole macroeconomic environment. Awartani and Maghyereh (2013) also regard June 2008 as the breaking point for their subsample analysis of the dynamic spillover of return and volatility between oil and equities in the Gulf Cooperation Council Countries during the period 2004 to 2012.

5.2.1. Pre-crisis period

For the subsamples defined above, the corresponding results of the Granger causality tests, the bivariate HAR regressions and the CCC/DCC-GARCH models applied to their residuals are given in Tables 5 to 8. To start with the pre-crisis period, the Granger causalities cannot reveal any significant transmission effects suggesting that during 'quieter' market times the equity and oil volatility series as exogenous variables in a bivariate model cannot contribute with information incremental to the dynamics of the own volatility components. This conclusion is supported by the regression coefficients which are not meaningful at any conventional levels of significance. A sole exception is observed for the orthogonalized elements of WTI in the bivariate model for S&P 500 volatility where the orthogonalized weekly and monthly elements are significant but of similar magnitude and opposite signs. These values correspond to those

Table 2
Unit root tests.

	ADF	PP	ERS
	H_0: unit root	H_0: unit root	H_0: unit root
	Futures		
S&P 500	−10.49	−13.88	−8.49
Nikkei 225	−13.97	−23.81	−8.03
FTSE 100	−14.08	−23.08	−13.52
WTI crude oil	−16.93	−29.54	−16.87

Note: Unit root tests are run for the daily log variances. ADF is the Augmented Dickey–Fuller test. PP is the Phillips–Perron test. ERS is the Elliott–Rothenberg–Stock test for stationarity. The *t*-values of the ADF and PP tests are compared with the Dickey–Fuller (DF) critical values. The critical values tabulated in Elliot et al. (1996) are used for to evaluate the EPS test. All test values are significant at the 1% level.

Table 3
Granger causality tests.

	S&P 500	Nikkei 225	FTSE 100
Equity Futures	8.03	7.28	9.00
	(0.01)	(0.01)	(0.01)
WTI	0.62	5.62	1.60
	(0.43)	(0.02)	(0.21)

Note: The table shows the *F*-values for the Granger causality tests. The *F*-values in the row labeled "Equity Futures" relate to the test whether the variable in the corresponding column causes the volatility of crude oil futures. The *F*-values in the row labeled "WTI" relate to the test of crude oil volatility causes equity volatility. The corresponding *p*-values of the *F*-statistics are shown in parentheses.

Table 4
Estimation results (whole sample).

	Model 1		Model 2		Model 3	
	S&P 500	WTI	Nikkei 225	WTI	FTSE 100	WTI
β_0	−0.16***	−0.27***	−0.21**	−0.21***	−0.18***	−0.22***
	(−3.37)	(−5.61)	(−3.12)	(−4.04)	(−3.84)	(−4.21)
$\beta_{E,1}$	0.35***	0.12***	0.15***	0.04*	0.17***	0.05*
	(10.64)	(3.54)	(4.15)	(1.78)	(5.62)	(2.20)
$\beta_{O,1}$	0.01	0.16***	0.04	0.12***	0.06*	0.13***
	(0.52)	(5.48)	(1.31)	(3.67)	(2.06)	(3.79)
$\beta_{E,5}$	0.43***	−0.02	0.44***	0.01	0.40***	0.04
	(11.16)	(−0.33)	(8.06)	(0.36)	(7.86)	(0.92)
$\beta_{O,5}$	−0.15***	0.36***	0.01	0.46***	0.03	0.45***
	(−3.83)	(6.43)	(0.09)	(8.28)	(0.63)	(8.20)
$\beta_{E,22}$	0.18***	−0.05	0.34***	−0.01	0.37***	−0.04
	(5.78)	(−1.17)	(6.53)	(−0.01)	(8.07)	(−0.83)
$\beta_{O,22}$	0.16***	0.37***	0.03	0.33***	−0.06	0.33***
	(3.92)	(7.00)	(0.63)	(6.00)	(−1.07)	(6.11)
R^2	0.76	0.48	0.57	0.49	0.58	0.49
DCC estimation						
α_{i1}	0.1238***	0.0096***	0.0418***	0.0134***	0.0100***	0.0130***
	(4.72)	(8.10)	(4.44)	(6.98)	(6.72)	(7.03)
γ_{i1}		0.9888***	0.9493***	0.9851***	0.9876***	0.9855***
		(862.11)	(80.67)	(526.42)	(619.02)	(551.81)
d_1	0.0109***		0.0278***		0.0106***	
	(3.63)		(5.67)		(3.12)	
d_2	0.9862***		0.9667***		0.9872***	
	(201.27)		(117.89)		(164.53)	
Log likelihood	−593.16		−2181.17		−1931.38	

Note: Parameter estimates for the final equations of the bivariate volatility transmission models are reported as follows: $\beta_{E,i}(i = 1, 5, 22)$ denotes the parameters of the previous daily, weekly and monthly logarithmic variance for equity futures, respectively. $\beta_{O,i}$ labels the corresponding variables for crude oil. In the equation for equity futures volatility, the oil volatility is orthogonalized and vice versa. The corresponding Newey–West *t*-statistics are given in parentheses. * (**, ***) denotes the significance at 10% (5%, 1%) level. α und γ are the GARCH(1,1) coefficients from the Eq. (5). d_1 and d_2 are the coefficients of the DCC-GARCH model from Eq. (7). The *t*-statistics are given in parentheses.

observed for the whole sample (Table 4) and accordingly, do not result in a strong and significant interrelationship as indicated by the Granger causality tests. Furthermore, the conditional correlation of the model residuals is in all three cases constant and rather low with values around 0.1 for Nikkei and FTSE and around 0.3 for SP futures. This indicates a weak instantaneous relationship between the volatilities of the individual markets.

Table 5
Subsample Granger causality tests.

	S&P 500	Nikkei 225	FTSE 100
2002–06/2008			
Equity Futures	1.70	1.87	0.94
	(0.19)	(0.17)	(0.33)
WTI	0.32	0.19	0.55
	(0.57)	(0.66)	(0.45)
07/2008–2009			
Equity Futures	3.27	0.92	3.96
	(0.07)	(0.34)	(0.05)
WTI	0.90	2.82	2.00
	(0.34)	(0.09)	(0.15)
2009–09/2012			
Equity Futures	1.30	0.20	2.94
	(0.25)	(0.66)	(0.09)
WTI	0.30	2.75	0.01
	(0.58)	(0.09)	(0.96)

Note: The table shows the *F*-values for the Granger causality tests. The *F*-values in the row labeled "Equity Futures" relate to the test whether the variable in the corresponding column causes the volatility of crude oil futures. The *F*-values in the row labeled "WTI" relate to the test of crude oil volatility causes equity volatility. The corresponding *p*-values of the *F*-statistics are shown in parentheses.

5.2.2. Crisis period

In the crisis period, the Granger causality tests reveal a different picture. The crude oil volatility appears to be driven in particular by the dynamics of the US and European equity markets. Contrarily, the Nikkei follows the crude oil volatility. Discussing the nature of the 2008 financial and banking crisis, it is obvious that it emerged primarily from the financial sector. The US sub-prime crisis affected first the markets for financial assets in the US and Europe and led the financial industry into a dangerous liquidity crunch. Oil prices, on the other hand, were rising until June 2008 and decreased dramatically when financial markets realized that the ongoing financial crisis and lack of market liquidity are going to affect the overall shape of the global economy. The substantial decrease of oil prices in mid 2008 went along with increased oil volatility. In contrast, the Japanese equity market was rather calm at the beginning of the crisis and the decrease in its evolvement can be regarded as a reaction to the turbulences of the world economy and lacking liquidity in the markets for financial instruments. Increased volatility in oil markets is often regarded as representing greater uncertainty in the aggregate economy which explains the unidirectional spillover from oil to the Japanese equity market. Summing up, increasing volatility in the market which builds the core of the financial turmoil led to the volatility surge of crude oil prices. Falling crude prices and rising volatility can be interpreted as a signal for the uncertainty spreading over the macroeconomy and also over markets which were not affected by the banking sector problems until now.

At the first glance, the analysis of the parameter estimates of the bivariate models does not reflect the aforementioned insights. While the own volatility components are for the most part highly significant, these of the second asset remain mostly insignificant probably due to the parameter instability associated with the shorter period under consideration (18 months). Following other studies utilizing the HAR model which discuss the sum of the individual autoregressive coefficients (e.g. Andersen et al., 2007; Corsi et al., 2008), we additionally address the sums of the coefficients assigned to the orthogonalized elements of the second asset given for each model in Tables 5 to 8.[7] The sums indicate that across all models the impact increased in the crisis and after-crisis period. The highest impact is observed exactly for S&P500 and FTSE 100 in the oil regression and for WTI in the model of Nikkei 225 for the crisis period (0.083, 0.092 and 0.142, respectively).

5.2.3. Post-crisis period

A large portion of the observed spillovers of equity to the oil market persists also in the third subsample period when the economic environment is driven by the ongoing uncertainty in the financial industry as well as the sovereign debt problem in Europe. The Granger causality tests show that FTSE 100 appears to have still a weak significant impact on WTI which itself continues to lead the Japanese market. Overall, the source of the causal relationship is the short-term equity volatility shock while weekly and monthly realized volatility components do not exhibit any or just a weak impact on the volatility of other futures. The previous day's volatility of FTSE 100 is assigned a significant weight of $\beta_{E,1} = 0.17$ in the WTI regression while the short-term oil volatility has a significant parameter estimate of $\beta_{E,1} = 0.11$ in the Nikkei 225 regression. Furthermore, the parameters of the short-term volatility of Nikkei 225 and S&P 500 in the WTI model and of WTI in the FTSE model are statistically significant but the Granger causality tests based on Wald statistics cannot confirm the existence of a pronounced causal relationship.[8] The stronger relative impact of FTSE 100 on the oil market is very likely due to the European sovereign debt crisis. Even though we

[7] Similar approach in a VAR model framework could be find in Jones and Kaul (1996).

[8] As discussed in the above section, the major source of information is usually the Granger causality analysis. Extending the model with additional variables might increase the risk of misinterpretation of single coefficient estimates due to multiple testing problems.

Table 6
Subsample estimation results for S&P 500 and WTI.

	2002–06/2008		07/2008–2009		2009–09/2012	
	S&P 500	WTI	S&P 500	WTI	S&P 500	WTI
β_0	−0.28***	−0.77***	−0.06	−0.04	−0.34***	−0.53***
	(−2.89)	(−3.99)	(−0.67)	(−0.84)	(−2.85)	(−4.18)
$\beta_{E,1}$	0.22***	0.06	0.38***	0.03	0.41***	0.11*
	(4.89)	(1.27)	(5.03)	(0.5)	(6.3)	(1.72)
$\beta_{O,1}$	0.01	0.02	−0.06	0.18***	0.08	0.42***
	(0.41)	(0.77)	(−0.8)	(2.74)	(1.22)	(6.77)
$\beta_{E,5}$	0.46***	−0.1	0.44***	0.13	0.41***	0.06
	(6.86)	(−1.08)	(3.96)	(1.05)	(5.36)	(0.75)
$\beta_{O,5}$	−0.21***	0.27***	−0.11	0.55***	−0.13	0.27***
	(−4.00)	(3.18)	(−0.77)	(4.22)	(−1.27)	(3.78)
$\beta_{E,22}$	0.25***	0.08	0.16**	−0.07	0.10	−0.1
	(4.22)	(1.01)	(2.06)	(−0.82)	(1.36)	(−1.49)
$\beta_{O,22}$	0.18***	0.41***	0.24***	0.24***	0.09	0.11
	(2.57)	(3.75)	(2.23)	(2.2)	(0.73)	(1.44)
R^2	0.64	0.10	0.80	0.76	0.63	0.44
Sum of coefficients	−0.03	0.04	0.06	0.09	0.04	0.06
CCC estimation						
ρ	0.3062***		0.4016***		0.5786***	
	(15.58)		(7.29)		(14.01)	

Note: Parameter estimates for the final equations of the bivariate volatility transmission models are reported as follows: $\beta_{E,i}(i = 1, 5, 22)$ denotes the parameters of the previous daily, weekly and monthly logarithmic variance for equity futures, respectively. $\beta_{O,i}$ labels the corresponding variables for crude oil. In the equation for equity futures volatility, the oil volatility is orthogonalized and vice versa. The corresponding Newey–West *t*-statistics are given in parentheses. * (**, ***) denotes the significance at 10% (5%, 1%) level. The sum of coefficients shows the sum of the parameter estimates of the orthogonalized elements in the corresponding model. ρ shows the CCC-GARCH estimate of constant conditional correlation within the subsample period. The *t*-statistics are given in parentheses.

cannot observe such a strong impact from the US equity, in the last period we find a very pronounced instantaneous correlation between S&P and crude volatility (see Section 5.3). This might indicate that the spillover effects in the volatility are still present; however, speed of the transmission is increasing. It is reasonable to assume that a European equity index is the most sensitive among the ones considered regarding news about financial market uncertainty and transmits its volatility dynamics in the most unambiguous way to the oil market. On the other hand, WTI acts again as a gauge of the prevailing uncertainty of the macroeconomic environment and leads the Japanese market in the short-term.

When we compare the results of the whole sample (Table 4) with those obtained for the subsample periods (Tables 5 to 8), it becomes obvious that the previously observed short-term impacts can be ascribed mostly to the time after the crisis period. Furthermore, the third subsample period is marked by the shifting importance of the various own volatility components. While before the crisis the own short-term volatility is of minor relative importance, it becomes much more

Table 7
Subsample estimation results for FTSE 100 and WTI.

	2002–06/2008		07/2008–2009		2009–09/2012	
	FTSE 100	WTI	FTSE 100	WTI	FTSE 100	WTI
β_0	−0.32***	−0.68***	−0.14	−0.05	−0.20**	−0.49***
	(−3.29)	(−4.08)	(−1.58)	(−1.2)	(−2.16)	(−4.38)
$\beta_{E,1}$	0.09***	0.01	0.24***	0.02	0.31***	0.17***
	(2.48)	(0.18)	(3.42)	(0.52)	(5.71)	(3.32)
$\beta_{O,1}$	0.04	0.02	0.02	0.21***	0.11*	0.43***
	(1.24)	(0.56)	(0.20)	(3.8)	(1.86)	(6.95)
$\beta_{E,5}$	0.32***	0.09	0.41***	0.06	0.39***	−0.11
	(4.65)	(1.37)	(3.32)	(0.79)	(4.92)	(−1.22)
$\beta_{O,5}$	−0.01	0.41***	−0.01	0.49***	0.06	0.24***
	(−0.14)	(5.21)	(−0.06)	(4.58)	(0.74)	(3.19)
$\beta_{E,22}$	0.48***	−0.06	0.28***	0.01	0.24***	0.01
	(7.92)	(−0.93)	(2.97)	(0.16)	(3.03)	(0.08)
$\beta_{O,22}0$	−0.08	0.31***	0.06	0.27***	−0.17*	0.15**
	(−0.96)	(3.39)	(0.68)	(2.81)	(−1.88)	(1.97)
R^2	0.35	0.14	0.56	0.77	0.63	0.40
Sum of coefficients	−0.05	0.03	0.07	0.09	−0.01	0.06
CCC estimation						
ρ	0.0844***		0.2099***		0.2986****	
	(2.97)		(4.39)		(6.91)	

Note: Parameter estimates for the final equations of the bivariate volatility transmission models are reported as follows: $\beta_{E,i}(i = 1, 5, 22)$ denotes the parameters of the previous daily, weekly and monthly logarithmic variance for equity futures, respectively. $\beta_{O,i}$ labels the corresponding variables for crude oil. In the equation for equity futures volatility, the oil volatility is orthogonalized and vice versa. The corresponding Newey–West *t*-statistics are given in parentheses. * (**, ***) denotes the significance at 10% (5%, 1%) level. The sum of coefficients shows the sum of the parameter estimates of the orthogonalized elements in the corresponding model. ρ shows the CCC-GARCH estimate of constant conditional correlation within the subsample period. The *t*-statistics are given in parentheses.

Table 8
Subsample estimation results for Nikkei 225 and WTI.

	2002–06/2008		07/2008–2009		2009–09/2012	
	Nikkei 225	WTI	Nikkei 225	WTI	Nikkei 225	WTI
β_0	−0.55***	−0.68***	−0.14	−0.06	−0.60***	−0.41***
	(−4.32)	(−4.04)	(−1.48)	(−1.28)	(−4.9)	(−3.59)
$\beta_{E,1}$	0.10***	0.01	0.10	0.03	0.42***	0.12*
	(2.56)	(0.29)	(1.56)	(0.95)	(4.03)	(1.75)
$\beta_{O,1}$	0.00	0.02	0.07	0.22***	0.11***	0.38***
	(−0.05)	(0.55)	(0.79)	(3.81)	(2.38)	(6.1)
$\beta_{E,5}$	0.35***	−0.01	0.57***	0.05	0.30***	−0.05
	(4.94)	(−0.22)	(3.95)	(0.99)	(3.98)	(−0.61)
$\beta_{O,5}$	−0.02	0.41***	−0.03	0.50***	−0.07	0.31***
	(−0.28)	(5.29)	(−0.14)	(4.58)	(−0.75)	(4.43)
$\beta_{E,22}$	0.39***	−0.01	0.26**	−0.05	0.10	−0.04
	(5.32)	(−0.19)	(2.02)	(−0.72)	(1.08)	(−0.52)
$\beta_{O,22}$	−0.06	0.31***	0.10	0.24***	0.05	0.16***
	(−0.77)	(3.36)	(0.57)	(2.49)	(0.37)	(2.23)
R^2	0.27	0.14	0.62	0.77	0.46	0.40
Sum of coefficients	−0.09	−0.02	0.14	0.03	0.10	0.02
CCC estimation						
ρ	0.1096***		0.1776***		0.3231***	
	(3.97)		(3.75)		(7.36)	

Note: Parameter estimates for the final equations of the bivariate volatility transmission models are reported as follows: $\beta_{E,i}(i = 1, 5, 22)$ denotes the parameters of the previous daily, weekly and monthly logarithmic variance for equity futures, respectively. $\beta_{O,i}$ labels the corresponding variables for crude oil. In the equation for equity futures volatility, the oil volatility is orthogonalized and vice versa. The corresponding Newey–West *t*-statistics are given in parentheses. * (**, ***) denotes the significance at 10% (5%, 1%) level. The sum of coefficients shows the sum of the parameter estimates of the orthogonalized elements in the corresponding model. ρ shows the CCC-GARCH estimate of constant conditional correlation within the subsample period. The *t*-statistics are given in parentheses.

relevant during periods of financial distress showing the value of short-term shocks for explaining futures volatility. Over time, especially the magnitude of the own long-term volatility component significantly decreases and becomes insignificant for WTI, SP and Nikkei. Even if the result that the spillover between equity and crude oil market volatility arises from the short-term component is not surprising at the first sight, it is worth to emphasize that we use a model framework which is able to uncover mid- and long-term spillovers as well. However, these appear to be less important especially in periods characterized by high volatility levels. With appropriate caution we can say, that while before crisis the volatility was mostly driven by longer term trends, during and after the crisis the short-term uncertainty levels gained on importance.

5.2.4. Comparison with previous results

Comparing our findings with previous studies on spillover effects between US, Asian or European equity markets and crude oil covering data of the recent years, our conclusions are in line with the results of Chang et al. (2010) and Thuraisamy et al. (in press). Chang et al. (2010) consider daily returns from January 1998 to November 2009 of the WTI and Brent markets, as well as the FTSE 100, NYSE, Dow Jones and S&P500 equity markets and using VARMA-GARCH and VARMA-AGARCH models find very little evidence of volatility spillovers between the crude oil and financial markets. Thuraisamy et al. (in press) study volatility transmission between 14 Asian equity indices (among which Japan) and the volatility of crude oil and gold futures. Using daily data from July 2005 to December 2011, they consider the pre-crisis and crisis period separately. Similar to our study, the sub-sample results show that most of the volatility interaction between oil futures and equity markets occurs during the crisis period.

On the other hand, the obtained results are at odds with Malik and Ewing (2009) and Arouri et al. (2011) who support the hypothesis of bidirectional volatility spillover in oil and US stock market sectors. Additionally, Arouri et al. (2011) identify a unidirectional spillover from oil to European stocks. However, both studies do not employ subsamples to identify the origin of the observed spillover effects although it is well known that volatility interrelations exhibit a substantially different course in turbulent and quiet periods (e.g. Bubák et al., 2011; Filis et al., 2011; Thuraisamy et al., in press). We would like to point out the importance of the sub-sample analysis, since our results support the view that literature considering the last decade as one sample without taking subperiods into account might reveal misleading results. Even though our results cannot support the bidirectional causal relationship between S&P 500 and crude oil futures, we find strong evidence for increasing instantaneous correlation using DCC-GARCH model for the full sample and CCC-GARCH specifications in the subsample periods (see Section 5.3).

To put the diverging results of the current study into perspective, note that the bivariate HAR models address the dynamics of realized volatility which is an advanced high-frequency volatility estimator known to significantly outperform GARCH models based on daily returns (e.g. Andersen et al., 2003; Blair et al., 2001). Daily realized volatility covers a substantially larger extent of the underlying price process and subsumes by nature a way more comprehensive information set than returns sampled a daily or lower volatility. Moreover, the model concerns the one-step ahead daily volatility while the findings of Arouri et al. (2011) and Malik and Ewing (2009) are based on data sampled at the weekly frequency.

5.3. Conditional correlations

5.3.1. Full sample

Finally, the evolution of dynamic conditional correlation between the equity and crude oil volatility is discussed. As introduced in Section 3, in the full sample we employ a DCC-GARCH(1,1) designed by Engle (2002) to study the innovation terms of the volatility transmission system. For all three estimated models, the parameters d_1 and d_2 from the Eq. (7) are significant, satisfy the non-negativity constraint, and $d_1 + d_2 < 1$ (Table 4). The sum of the parameters is close to unity, which implies persistence in the correlations, with a rather small news parameter d_1 and slow decay d_2 (Engle and Sheppard, 2001). The testing procedure introduced in Engle and Sheppard (2001), however, rejects the null hypothesis of constant conditional correlation and the fluctuating estimates of the constant conditional correlations over the three subsamples support the assumption of a time varying correlation structure.

Looking at the pattern of all three curves in Fig. 3, we observe a remarkable increase in the dynamic correlation during the last financial

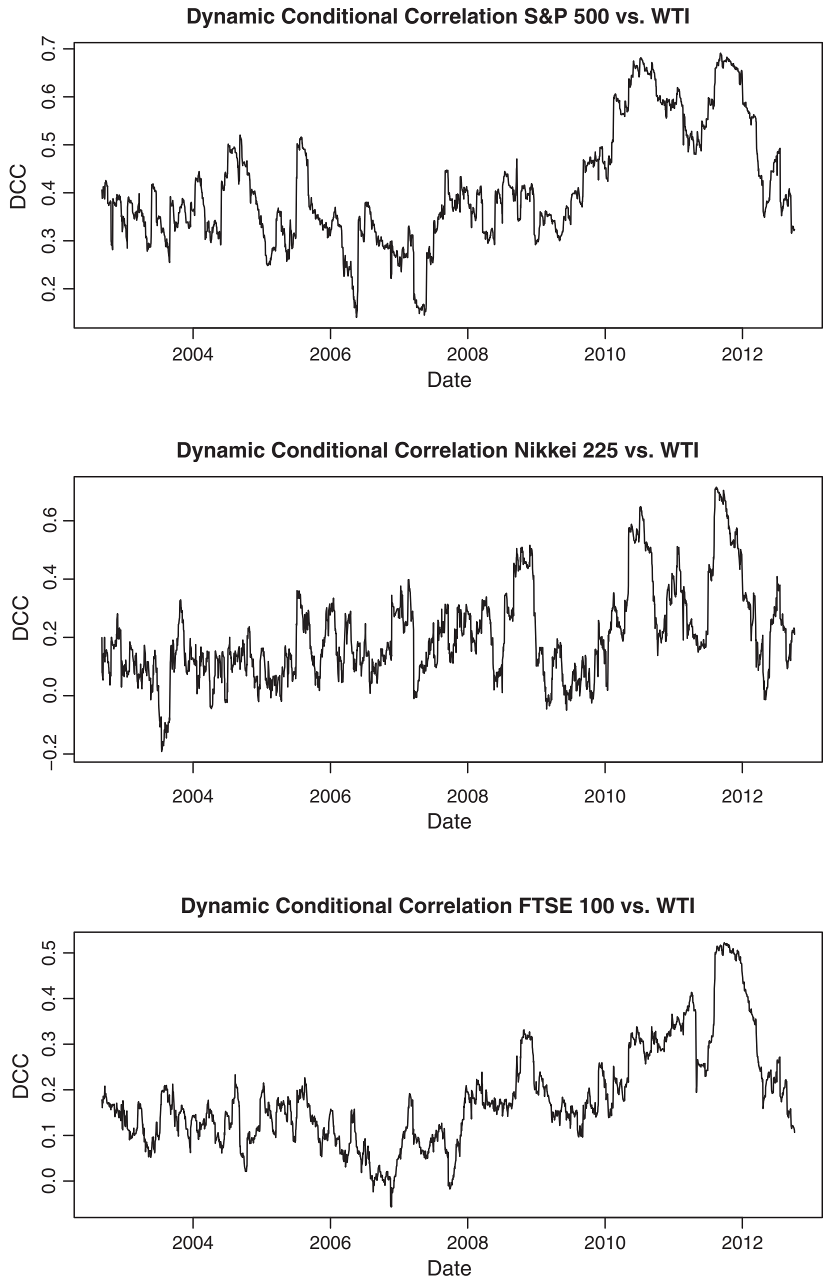

Fig. 3. Plots of conditional correlations implied by the DCC-GARCH(1,1) model.

market turmoil. During the economic crisis which followed the burst of the dot com bubble in 2001/2002, the correlation between the realized volatility of S&P 500 and WTI crude oil futures remained around 0.4. We observe a slight decrease in the correlation between 2004 and 2007 with a few drops down to the 0.2 mark. However, with the start of the recent financial crisis, the dynamic correlation dramatically increased up to 0.7 with a slight decrease to 0.6 in 2011 before getting back to 0.7 at the beginning of 2012. Currently, the volatility correlation is decreasing again. Even if the level of the correlation between Nikkei 225 and WTI, and FTSE 100 and WTI is with 0.2 around 2004 lower than in the case of S&P 500 futures, the course of the curve over time is similar. During the financial market turmoil starting at the end of 2007, the correlation almost doubled in terms of magnitude. Dynamic correlation between stock and oil markets reacting to external information shocks has been described by Filis et al. (2011) and Choi and Hammoudeh (2010), among others. This paper is the first looking at the dynamic correlation of realized variances and with appropriate caution the results indicate increasing level of integration of energy and equity markets. The results of Filis et al. (2011) indicate weak negative correlation between the US stock index and crude oil prices during the financial crises, turning weak positive in 2009. This negative spike is also presented in the results by Choi and Hammoudeh (2010) and Awartani and Maghyereh (2013). Our results on the other hand, show a moderate dynamic correlation of the volatilities during the whole crisis and its aftermath. This is a completely new insight about the dynamics of market co-movements. It indicates that the magnitude of the simultaneous volatility movements increased at the beginning of the crisis and is still present, while the correlation between the returns, as described in the literature, turned to be rather low again.

5.3.2. Subsample periods

Looking at the residual envelopment in the subsamples, we observe rather a constant covariance matrix in the separate subperiods, which supports our decision regarding the choice of the subsample breaking points, as well as the shape of the dynamic correlation pattern described for the full sample.[9] The level of the correlation differs significantly over subsamples and models. We confirm our conclusion of constant conditional correlation in the subsamples using the Engle and Sheppard (2001) test.[10] The only exception where the test rejects the null hypothesis of constant conditional covariance matrix $\mathbf{\Gamma}$ at the 5% level is in the last subperiod for the FTSE model. Nevertheless, when we estimate the DCC coefficients d_1 and d_2, d_1 remains insignificant. The estimated conditional correlations and corresponding robust standard errors can be found in Tables 6 to 8. We find the conditional correlation being significantly different from zero and increasing over the subperiods for all three models. The highest correlation in terms of magnitude is observable in the case of US equity futures, being in the last subsample period up to 0.6. Relating this finding to the results of the causality analysis, while the causality link for the US equity futures is weaker in the last subsample, the time series exhibit increasing instantaneous relationship. This is obviously a signal for increasing market integration and it might indicate that the spillover effects are still present, while the speed of the market reaction is increasing. This question is at this point left for further research.

6. Conclusion

This paper analyzes volatility transmission patterns between oil and equity futures markets using a unique multivariate extension of HAR model by Corsi (2009). The main advantage of the vector HAR (VHAR) model is its ability to split spillover effects in daily, weekly and monthly horizons, which cannot be done by means of the widely established multivariate GARCH framework. Our methodological contribution to Bubák et al. (2011) who first use a similar specification is to utilize the asset's own lagged volatility components and lagged orthogonalized volatility components of the second asset in bivariate vector HAR models. Assigning spillovers to short-, mid- and long-term volatility effects contributes to a more profound understanding of the origin and nature of the observed volatility transmission. Moreover, different than other studies in this area, we utilize high-frequency data for establishing realized volatility. This estimator allows for a more precise estimation of volatility and, consequently, an improved inference about volatility spillovers.

We uncover a number of interesting and significant spillover effects between the UK, US and Japanese equity markets and the oil market. Analyzing first the whole sample period, we identify several causality relationships indicating that the equity markets were leading the volatility of crude oil. The interrelation between the realized volatilities in the full sample is mostly driven by the short term shocks. Since over the last decade, the markets experienced several significant events, we divide the sample in pre-crisis, crisis and after-crisis subperiods in order to obtain a clear understanding of the source of the volatility co-movements between crude oil and equity futures.

The source of the volatility transmission in these markets appears to be the period starting with the financial crisis. Until 2008, we find no evidence for significant Granger causalities and only a few significant coefficients being mostly related to the mid- or long-term volatility component. Also the conditional correlation of the residuals of the models remains rather low. During the crisis period of higher volatility levels, we can observe significant Granger causality going from the US and UK market to the oil futures volatility. The explanation is on hand, since the recent financial crisis originated from the markets for financial assets rather than from the overall shape of the economy. When the sub-prime market collapsed in 2008, the equity and derivatives markets were already falling. The world economy followed these developments from the mid 2008 on realizing that the ongoing liquidity crunch is going to affect the macroeconomic environment. Japan, on the other hand, was rather following the development in the western part of the world and was pulled into the crisis through an overall uncertainty and liquidity outflow. In the last subsample, the volatility on the financial and commodity markets remained rather high. The strongest impact from the equity to oil market is observed for FTSE, most likely due to the European sovereign debt crisis. For this period, we can still observe significant Granger causalities and more importantly, we see that the short term volatility components are gaining in importance, while the long term volatility components are becoming less relevant, similar to Bubák et al. (2011). Overall, we can also observe, that the own long-term volatility components are losing importance over time. In the post-crisis period, the monthly volatility component becomes insignificant for SP, WTI and Nikkei, while the magnitude of the own short-term volatility component significantly increases.

This paper is also unique in the way of considering the second moments of the realized volatility series. Modeling the residuals of the bivariate transmission models by means of a DCC-GARCH framework for the whole sample, we show that the correlation between the volatilities of these futures almost doubled during the recent financial market turmoil. Looking at the individual subsamples, we fit CCC-GARCH to the residuals' series and document a significant constant correlation structure of increasing magnitude in the course of time. The results point at the increasing integration of various asset markets over the last decade.

The results of our study allow for some policy implications. The equity indices seem to be early indicators of economic risk causing volatility changes in the oil market. Since the energy and equity markets appear to be more integrated in terms of volatility as described before, it is important to consider this fact for derivatives valuation and potential regulation. Implications for portfolio allocation are obvious as well. The findings show the importance of investors to beware of a variety of different markets since news in one market may impact other markets through a number of interrelations.

For further research, the simultaneous consideration of multiple assets may be necessary to gain additional insights into the volatility transmission process between energy and equity markets. As emphasized in Corsi et al. (2012), the need of "a flexible yet parsimonious multivariate HAR-type extensions that remain computationally feasible in large dimensions" indicates the imperative of further theoretical and empirical work.

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[9] The characteristics is similar to the finding in Bubák et al. (2011) who assume constant conditional covariance in their second subsample.

[10] The presentation of the test statistics values has been omitted in order to save space. The results are available upon request.

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