Empir Econ (2016) 50:1481–1509
DOI 10.1007/s00181-015-0983-2

# Crude oil and world stock markets: volatility spillovers, dynamic correlations, and hedging

**Yudong Wang**[1] · **Li Liu**[2]

Received: 21 May 2013 / Accepted: 4 May 2015 / Published online: 19 July 2015


**Abstract** In this paper, we investigate volatility spillovers and dynamic correlations between crude oil and stock markets using GARCH-class models. We focus on the dynamic relationships of seven major oil-exporting countries and nine oil-importing countries. Our main findings based on in-sample and out-of-sample evidence suggest that the volatility spillovers and dynamic correlations between global crude oil market and a country's stock market depend on the net position of oil imports and exports of this country in the world market. In addition, crude oil risk can be better hedged by investing in stocks of oil-exporting countries than in those of oil-importing countries.

**Keywords** Crude oil price · Stock prices · Volatility · Hedging · Out of sample

**JEL Classification** C22 · C32 · G11 · G17 · G32

## 1 Introduction

In recent years, the impact of oil price shocks on stock markets has been of great interests among energy economists (see, e.g., Kilian and Park 2009; Jung and Park 2011; Park and Ratti 2008; Apergis and Miller 2009; Sadorsky 1999; Elder and Serletis 2010; Wei 2003; Ferderer 1996; Arouri 2011; Arouri et al. 2011). The economic

✉ Yudong Wang
wangyudongnj@126.com

Li Liu
liuli840821@nau.edu.cn

1 School of Economics and Mangement, Nanjing University of Science and Technology, XiaoLinwei 200, Xuanwu District, Nanjing, China

2 School of Finance, Nanjing Audit University, Nanjing, China

rationale can be explained by the theory of stock valuation in which stock price is the discounted value of expected future cash flows. It has been well documented in the literature that several determinants of expected future cash flows of stocks such as economic activities (Hamilton 1983, 1996, 2003; Kilian 2009), inflation rates (LeBlanc and Chinn 2004; Chen 2009), and exchange rates (Amano and Norden 1998; Akram 2004; Wang and Wu 2012a) can be affected by oil prices. Therefore, oil price may have significant impacts on stock market returns.

In the existing studies, researchers are more interested in the relationships of conditional means between stock and oil markets rather than volatility comovement. As pointed out by Hamilton (2008), even if one mainly concentrates on conditional mean, correctly modeling conditional variance can still be quite important. Without modeling conditional variance, the OLS standard errors may be misleading due to the possibility of "spurious regression." The inference about the conditional mean may be inappropriately affected by outliers and some extreme fluctuations in prices. However, to the best of our knowledge, only a few studies focus on the volatility comovement between stock and oil markets. For example, Malik and Hammoudeh (2007) investigate the volatility transmission between the crude oil market and stock markets in the USA and Gulf countries and find that oil return volatility significantly affects stock return volatility in Saudi Arabia, but not in Kuwait or Bahrain. Sadorsky (2012) examines the volatility spillovers and correlations between oil and stock markets of clean energy and technology companies. Using multivariate GARCH models, Sadorsky (2012) finds the significant volatility spillovers from oil to stock markets, but their correlations are relatively weak. Aloui and Jammazi (2009) find that the volatility transmission between oil and stock markets is regime-dependent. More recently, Arouri et al. (2012) investigate the effects of oil price fluctuations on European stock markets and develop the strategies of using stocks to hedge crude oil risk based on multivariate GARCH models. The authors find that the volatility spillovers are more apparent from oil to stock markets, and the correlations are heterogeneous between oil and stock returns of different sectors. Arouri et al. (2011) also investigate the volatility spillovers between oil and stock markets in Gulf Cooperation Council (GCC) countries and find the existence of volatility spillovers from oil to stock markets.

There are several limitations in the related studies on the volatility linkages which deserve our further investigation. First, very few studies differentiate oil-exporting countries from oil-importing countries except for the notable papers of Filis et al. (2011) and Wang et al. (2013). As shown in Wang et al. (2013), the impacts of oil price shocks on the economic activities of oil-exporting countries and oil-importing countries are different. For example, higher oil prices can increase production costs, induce higher inflation rates, and reduce expenditure on non-oil goods (see, e.g., Barsky and Kilian 2004). Thus, the negative linkages between oil price shocks and macroeconomy are always reported in the literature (see Bjørnland (2009) for the general literature review) and have been accepted as a general conclusion. However, increases in oil prices can generate more income for the oil-exporting countries due to the low price elasticity of crude oil demand, inducing positive effects on their economies (Bjørnland 2009; Jung and Park 2011). In this sense, the responses of stock market in oil-exporting countries to oil price shocks can be either positive or negative and are determined by the relative importance of the positive and negative impacts. Thus, volatility transmission and dynamics of correlations between oil and stock markets in oil-exporting countries can be different from those in oil-importing countries.

Second, the existing studies on the volatility relationships between oil and stock markets only report the in-sample results of predictability but do not show the out-of-sample evidence. It is widely known that significant in-sample evidence of predictability does not ensure the significant out-of-sample predictability (Inoue and Kilian 2004). Out-of-sample evidence may be more important because an out-of-sample comparison of forecasting performance can yield the maximum amount of information that is more consistent with the spirit of Granger causality (Ashley et al. 1980). A conclusion drawn based only on the in-sample evidence is incomplete.

In this paper, we address aforementioned two limitations in several ways. First, different from Wang et al. (2013) who investigate the effects of oil shocks on stock price changes, we investigate volatility transmission. In detail, we investigate the volatility spillovers and dynamics of correlation between oil and stock markets for oil-importing countries and for oil-exporting countries separately. We consider seven oil-exporting countries and nine oil-importing countries. Our findings from multivariate GARCH-class models indicate that volatility transmission and correlations are heterogeneous across countries. Specifically, the significant unidirectional volatility spillovers from crude oil to stock markets in several oil-exporting countries are present. The plausible explanation is that oil exports account for a large fraction of trade in the oil-exporting countries. We also find significant volatility spillovers from stock markets in several large oil-importing countries to crude oil market. The reason may be that stock markets in these large economies can reflect business cycle, which has been the major determinant of oil price changes in recent years (Malik and Hammoudeh 2007; Hamilton 2009; Kilian 2009). The findings from the CCC- and DCC-GARCH specifications indicate that the correlations between oil and stock markets are always positive and stronger for the oil-exporting countries than the oil-importing countries. The reason is that higher oil prices driven by higher global economic activity have more positive impacts on oil-exporting economies (Jung and Park 2011; Wang et al. 2013).

Second, we investigate oil–stock volatility transmission in the sense of *out-of-sample* predictability of volatility. This is different from Filis et al. (2011) who perform *in-sample* analysis based on a DCC–GARCH–GJR model. For this purpose, we compare the forecasting ability of multivariate GARCH-class models considering volatility spillovers between oil and stock return volatility with the standard univariate GARCH(1,1).[1] Our results based on the superior predictive ability (SPA) tests indicate that multivariate models perform better in forecasting stock market volatility in most countries but not in forecasting crude oil volatility, that is, out-of-sample findings support the volatility spillovers from oil market to stock markets, but not consistently indicate the existence of volatility transmission from stock markets to oil market.

[1] It is known that more complex models always have more parameters to be estimated, and therefore, they always have greater estimation errors in the process of out-of-sample forecasting (see, e.g., Jorion 1992; DeMiguel et al. 2009). Due to the existence of estimation error, it is not necessary that multivariate GARCH models generate more accurate forecasts than simple univariate ones.

Third, as oil price uncertainty has caused great concerns among market participants, it is not surprised that there are many studies on hedging oil price risk (see, e.g., Chang et al. 2010, 2011; Wang and Wu 2012b). In this paper, we investigate whether the stock markets across oil-importing and oil-exporting countries can be used to effectively hedge the crude oil risk. The investigation of hedging performance can also answer an interesting research question which of the multivariate GARCH-class models is the most suitable specification to model and forecast oil–stock market relationships. Our out-of-sample findings indicate that the stock markets of the oil-exporting countries that are less affected by geopolitical events such as Canada, Russian, Norway, and Mexico can effectively hedge crude oil risk. The hedging strategies based on the RS–DCC and DCC–GARCH specification can significantly outperform other alternative strategies such as BEKK–GARCH and OLS. The investigation of hedging performance is also our third contribution to the literature.

The remainder of this paper is organized as follows. Section 2 briefly discusses the specifications of univariate and multivariate GARCH models that are utilized in this paper. Section 3 provides the preliminary analysis results. Section 4 presents the empirical findings and relevant discussions. Section 5 concludes.

## 2 Econometric models

The most popular model for investigating the volatility spillovers between the two markets is the BEKK–GARCH model proposed by Engle and Kroner (1995).[2] A bivariate BEKK (1, 1) specification is defined as:

$$\mathbf{H}_t = \mathbf{\Omega}'\mathbf{\Omega} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}{}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B}, \tag{1}$$

where $\mathbf{\Omega}$, $\mathbf{A}$ and $\mathbf{B}$ are $2 \times 2$ matrices, and the individual elements in $\mathbf{\Omega}$, $\mathbf{A}$, and $\mathbf{B}$ are given as,

$$\mathbf{A} = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}, \quad \mathbf{\Omega} = \begin{pmatrix} \omega_{11} & 0 \\ \omega_{21} & \omega_{22} \end{pmatrix},$$

$\mathbf{H}_t$ is the conditional covariance matrix. The parameters $\alpha_{12}, \alpha_{21}, \beta_{12}$, and $\beta_{21}$ capture volatility transmission and spillovers between the two markets.

Estimation of a BEKK model bears large computations due to several matrix transpositions. The number of parameters of a full BEKK(1,1) model is $N(5N+1)/2$. The BEKK form is not linear in parameters, which makes the convergence of the model difficult. A major shortcoming of BEKK model is that a full BEKK has no known properties, except under the untestable assumption of the existence of 8th moments. Engle (2002) develops a dynamic correlation GARCH (DCC–GARCH) model which is more parsimonious in parameters and has explicit properties of parameters. DCC can be taken as a generalization of CCC model of Bollerslev (1990).

[2] The acronym comes from synthesized work on multivariate GARCH models by Baba, Engle, Kraft, and Kroner. Unlike the VEC model of Bollerslev et al. (1988), the BEKK model does not need to impose strong restrictions on the parameters to ensure the positivity of variance and covariance matrix, $\mathrm{H_t}$.

In CCC and DCC models, the dynamic variance and covariance correlations are defined as:

$$H_t = D_t \Gamma_t D_t, \tag{2}$$

where $\mathbf{D}_t = diag(h_{11}^{1/2}, \ldots, h_{mm}^{1/2})$, $h_{iit}$ is the variances defined as the standard univariate GARCH(1,1) model (Engle 1982; Bollerslev 1986). It is assumed in the CCC–GARCH that $\boldsymbol{\Gamma}_t = (\rho_{ij})$ is constant over time. As the assumption of constant conditional correlation seems unrealistic, Engle (2002) proposes a DCC as the generalization of CCC. In the DCC specification, $\Gamma_t = diag(q_{11,t}^{-1/2}, \ldots, q_{mm,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2}, \ldots, q_{mm,t}^{-1/2})$ is a symmetric positive definite matrix of correlation coefficients with $\rho_{ii} = 1$, $\forall i$.

The symmetric positive definite matrix $Q_t$ is given by

$$Q_t = \bar{\boldsymbol{\rho}}(1 - \lambda_1 - \lambda_2) + \lambda_1(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + \lambda_2 \Gamma_{t-1}, \tag{3}$$

where $\bar{\boldsymbol{\rho}}$ is the unconditional correlation matrix of $\varepsilon_t$, and $\lambda_1$ and $\lambda_2$ are two nonnegative scalar parameters satisfying $\lambda_1 + \lambda_2 < 1$. When $\lambda_1 = \lambda_2 = 0$, the DCC model is reduced to the CCC model. Since we use the two-step estimation approach, the volatilities obtained from the CCC or the DCC models are equivalent to those from their corresponding univariate GARCH models.

It is argued that some factors such events, business cycle, and macroeconomic policy can result in regime switching in the relationships between crude oil and stock markets. Aloui and Jammazi (2009) develop a two-regime Markov-switching EGARCH model by allowing both real stock returns and probability of transitions from one regime to another to depend on net increases in oil prices. They find that rises in oil prices play an essential role in determining both stock return volatility and the probability of transition across regimes. To consider the regime switching of correlations, we use a regime switching DCC (RS–DCC) model introduced by Billio and Caporin (2005). The specification of RS–DCC can be written as follows:

$$Q_t = \bar{\boldsymbol{\rho}}(1 - \lambda_1(s_t) - \lambda_2(s_t)) + \lambda_1(s_t)(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + \lambda_2(s_t)\Gamma_{t-1}, \tag{4}$$

where $s_t = 0, 1$ is unobserved random variable, which is called the regime or state and governed by transition probabilities, i.e., $p_{ij} = \Pr(s_{t+1} = j \,|s_t = i)$. The two regimes are separated according to the average levels of conditional correlations. The parameters of RS–DCC are estimated according to two-step MLE.

It should be noted that BEKK model can also yield dynamic conditional correlations. From a theoretical perspective, Caporin and McAleer (2012) compare the usefulness of BEKK and DCC models. They show that the optimal model for estimating conditional covariances (and thereby also conditional correlations) is the scalar BEKK model, regardless of whether targeting was used. However, it is still inconclusive on whether the BEKK can overwhelmingly outperform DCC in the empirical literature. For example, Chang et al. (2011) find that diagonal BEKK performs better than DCC, but full BEKK performs worse than DCC in oil futures hedging. Sadorsky (2012) finds that DCC captures the dynamic correlations between oil prices and stock prices of clean energy and technology companies. Sadorsky (2014) also shows that

DCC fit the joint dynamics among oil, copper, and wheat prices better than BEKK models. Given the disagreement in the empirical literature, we use DCC to study dynamic correlations between oil and stock prices as it is more popular than BEKK in modeling dynamic correlations.

## 3 Data

We employ weekly data of West Texas Intermediate (WTI) crude oil price as the proxy of oil price because it is widely taken as a benchmark of oil pricing. The data sample covers the period from January 4, 2000 to December 27, 2011. The oil price data are collected from the US Energy Information Administrate (EIA) (www.eia.gov).

Figure 1 plots the oil price evolutions over the sample period. We can see that oil price varied fiercely, and some exogenous events caused large price jumps. During the period of 2001–2003, oil price changed in a range of 20–40 dollars per barrel. From 2003 to 2008, oil price maintained an upward momentum and reached about 140 dollars per barrel in mid-2008. The persistent increases in oil prices over this period can be explained by the following two aspects: (1) strong oil demand driven by economic growth in emerging countries (see, e.g., Hamilton 2009; Kilian 2009), and (2) a vast number of speculative funds pouring into crude oil derivative markets since 2003 (see, e.g., Fan and Xu 2011). The global economic depression triggered by financial crisis in the USA caused a large crash in oil prices. As a result of the financial crisis, oil price went back to 40 dollars per barrel at the beginning of 2009. With the recovery of the world economy from economic depression, oil price kept rising up from 2009 to 2010. However, in mid-2011, the European debt crisis and the earthquake in Japan pushed down the oil price again.

For stock markets, we follow Wang et al. (2013) in choosing stock markets in seven oil-exporting countries and nine oil-importing countries. The stock indices are Chinese SSEC index, French FCHI index, German GDAXI index, Indian BSESN index, Japanese NIKKI 225 index, Korean KS11 index, British FTSE index, S&P 500 index, Canadian TSX index, Saudi Arabian TASI index, Kuwaiti SEWI index, Mexican MXX index, Norwegian OSEAX index, Russian MICEX index, Spanish SMSI index, and Venezuelan IBVC index. All stock indexes are denominated by the

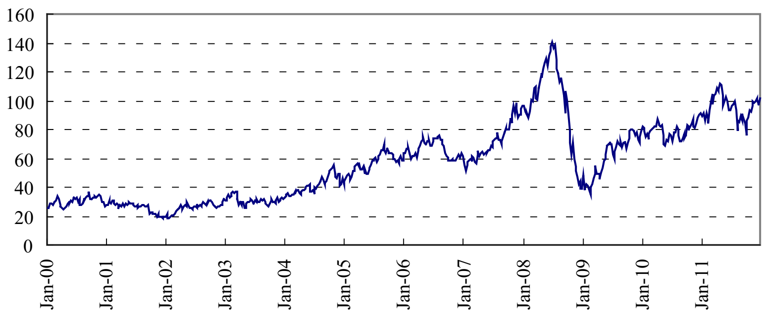


**Fig. 1** WTI oil prices

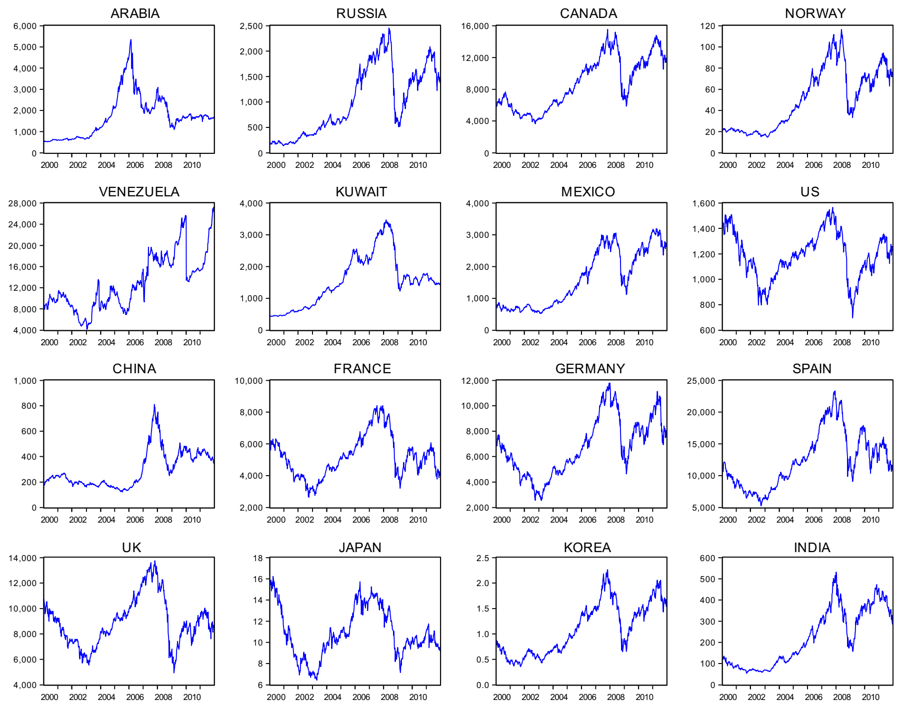


**Fig. 2** Stock prices of oil-importing and oil-exporting countries

US dollar and are collected from *Datastream*. Our empirical analysis is based on oil and stock returns, the first-order differences in logarithmic prices. We will use “op” to denote oil price return and use a country’s name to denote stock returns in this country. The stock prices of these 16 countries are shown in Figure 2.

# 4 Empirical results

## 4.1 In-sample performance

Table 1 shows the in-sample estimates of the bivariate BEKK–GARCH(1,1)[3] models for oil and stock returns in the oil-exporting countries. The standard errors are computed according to Bollerslev and Wooldridge (1992) methods. In the model, we use oil return as variable 1 and use stock return as variable 2. Thus, the significance

[3] It may be argued that in prior to model the volatility relationships, we should model the return relationships. For example, Aloui and Jammazi (2009) consider the stylized fact that stock returns react asymmetrically to changes in price of crude oil, depending on whether stock markets are in bullish or bearish phases (also see the references therein). Actually, we find that if we do so, we can obtain the similar results with those in Table 1. As our main interest is volatility comovement rather than return comovement and also for the purpose of reducing the burden of estimating and forecasting, we assume that the conditional mean is a constant following Koopman et al. (2005) and Wang and Wu (2012a, b).

**Table 1** Estimation results of BEKK–GARCH for oil prices and stock prices in oil-exporting countries

| | op-S. Arabia | op-Canada | op-Kuwait | op-Mexico | op-Norway | op-Russia | op-Venezuela |
|---|---|---|---|---|---|---|---|
| $\omega_{11}$ | 1.194*** | 0.889*** | 1.569** | 1.077*** | 0.742 | 1.230* | 1.467*** |
| | (3.950) | (3.289) | (2.426) | (4.250) | (1.576) | (1.893) | (4.872) |
| $\omega_{12}$ | 0.407 | 0.486** | −0.033 | 0.478 | 0.143 | −0.412 | 0.527** |
| | (0.201) | (1.967) | (−1.460) | (1.547) | (0.276) | (−0.614) | (2.512) |
| $\omega_{22}$ | 0.810 | 0.412** | 0.919*** | 0.415 | 0.704*** | 0.001 | −0.001 |
| | (0.773) | (2.578) | (4.464) | (0.782) | (2.732) | (0.001) | (−0.002) |
| $\alpha_{11}$ | 0.173*** | 0.165*** | 0.186*** | 0.223*** | 0.165** | 0.220 | 0.223*** |
| | (3.673) | (3.266) | (3.129) | (5.877) | (2.275) | (1.285) | (5.568) |
| $\alpha_{12}$ | 0.040 | 0.188* | −0.061 | 0.033 | 0.121 | −0.021 | 0.014 |
| | (0.358) | (1.815) | (−0.158) | (0.362) | (1.309) | (0.086) | (0.757) |
| $\alpha_{21}$ | −0.012 | −0.015 | 0.021 | 0.094 | −0.042* | −0.216** | 0.026 |
| | (−0.200) | (−0.511) | (0.478) | (1.172) | (−1.687) | (−2.313) | (0.977) |
| $\alpha_{22}$ | 0.636*** | 0.357*** | 0.488*** | 0.262*** | 0.339*** | 0.382*** | 0.346*** |
| | (8.425) | (4.528) | (7.004) | (4.236) | (4.765) | (5.596) | (3.723) |
| $\beta_{11}$ | 0.957*** | 0.976*** | 0.930*** | 0.955*** | 0.976*** | 0.950*** | 0.935*** |
| | (72.94) | (77.38) | (19.85) | (74.48) | (33.31) | (11.54) | (46.77) |
| $\beta_{12}$ | 0.007 | −0.077 | 0.146 | −0.018 | −0.034 | −0.013 | −0.011 |
| | (0.134) | (−1.640) | (0.480) | (−0.715) | (−0.793) | (−0.010) | (−1.332) |
| $\beta_{21}$ | −0.007 | 0.002 | −0.017 | −0.027 | 0.015 | 0.095** | −0.029** |
| | (−0.075) | (0.204) | (−0.810) | (−1.016) | (1.095) | (1.668) | (−2.284) |
| $\beta_{22}$ | 0.784*** | 0.916*** | 0.791*** | 0.946*** | 0.924*** | 0.895*** | 0.937*** |
| | (11.59) | (27.87) | (10.72) | (49.30) | (25.38) | (15.41) | (29.59) |
| *Diagnostic* | | | | | | | |
| Log($L$) | −3512.4 | −3428.3 | −3321.3 | −3626.3 | −3560.6 | −3768.9 | −3632.3 |
| $Q_{op}(10)$ | 9.018 | 4.898 | 7.261 | 6.058 | 5.444 | 5.331 | 7.835 |
| | [0.580] | [0.898] | [0.701] | [0.810] | [0.860] | [0.868] | [0.645] |
| $Q_{op}(20)$ | 13.60 | 9.676 | 11.65 | 9.831 | 8.271 | 10.03 | 12.35 |
| | [0.850] | [0.974] | [0.928] | [0.971] | [0.990] | [0.968] | [0.904] |
| $Q_{sp}(10)$ | 3.292 | 14.12 | 7.797 | 6.190 | 13.22 | 14.98 | 12.46 |
| | [0.974] | [0.168] | [0.649] | [0.799] | [0.212] | [0.133] | [0.255] |
| $Q_{sp}(20)$ | 8.832 | 22.37 | 23.03 | 8.772 | 20.36 | 19.95 | 21.44 |
| | [0.985] | [0.321] | [0.287] | [0.985] | [0.436] | [0.461] | [0.372] |
| $\mathrm{ARCH}_{op}(10)$ | 0.895 | 0.525 | 0.729 | 0.616 | 0.583 | 0.506 | 0.757 |
| | [0.538] | [0.873] | [0.698] | [0.801] | [0.828] | [0.887] | [0.671] |
| $\mathrm{ARCH}_{op}(20)$ | 0.675 | 0.505 | 0.595 | 0.500 | 0.436 | 0.492 | 0.601 |
| | [0.852] | [0.965] | [0.918] | [0.967] | [0.985] | [0.970] | [0.913] |

**Table 1** continued

| | op-S.Arabia | op-Canada | op-Kuwait | op-Mexico | op-Norway | op-Russia | op-Venezuela |
|---|---|---|---|---|---|---|---|
| $\text{ARCH}_{\text{sp}}(20)$ | 0.467 | 1.424 | 1.039 | 0.436 | 0.993 | 1.010 | 1.091 |
| | [0.978] | [0.104] | [0.414] | [0.985] | [0.468] | [0.448] | [0.354] |

The numbers in parentheses are $t$-statistics of the estimations. Log($L$) is the logarithm maximum likelihood function value. $Q_{\text{op}}(i)$ and $Q_{\text{sp}}(i)$ are the Ljung–Box (1982) Q-statistic of order $i$ computed on the squared standardized residuals for returns oil price and stock price, respectively. $\text{ARCH}_{\text{op}}(i)$ and $\text{ARCH}_{\text{sp}}(i)$ are the nonheteroscedasticity statistics of order $i$ for standardized residuals of oil price and stock price returns, respectively. $p$ values of the statistics are reported in square brackets. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

of coefficients $\alpha_{21}$ and $\beta_{21}$ reflects the volatility spillovers from oil market to stock markets. We can see that the estimates of $\alpha_{21}$ for two pairs of series (OR-Norway and OR-Russia) are significantly different from zero at the 10 % level. The estimates of $\beta_{21}$ for another two pairs of series (OR-Norway and OR-Venezuela) are significant at the 5 % level, that is, oil return volatility can affect stock market volatility in Norway, Russia, and Venezuela. The significance of $\alpha_{12}$ and $\beta_{12}$ reflects volatility spillovers from stock markets to oil markets. We can see that $\alpha_{12}$ or $\beta_{12}$ in most of the oil-exporting countries is not significant. Thus, stock market volatility in the oil-exporting countries does not affect the oil market volatility.

Table 2 reports the estimates of the BEKK–GARCH models for oil and stock markets in the oil-importing countries. The estimates of $\alpha_{12}$ and $\beta_{12}$ for the three pairs of series (OR-US, OR-Germany, and OR-UK) are significant, whereas $\alpha_{21}$ or $\beta_{21}$ is not significant for any pairs of series, that is, stock market volatility in the USA, Germany, and UK affects oil market volatility, but oil market volatility does not affect stock market volatility in any of the oil-importing countries under consideration.

From the above analysis, we can see that there are volatility spillovers from crude oil to stock markets in several oil-exporting countries (Norway, Russia, and Venezuela), but not vice versa. The oil exports in each of the oil-exporting countries account for a large percent of terms of trade. Thus, it is plausible that stock markets in the oil-exporting countries are affected by "news" emanating from global oil markets (Malik and Hammoudeh 2007). The markets in the Middle East are frequently influenced by some other factors besides oil prices shocks (e.g., geopolitical events). This may be the plausible reason why oil market volatility has no impact on stock market volatility in the Middle East. We also find significant volatility spillovers from stock markets in major oil-importing countries (the USA, UK, and Germany) to oil market, but that the spillovers in the reverse direct do not exist. The reason may be that the major stock markets reflect world business cycle (Malik and Hammoudeh 2007), which is a major determinant of world oil price in recent years (see, e.g., Hamilton 2009; Kilian 2009).

The lower parts of Tables 1 and 2 provide the results of diagnostic tests on the squared standardized residuals. The Ljung and Box (1978)'s Q statistics suggest that the null hypothesis of no serial correlations cannot be rejected at the 10 % significance level. These results are generally confirmed by the $F$-statistics of Engle (1982)'s ARCH test based on the autoregression for the squared standardized residuals. The only exception is that heteroscedasticity still exists in the standardized residuals of

**Table 2** Estimation results of BEKK–GARCH for oil prices and stock prices in oil-importing countries

| | op-USA | op-China | op-France | op-Germany | op-Spain | op-UK | op-Japan | op-Korea | op-India |
|---|---|---|---|---|---|---|---|---|---|
| $\omega_{11}$ | 3.879*** | 1.406*** | 0.889** | 0.861** | 0.984 | 0.675** | 1.230*** | 1.124*** | 1.063 |
| | (15.04) | (3.900) | (2.315) | (2.266) | (0.508) | (2.001) | (3.253) | (4.111) | (0.783) |
| $\omega_{12}$ | 0.222 | 0.184 | −0.143 | 0.411 | −0.505 | 0.290 | 0.705 | 0.378 | 0.194 |
| | (1.281) | (1.045) | (−0.334) | (0.520) | (−0.538) | (0.518) | (1.124) | (0.718) | (0.274) |
| $\omega_{22}$ | 0.350*** | 0.389** | 0.617** | 0.887*** | 0.477 | 0.512* | 0.985*** | 0.739*** | 0.673* |
| | (3.083) | (2.325) | (2.568) | (2.681) | (0.925) | (1.833) | (3.178) | (3.619) | (1.828) |
| $\alpha_{11}$ | 0.217*** | 0.236*** | 0.209*** | 0.221*** | 0.180* | 0.186*** | 0.225*** | 0.201*** | 0.196 |
| | (4.097) | (4.571) | (4.683) | (5.626) | (1.932) | (4.421) | (3.123) | (3.359) | (1.123) |
| $\alpha_{12}$ | 0.316** | 0.024 | 0.140 | 0.244** | 0.114 | 0.226** | −0.008 | 0.084 | 0.066 |
| | (2.482) | (0.215) | (1.393) | (2.288) | (0.446) | (2.197) | (−0.142) | (0.944) | (0.302) |
| $\alpha_{21}$ | 0.011 | −0.017 | 0.012 | 0.023 | 0.023 | 0.009 | −0.029 | −0.043 | −0.001 |
| | (0.244) | (−0.690) | (0.461) | (0.347) | (0.646) | (0.450) | (−0.236) | (−0.459) | (−0.045) |
| $\alpha_{22}$ | 0.402*** | 0.212*** | 0.373*** | 0.441*** | 0.355*** | 0.366*** | 0.342*** | 0.319*** | 0.275*** |
| | (7.024) | (5.805) | (5.480) | (6.130) | (2.741) | (6.481) | (4.785) | (6.526) | (2.991) |
| $\beta_{11}$ | 0.951*** | 0.934*** | 0.963*** | 0.955*** | 0.963*** | 0.972*** | 0.951*** | 0.960*** | 0.960*** |
| | (62.66) | (34.22) | (53.53) | (52.36) | (11.07) | (76.24) | (30.22) | (57.04) | (11.12) |
| $\beta_{12}$ | −0.132*** | 0.004 | −0.056 | −0.115** | −0.025 | −0.088* | −0.052 | −0.059 | −0.032 |
| | (−2.711) | (0.130) | (−1.185) | (−2.384) | (−0.171) | (−1.691) | (−0.620) | (−1.583) | (−0.290) |
| $\beta_{21}$ | −0.004 | −0.007 | 0.012 | −0.004 | 0.016 | −0.001 | 0.001 | 0.026 | 0.006 |
| | (−0.263) | (−0.443) | (0.626) | (−0.089) | (0.766) | (−0.028) | (0.018) | (0.646) | (0.473) |
| $\beta_{22}$ | 0.909*** | 0.971*** | 0.908*** | 0.864*** | 0.911*** | 0.911*** | 0.858*** | 0.927*** | 0.947*** |
| | (43.10) | (86.16) | (24.54) | (21.61) | (12.14) | (28.39) | (17.68) | (49.96) | (19.65) |

**Table 2** continued

| | op-USA | op-China | op-France | op-Germany | op-Spain | op-UK | op-Japan | op-Korea | op-India |
|---|---|---|---|---|---|---|---|---|---|
| *Diagnostic* | | | | | | | | | |
| Log($L$) | −3311.6 | −3588.3 | −3517.4 | −3568.6 | −3545.5 | −3394.9 | −3493.6 | −3712.4 | −3679.5 |
| $Q_{\mathrm{op}}(10)$ | 2.988 | 7.237 | 4.867 | 3.762 | 8.624 | 4.821 | 7.376 | 6.230 | 7.015 |
| | [0.982] | [0.703] | [0.900] | [0.957] | [0.568] | [0.903] | [0.690] | [0.796] | [0.724] |
| $Q_{\mathrm{op}}(20)$ | 7.553 | 11.73 | 8.083 | 7.363 | 13.09 | 8.131 | 10.72 | 10.02 | 10.42 |
| | [0.994] | [0.925] | [0.991] | [0.995] | [0.874] | [0.991] | [0.953] | [0.968] | [0.960] |
| $Q_{\mathrm{sp}}(10)$ | 5.053 | 3.993 | 10.08 | 6.380 | 8.470 | 3.699 | 2.952 | 4.295 | 6.792 |
| | [0.888] | [0.948] | [0.434] | [0.782] | [0.583] | [0.960] | [0.983] | [0.933] | [0.745] |
| $Q_{\mathrm{sp}}(20)$ | 13.15 | 9.991 | 21.04 | 12.861 | 13.25 | 9.532 | 5.397 | 12.49 | 12.10 |
| | [0.871] | [0.968] | [0.395] | [0.883] | [0.266] | [0.976] | [1.000] | [0.898] | [0.913] |
| $\mathrm{ARCH}_{\mathrm{op}}(10)$ | 0.319 | 0.713 | 0.495 | 0.400 | 0.850 | 0.512 | 0.719 | 0.677 | 0.762 |
| | [0.976] | [0.712] | [0.894] | [0.947] | [0.581] | [0.882] | [0.707] | [0.747] | [0.666] |
| $\mathrm{ARCH}_{\mathrm{op}}(20)$ | 0.389 | 0.572 | 0.411 | 0.380 | 0.642 | 0.429 | 0.547 | 0.523 | 0.549 |
| | [0.993] | [0.932] | [0.990] | [0.994] | [0.882] | [0.987] | [0.946] | [0.958] | [0.945] |
| $\mathrm{ARCH}_{\mathrm{sp}}(10)$ | 0.469 | 0.379 | 1.082 | 0.599 | 0.823 | 0.346 | 0.277 | 0.478 | 0.679 |
| | [0.910] | [0.956] | [0.374] | [0.815] | [0.607] | [0.968] | [0.986] | [0.905] | [0.745] |
| $\mathrm{ARCH}_{\mathrm{sp}}(20)$ | 0.632 | 0.471 | 1.049 | 0.588 | 0.628 | 0.512 | 0.253 | 0.633 | 0.498 |
| | [0.890] | [0.976] | [0.402] | [0.922] | [0.894] | [0.962] | [1.000] | [0.889] | [0.968] |

The numbers in parentheses are $t$-statistics of the estimations. Log($L$) is the logarithm maximum likelihood function value. $Q_{\mathrm{op}}(i)$ and $Q_{\mathrm{sp}}(i)$ are the Ljung–Box (1982) Q-statistic of order $i$ computed on the squared standardized residuals for returns oil price and stock price, respectively. $\mathrm{ARCH}_{\mathrm{op}}(i)$ and $\mathrm{ARCH}_{\mathrm{sp}}(i)$ are the nonheteroscedasticity statistics of order $i$ for standardized residuals of oil price and stock price returns, respectively. $p$ values of the statistics are reported in square brackets. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively.

**Table 3** Estimates of conditional correlations based on CCC–GARCH

| | Correlations |
|---|---|
| op-Arabia | 0.209*** (4.967) |
| op-Russia | 0.325*** (9.483) |
| op-Canada | 0.384*** (11.13) |
| op-Norway | 0.429*** (13.10) |
| op-Venezuela | 0.069* (1.837) |
| op-Kuwait | 0.037 (0.876) |
| op-Mexico | 0.245*** (5.434) |
| op-USA | 0.135*** (2.907) |
| op-China | 0.115*** (2.986) |
| op-France | 0.194*** (4.770) |
| op-Germany | 0.173*** (4.315) |
| op-Spain | 0.161*** (4.224) |
| op-UK | 0.230*** (4.794) |
| op-Japan | 0.142*** (3.634) |
| op-Korea | 0.210*** (5.141) |
| op-India | 0.165*** (4.395) |

The numbers in parentheses are $t$-statistics of the estimations. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

the Canadian stock returns at the 10th order. Thus, we conclude that the full BEKK model specification can well capture the ARCH effects in volatility of crude oil and stock markets in most oil-exporting countries and all the oil-importing countries.

Table 3 reports the conditional correlations between oil and stock returns estimated from the CCC–GARCH specification. We can see that the correlations are significantly different from zero at the 1 % level for crude oil and stock returns in most countries. The correlations between oil returns and stock returns in Kuwait and Venezuela are much close to zero, implying the weakly correlated behavior. The plausible explanations are that geopolitical events frequently broke out the Middle East and Venezuela, breaking the linkages between oil and stock markets. Moreover, model misspecification may be also responsible for this result. The extreme events in these countries can cause structural breaks which cannot be captured by the CCC–GARCH specification. More importantly, oil and stock returns in both oil-exporting countries and oil-importing countries are positive, in contrast to the traditional view that higher oil prices depress economic activity (see, e.g., Hamilton 1983, 2003; Mork, 1989). Kilian (2009) firstly points out that one should disentangle the effects of oil supply and demand shocks on economic activity. It has been widely considered that the major determinants of oil prices in recent years are the global economic activity, rather than changes in oil production (see, e.g., Kilian 2009; Hamilton 2009). Higher global economic activity can stimulate both oil price and world stock prices (Kilian and Park 2009), leading to the positive correlations between crude oil and stock returns. However, higher oil prices can improve the terms of trade in oil-exporting countries, resulting to the revenue transferred from the oil-importing countries to the oil-exporting countries. The positive impacts of higher global economic activity on stock markets in oil-exporting countries are stronger. Thus, it is reasonable that the correlations between oil returns and stock returns in some oil-exporting countries are always stronger.

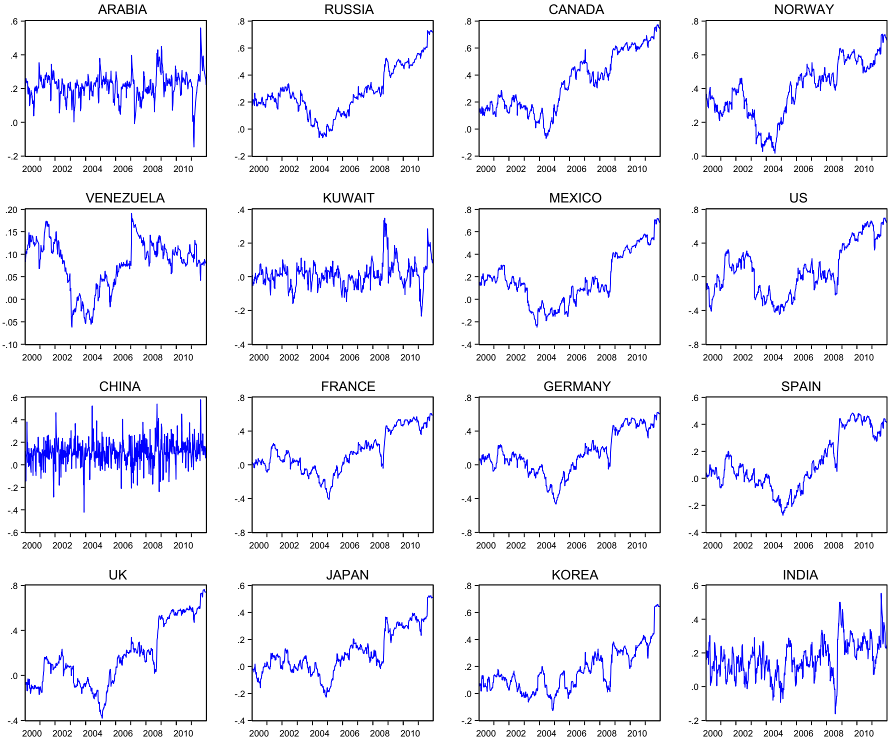


**Fig. 3** Dynamic conditional correlations estimated from the DCC–GARCH model

The CCC–GARCH model cannot capture the time-varying behaviors of correlations. For this consideration, we employ the DCC–GARCH model to describe the time-varying correlations. Figure 3 shows the dynamic conditional correlations implied by the DCC models.[4] We can see that the time-varying correlations are heterogeneous across countries. The correlations between oil and stock returns in the oil-exporting countries (except for Kuwait) are greater than those between oil and stock returns in the oil-importing countries, further confirming the results from the CCC model. The correlations are positive in more time, but some geopolitical events can cause abrupt rise or fall in correlations. For example, the second Gulf War in 2003 resulted in the weaker correlations between oil and stock returns in the two Middle East countries (Saudi Arabia and Kuwait) in a short period of time. The Venezuela oil crisis, a production cutback caused by civil unrest, led to weaker correlations between oil and stock returns in Venezuela in 2002–2003. Besides the abovementioned two events, Hurricanes Ivan and Katrina in the USA, the oil workers' strikes in Norway and production disruption in Nigeria could also be responsible for the weaker correlations between oil and stock returns in the oil-exporting countries and even negative

[4] We also calculate the conditional correlations using BEKK models. They are similar to the correlations from DCC models. To save space, we do not report these correlations but they are available upon request.

correlations between oil and stock returns in the oil-importing countries during the period of 2003–2004.

These oil supply shocks cause the negative correlations for the oil-importing countries because the decrease in oil supply results in higher oil prices. Higher oil prices imply the higher industry cost, having negative impacts on their economic activities (Kilian and Park 2009). Thus, unlike the effects of aggregate demand shocks, increases in oil prices driven by supply shocks are always related to negative oil–stock correlations for the oil-importing countries. Different from the oil-importing countries, higher oil prices can improve the terms of trade of the oil-exporting countries (Kilian and Park 2009). This effect partly offsets and may be even stronger than the negative impacts of higher oil price on economic activity in the oil-exporting countries. During the period of oil supply shocks, the correlations for the oil-exporting countries are weaker than those during the normal period.

The global economic depression triggered by a financial crisis in 2008 is a typical case of aggregate demand shock. We find an upward jump of correlations between oil and stock returns in most countries during this period. The reason is that the financial crisis depresses economic activity and causes lower oil prices, resulting in stronger correlated behavior between oil and stock markets.

Figure 4 gives the smoothed transition probability of the regime of high correlations (regime 1) between crude oil and stock returns.[5] It is evident that some extreme events can lead to low probabilities of high correlations. More importantly, the probabilities of high correlations are always greater than probabilities of low correlations (regime 0) for most countries except for Kuwait and Venezuela. In particular for Kuwait, the probabilities of high correlations frequently reached the level of zero. The reason may be that the political disturbances in these two countries disrupted linkages between crude oil and stock markets and cause the low correlations between stock and crude oil returns.

From the above analysis, we conclude that the relationships between oil and stock markets in a country depend greatly on the driving forces behind oil price changes, generally reinforcing the results in Kilian and Park (2009) and Filis et al. (2011). Moreover, our new finding based on the DCC–GARCH framework is that oil–stock market relationships also rely greatly on whether a country is a net oil importer or net oil exporter.

### 4.2 Volatility spillovers between oil and stock markets: out-of-sample evidence

We have investigated the volatility spillovers between oil and stock markets using the BEKK–GARCH models and show the evidence based on in-sample analysis. However, out-of-sample evidence may be more important because an out-of-sample comparison of forecasting performance can yield the maximum amount of information that is more relevant to the hypothesis of Granger causality (Ashley et al. 1980). Market participants are more concerned about out-of-sample performances of the

[5] To save space, we only give the probabilities of regime 1. The probabilities of regime 2 is equal to 1 minus those of regime 1.

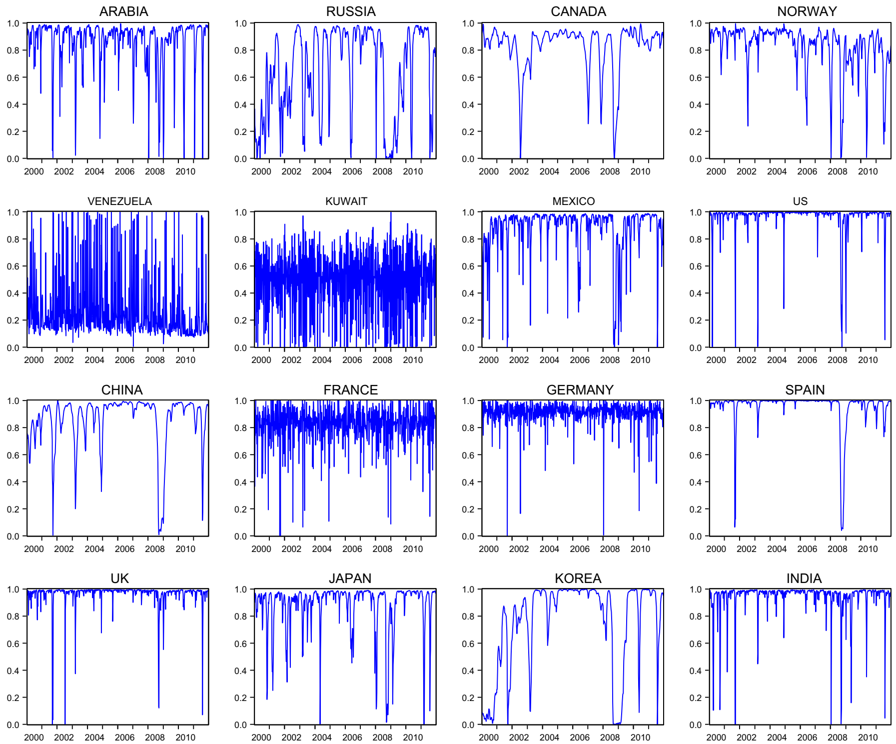


**Fig. 4** Smoothed transition probabilities of regime 1 (high correlation regime)

models in terms of their ability to predict the market volatility. Due to these two considerations, we compare forecasting accuracy of the multivariate GARCH-class models when volatility spillovers are taken into consideration with the accuracy of the standard univariate GARCH(1,1). We examine whether multivariate GARCH-class models can more accurately predict the market volatility than the GARCH(1,1) model.[6] Our forecasting procedure is handled as follows.

The data of stock and oil returns cover the period from January 11, 2000 to December 27, 2011 (625 weeks in total). The returns are classified into two groups: the in-sample data for volatility modeling, covering the period from January 11, 2000 to August 4, 2009 (500 observations), and the out-of-sample data for evaluating the forecasting performance, covering the period from August 11, 2009 to December 27, 2011 (125 observations). The estimation period is then rolled forward by adding a new observation and dropping the most distant observation. In this way, the sample size

[6] According to Engle (2002) and Caporin and McAleer (2012), the DCC and CCC parameters can be estimated using a two-step method, the first step being univariate model estimates for each series and the second step being the correlation estimates. Based on the two-step method, the volatility forecasts obtained from the CCC and the DCC model are equivalent to those from the univariate GARCH model. The only difference is the correlation term. Thus, in this paper, the performances of the CCC and the DCC models are not evaluated in the sense of volatility forecasting.

employed to estimate the model parameters is fixed, and we re-estimate the parameters of the models each week to obtain next week's volatility forecasts.

As discussed by Bollerslev et al. (1994), Diebold and Lopez (Diebold and Lopez 1996), and Lopez (2001), it is not obvious which loss function is more appropriate for evaluating the forecasting accuracy of volatility models. For this consideration, rather than make a single choice, we employ four loss functions as the forecasting error criterions:

$$\text{MSE} = n^{-1} \sum_{t=1}^{n} (\sigma_t^2 - \hat{\sigma}_t^2)^2, \tag{5}$$

$$\text{MAE} = n^{-1} \sum_{t=1}^{n} \left| \sigma_t^2 - \hat{\sigma}_t^2 \right|, \tag{6}$$

$$\text{HMSE} = n^{-1} \sum_{t=1}^{n} (1 - \sigma_t^2 / \hat{\sigma}_t^2)^2, \tag{7}$$

$$\text{HMAE} = n^{-1} \sum_{t=1}^{n} \left| 1 - \sigma_t^2 / \hat{\sigma}_t^2 \right|, \tag{8}$$

where $n$ is the number of volatility forecasts (in our case, $n = 125$), $\sigma_t^2$ is the actual volatility, and $\hat{\sigma}_t^2$ is the volatility forecast. Hansen and Lunde (2006) and Patton (2011) point out that the evaluation of forecasting performance of a volatility model should be done with a volatility proxy as accurate as possible.[7] For this reason, we use a weekly realized volatility (RV) constructed on daily returns as the proxy of actual volatility. The specification of RV can be written as follows:

$$\text{RV}_t = \sum_{i=1}^{5} r_{t,i}^2, \tag{9}$$

where $r_{t,i}$ is the return at the $i$th day of week $t$.

Above loss functions of forecast errors do not provide statistical tests of the difference between the two models of interests. It is necessary to determine whether the differentials between forecasting errors of the two models are significant, rather than comparing only the nominal values of loss functions. Thus, we employ a superior predictive accuracy (SPA) test (Hansen 2005).

In the SPA test, forecasts are evaluated using a pre-specified loss function. The null hypothesis is that the benchmark model cannot be outperformed by any of its competing models. The estimates of SPA statistics and the corresponding $p$ values are obtained using the stationary bootstrap procedure (Politis and Romano 1994). The detailed discussion of the SPA test can be seen in Hansen (2005) and Koopman et al. (2005). In summary, a significant test statistic indicates that the null hypothesis that "the base model is not outperformed" is rejected. Thus, a bootstrapped $p$ value implies

[7] Here, we thank an anonymous referee for this suggestion.

the relative performance of the benchmark model in comparison with its competing models. In this paper, the $p$ value is obtained based on 10,000 stationary bootstraps. The application of similar bootstrapped methods to volatility forecasting can be seen some of recent studies (e.g., Nomikos and Pouliasis 2011; Wang and Wu 2012a, b).

Tables 4, 5, 6, and 7 report the comparison results of various GARCH-class models under four criteria of loss functions in terms of forecasting stock market volatility. The first column of each table lists the name of benchmark model. Thus, the remaining models are the competitors. We show the values of loss functions and the corresponding $p$ values based on the SPA tests.

Under the criterion of MAE (see Table 4), we find that multivariate GARCH models have the smaller loss functions than the standard univariate GARCH(1,1) in forecasting stock market volatility for 15 out of 16 countries, indicating that the multivariate GARCH models have greater forecasting accuracy. In particular, the scalar BEKK–GARCH seems to be the most accurate model one in forecasting volatility of 13 out of 16 stock markets, evidenced by the smallest loss function. Moreover, the bootstrapped $p$ values based on the SPA tests indicate that at the 10 % significance level, the univariate GARCH(1,1) model is significantly outperformed by the multivariate GARCH for 12 of 16 countries. Overall, we can see that under the criterion of MAE, multivariate GARCH model is the better choice than the univariate one in forecasting stock market volatility for most countries.

Under the criterion of MSE (see Table 5), the scalar BEKK displays the greatest accuracy for 15 out of 16 countries. The standard GARCH(1,1) model is significantly outperformed by its competing models for three oil-exporting countries (Saudi Arabia, Russia, and Venezuela) and two oil-importing countries (the USA and India). Under the other two criterions adjusted for heteroscedasticity (HMAE and HMSE) (see Tables 6, 7), we find that the full BEKK model seems to be the most accurate for most countries. The results of SPA tests indicate that the univariate GARCH(1,1) is significantly beaten by multivariate models for most of the cases at the 10 % level, similar to the result based on the criterion of MAE.

Overall, from the above analysis, we can conclude that the multivariate GARCH models always have significantly greater forecasting accuracy than the univariate GARCH(1,1) under three of four loss criterions in forecasting stock market volatility. The multivariate models take into account the volatility comovement between crude oil and stock markets, whereas the univariate one does not. Thus, taking into account volatility spillovers can significantly improve the forecasting accuracy of stock volatility, that is, crude oil market can provide useful information about future stock market volatility. This out-of-sample evidence further confirms our in-sample result that crude oil market volatility affects volatility in stock markets.

We also compare the model performance in forecasting crude oil volatility and show the results in Table 8.[8] We find that some multivariate models seem to have greater accuracy than the univariate GARCH(1,1) under all four criterions of loss functions. However, the results from the SPA tests indicate that univariate GARCH(1,1) cannot be significantly outperformed by any multivariate models under two of four loss criterions

[8] The recent studies on forecasting oil market can be seen in Nomikos and Pouliasis (2011) and Wang and Wu (2012a, b).

**Table 4** Comparison of forecasting accuracy in forecasting stock price volatility under the criterion of MAE

| | S. Arabia | Canada | Kuwait | Mexico | Norway | Russia | Venezuela | USA | China | France | Germany | Spain | UK | Japan | Korea | India |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GARCH | 9.143** | 6.169** | 6.032 | 13.87* | 13.32** | 16.36* | 7.827*** | 6.563** | 12.10* | 19.01** | 19.22** | 23.67*** | 11.83** | **10.42** | 16.34 | 14.75 |
| | (0.045) | (0.021) | (0.449) | (0.062) | (0.040) | (0.085) | (0.001) | (0.017) | (0.066) | (0.030) | (0.034) | (0.004) | (0.039) | (1) | (0.560) | (0.171) |
| Full BEKK | 9.669*** | 6.255*** | 6.160 | 13.96** | 13.39** | 16.11 | 10.10*** | 6.903*** | **11.90**** | 19.65*** | 19.48*** | 24.00*** | 12.21*** | 10.54 | 16.74** | 15.34** |
| | (0.006) | (0.005) | (0.120) | (0.037) | (0.046) | (0.334) | (0) | (0.001) | (1) | (0.009) | (0.008) | (0) | (0.004) | (0.101) | (0.029) | (0.011) |
| Diagonal BEKK | 9.517** | 6.094*** | 6.076*** | 13.25 | 13.20** | 16.41*** | **7.193** | 6.486*** | 12.30** | 18.97** | 19.03** | 23.56*** | 11.68** | 10.45 | 16.46 | 14.77 |
| | (0.011) | (0.001) | (0.009) | (0.947) | (0.032) | (0.004) | (1) | (0.002) | (0.030) | (0.011) | (0.017) | (0.004) | (0.015) | (0.674) | (0.287) | (0.153) |
| Scalar BEKK | **8.712** | **5.965** | **5.970** | **13.25** | **12.81** | **15.84** | 7.489 | **6.266** | 11.99 | **18.30** | **18.40** | **22.52** | **11.37** | 10.60 | **16.28** | **14.23** |
| | (1) | (1) | (1) | (1) | (1) | (1) | (0.258) | (1) | (0.476) | (1) | (1) | (1) | (1) | (0.151) | (1) | (1) |

The values in bold face refer to the highest $p$ values and the smallest loss under a pre-specified criterion. $p$ values obtained from SPA tests based on 10,000 bootstraps are reported in parentheses. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

**Table 5** Comparison of forecasting accuracy in forecasting stock price volatility under the criterion of MSE

| | S. Arabia | Canada | Kuwait | Mexico | Norway | Russia | Venezuela | USA | China | France | Germany | Spain | UK | Japan | Korea | India |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GARCH | 300.9*** | 85.34 | 114.6 | 404.2 | 331.7 | 528.5* | 111.6*** | 85.86** | 323.8 | 745.5 | 985.5 | 1222 | 336.0 | **1015** | 1563 | 393.8* |
| | (0.008) | (0.185) | (0.212) | (0.142) | (0.103) | (0.076) | (0.005) | (0.044) | (0.865) | (0.283) | (0.209) | (0.302) | (0.357) | (1) | (0.172) | (0.093) |
| BEKK | 330.3*** | 83.80 | 113.8** | 426.8* | 330.5 | 502.7* | 114.5*** | 89.08** | 327.8 | 751.3 | 979.4 | 1222 | 340.2* | 1027 | 1569** | 412.5* |
| | (0.002) | (0.236) | (0.032) | (0.071) | (0.284) | (0.085) | (0.001) | (0.037) | (0.266) | (0.235) | (0.302) | (0.490) | (0.094) | (0.161) | (0.028) | (0.079) |
| Diag | 326.1*** | 81.54 | 114.8 | 398.1 | 320.8 | 516.9* | 100.2 | 84.53* | 324.4 | 742.5 | 972.9 | 1216 | 333.8 | 1017 | 1561** | 391.6 |
| | (0.005) | (0.398) | (0.194) | (0.214) | (0.228) | (0.068) | (0.454) | (0.075) | (0.533) | (0.808) | (0.446) | (0.928) | (0.770) | (0.580) | (0.026) | (0.108) |
| Scalar | **232.3** | **79.08** | **110.4** | **396.8** | **311.9** | **483.5** | **99.93** | **83.09** | **322.3** | **737.8** | **961.3** | **1214** | **332.3** | 1037 | **1547** | **366.4** |
| | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (1) | (0.138) | (1) | (1) |

The values in bold face refer to the highest $p$ values and the smallest loss under a pre-specified criterion. $p$ values obtained from SPA tests based on 10,000 bootstraps are reported in parentheses. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

**Table 6** Comparison of forecasting accuracy in forecasting stock price volatility under the criterion of HMAE

| | S. Arabia | Canada | Kuwait | Mexico | Norway | Russia | Venezuela | USA | China | France | Germany | Spain | UK | Japan | Korea | India |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GARCH | 1.188* | 1.063*** | 1.121*** | 0.997*** | 1.123 | 1.242*** | 1.307 | 1.102 | 0.953*** | 1.191** | 1.170*** | 1.210* | 1.120*** | 1.264** | 1.135*** | 1.030*** |
| | (0.075) | (0.003) | (0.004) | (0.006) | (0.483) | (0.001) | (0.162) | (0.172) | (0) | (0.049) | (0.008) | (0.052) | (0) | (0.042) | (0.009) | (0) |
| BEKK | 1.216 | **1.037** | **1.094** | **0.941** | 1.119 | 1.227 | **0.901** | **1.069** | 0.991*** | **1.160** | **1.133** | **1.171** | **1.069** | 1.264 | 1.122* | **0.995** |
| | (0.129) | (1) | (1) | (1) | (0.690) | (0.135) | (1) | (1) | (0.001) | (1) | (1) | (1) | (1) | (0.208) | (0.070) | (1) |
| Diag | 1.166 | 1.052*** | 1.109 | 0.987*** | **1.115** | 1.223* | 1.281 | 1.101* | **0.932** | 1.183 | 1.166** | 1.206* | 1.119** | **1.253** | 1.115*** | 1.016*** |
| | (0.490) | (0.002) | (0.239) | (0.009) | (1) | (0.074) | (0.209) | (0.099) | (1) | (0.108) | (0.011) | (0.085) | (0.011) | (1) | (0.002) | (0.007) |
| Scalar | **1.143** | 1.058* | 1.110 | 0.987*** | 1.125** | **1.214** | 1.260 | 1.110 | 0.948 | 1.226** | 1.163 | 1.264** | 1.157** | 1.253 | **1.098** | 1.005 |
| | (1) | (0.091) | (0.166) | (0.007) | (0.021) | (1) | (0.211) | (0.067) | (0.126) | (0.044) | (0.276) | (0.015) | (0.014) | (0.822) | (1) | (0.236) |

The values in bold face refer to the highest *p* values and the smallest loss under a pre-specified criterion. *p* values obtained from SPA tests based on 10,000 bootstraps are reported in parentheses. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

**Table 7** Comparison of forecasting accuracy in forecasting stock price volatility under the criterion of HMSE

| | S. Arabia | Canada | Kuwait | Mexico | Norway | Russia | Venezuela | USA | China | France | Germany | Spain | UK | Japan | Korea | India |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GARCH | 8.280 | 2.430* | 3.385** | 3.538* | 5.112 | 11.56 | 13.00* | 3.098 | 1.715*** | 3.279* | 3.740** | 3.585 | 3.054*** | 23.29* | 11.60* | 2.555*** |
| | (0.136) | (0.072) | (0.024) | (0.062) | (0.293) | (0.136) | (0.091) | (0.157) | (0) | (0.060) | (0.044) | (0.152) | (0) | (0.081) | (0.072) | (0.003) |
| BEKK | 10.01* | **2.298** | **3.239** | **2.911** | 4.968 | 11.50 | **1.013** | 2.567 | 1.988*** | **2.941** | **3.318** | **3.204** | **2.749** | 24.54 | 10.91 | **2.231** |
| | (0.080) | (1) | (1) | (1) | (0.785) | (0.238) | (1) | (1) | (0.003) | (1) | (1) | (1) | (1) | (0.182) | (0.145) | (1) |
| Diag | 7.461 | 2.389*** | 3.270 | 3.240* | **4.964** | 11.17 | 11.17* | 2.925* | **1.580** | 3.145 | 3.633*** | 3.550 | 3.085** | **22.57** | 10.97* | 2.391*** |
| | (0.637) | (0.009) | (0.515) | (0.059) | (1) | (0.531) | (0.096) | (0.090) | (1) | (0.143) | (0.22) | (0.133) | (0.037) | (1) | (0.055) | (0.003) |
| Scalar | **7.379** | 2.455 | 3.520 | 3.174** | 5.074** | **10.86** | 10.30 | 2.943** | 1.723* | 3.295 | 3.430 | 4.074*** | 3.437** | 22.91 | **10.58** | 2.262 |
| | (1) | (0.150) | (0.204) | (0.016) | (0.032) | (1) | (0.173) | (0.017) | (0.058) | (0.157) | (0.453) | (0.006) | (0.038) | (0.606) | (1) | (0.276) |

The values in bold face refer to the highest $p$ values and the smallest loss under a pre-specified criterion. $p$ values obtained from SPA tests based on 10,000 bootstraps are reported in parentheses. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

**Table 8** Comparison of forecasting accuracy in forecasting crude oil price volatility

| | MAE | | MSE | | HMAE | | HMSE | |
|---|---|---|---|---|---|---|---|---|
| | Loss | *p* value | Loss | *p* value | Loss | *p* value | Loss | *p* value |
| GARCH | 22.40 | 0.232 | 1236 | 0.982 | 0.920** | 0.044 | 2.471** | 0.011 |
| BEKK (op-Arabia) | 24.11** | 0.022 | 1345* | 0.089 | 0.884 | 0.425 | 2.220 | 0.455 |
| BEKK (op-Russia) | 23.14** | 0.018 | 1273* | 0.094 | 0.904 | 0.147 | 2.405 | 0.165 |
| BEKK (op-Canada) | 23.21** | 0.049 | 1271 | 0.150 | 0.904 | 0.166 | 2.421 | 0.172 |
| BEKK (op-Norway) | 23.43** | 0.020 | 1284** | 0.044 | 0.912 | 0.121 | 2.510 | 0.219 |
| BEKK (op-Venezuela) | 22.54 | 0.180 | 1241 | 0.757 | 0.921 | 0.124 | 2.533 | 0.165 |
| BEKK (op-Kuwait) | 23.25*** | 0.001 | 1273 | 0.102 | 0.888 | 0.427 | 2.151 | 0.345 |
| BEKK (op-Mexico) | 23.67*** | 0.001 | 1296*** | 0.001 | 0.892 | 0.504 | 2.346 | 0.299 |
| BEKK (op-USA) | 23.08* | 0.065 | 1276* | 0.058 | 0.909 | 0.150 | 2.530 | 0.203 |
| BEKK (op-China) | 22.93** | 0.024 | 1261** | 0.014 | 0.920* | 0.061 | 2.469 | 0.157 |
| BEKK (op-France) | 23.14** | 0.010 | 1267** | 0.025 | 0.920*** | 0.003 | 2.493* | 0.098 |
| BEKK (op-Germany) | 23.85*** | 0.003 | 1327** | 0.011 | 0.940*** | 0.004 | 2.609* | 0.050 |
| BEKK (op-Spain) | 23.81*** | 0.000 | 1287*** | 0.001 | 0.891 | 0.291 | 2.255 | 0.416 |
| BEKK (op-UK) | 24.04*** | 0.006 | 1330** | 0.040 | 0.907 | 0.281 | 2.483 | 0.263 |
| BEKK (op-Japan) | **22.12** | 1.000 | 1242 | 0.708 | 0.940** | 0.023 | 2.817* | 0.089 |
| BEKK (op-Korea) | 23.15** | 0.029 | 1278 | 0.107 | 0.901 | 0.132 | 2.355* | 0.069 |
| BEKK (op-India) | 22.65** | 0.012 | 1249** | 0.013 | 0.920** | 0.039 | 2.520 | 0.125 |
| Diag (op-Arabia) | 23.32** | 0.049 | 1274 | 0.204 | 0.902 | 0.261 | 2.278 | 0.148 |
| Diag (op-Russia) | 22.81*** | 0.002 | 1251** | 0.027 | 0.908 | 0.167 | 2.417 | 0.183 |
| Diag (op-Canada) | 22.72 | 0.143 | 1251 | 0.294 | 0.921** | 0.029 | 2.518 | 0.174 |
| Diag (op-Norway) | 22.66 | 0.237 | 1254 | 0.254 | 0.930** | 0.014 | 2.608 | 0.128 |
| Diag (op-Venezuela) | 22.75** | 0.049 | 1250 | 0.352 | 0.914 | 0.149 | 2.393** | 0.046 |
| Diag (op-Kuwait) | 23.08** | 0.038 | 1262 | 0.181 | 0.908 | 0.179 | 2.353* | 0.054 |
| Diag (op-Mexico) | 22.57 | 0.154 | 1244 | 0.488 | 0.924*** | 0.003 | 2.531** | 0.030 |
| Diag (op-USA) | 22.77* | 0.078 | 1251 | 0.180 | 0.924** | 0.039 | 2.557 | 0.222 |
| Diag (op-China) | 22.54** | 0.049 | 1241 | 0.370 | 0.907* | 0.075 | 2.381* | 0.084 |
| Diag (op-France) | 22.52 | 0.116 | 1241 | 0.610 | 0.921*** | 0.005 | 2.510 | 0.182 |
| Diag (op-Germany) | 22.73** | 0.048 | 1252 | 0.225 | 0.920* | 0.066 | 2.519 | 0.213 |
| Diag (op-Spain) | 22.48 | 0.340 | 1240 | 0.893 | 0.920** | 0.037 | 2.461** | 0.049 |
| Diag (op-UK) | 22.64 | 0.115 | 1246 | 0.357 | 0.924** | 0.016 | 2.554 | 0.207 |
| Diag (op-Japan) | 22.77** | 0.020 | 1250 | 0.284 | 0.915** | 0.040 | 2.459 | 0.179 |
| Diag (op-Korea) | 22.82*** | 0.000 | 1250 | 0.159 | 0.910 | 0.192 | 2.407 | 0.163 |
| Diag (op-India) | 22.54** | 0.039 | 1241 | 0.578 | 0.912* | 0.099 | 2.435 | 0.174 |
| Scalar (op-Arabia) | 24.14*** | 0.000 | 1323*** | 0.007 | **0.864** | 1.000 | **1.941** | 1.000 |
| Scalar (op-Russia) | 22.98** | 0.016 | 1261** | 0.032 | 0.907* | 0.083 | 2.410 | 0.121 |
| Scalar (op-Canada) | 23.13* | 0.070 | 1270 | 0.227 | 0.923** | 0.030 | 2.540 | 0.186 |
| Scalar (op-Norway) | 22.91 | 0.238 | 1266 | 0.283 | 0.934** | 0.011 | 2.632* | 0.052 |

**Table 8** continued

| | MAE | | MSE | | HMAE | | HMSE | |
|---|---|---|---|---|---|---|---|---|
| | Loss | *p* value | Loss | *p* value | Loss | *p* value | Loss | *p* value |
| Scalar (op-Venezuela) | 23.36* | 0.067 | 1271 | 0.185 | 0.919** | 0.021 | 2.407** | 0.043 |
| Scalar (op-Kuwait) | 23.06*** | 0.001 | 1258** | 0.035 | 0.892* | 0.081 | 2.244 | 0.245 |
| Scalar (op-Mexico) | 22.60 | 0.139 | 1246 | 0.418 | 0.922*** | 0.006 | 2.537 | 0.204 |
| Scalar (op-USA) | 23.59* | 0.054 | 1292* | 0.082 | 0.927** | 0.043 | 2.573 | 0.132 |
| Scalar (op-China) | 23.25 | 0.168 | 1275 | 0.234 | 0.920* | 0.099 | 2.456* | 0.075 |
| Scalar (op-France) | 23.32* | 0.065 | 1278 | 0.100 | 0.920* | 0.052 | 2.520 | 0.144 |
| Scalar (op-Germany) | 23.17* | 0.059 | 1271* | 0.054 | 0.919* | 0.075 | 2.536 | 0.208 |
| Scalar (op-Spain) | 23.28 | 0.111 | 1274 | 0.183 | 0.923** | 0.047 | 2.517 | 0.112 |
| Scalar (op-UK) | 23.16 | 0.120 | 1272 | 0.172 | 0.926** | 0.039 | 2.588 | 0.119 |
| Scalar (op-Japan) | 22.44 | 0.143 | **1235** | 1.000 | 0.909** | 0.036 | 2.375** | 0.025 |
| Scalar (op-Korea) | 23.04*** | 0.000 | 1264 | 0.118 | 0.911 | 0.108 | 2.424 | 0.146 |
| Scalar (op-India) | 23.34* | 0.064 | 1281 | 0.180 | 0.920 | 0.109 | 2.499 | 0.155 |

Model (op-country name) denotes a model for oil return and stock return in a country. Here, "BEKK," "diag," and "scalar" denote the full BEKK, diagonal BEKK, and the scalar BEKK specifications, respectively. The values in bold face refer to the highest *p* values and the smallest loss under a pre-specified criterion. The *p* values are obtained from SPA tests based on 10,000 bootstraps. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively

(MAE and MSE). Thus, we should be cautious about whether stock market volatility has explanatory ability for future crude oil price volatility.

### 4.3 Applications of correlations: Can stock market be used to hedge crude oil risk?

In recent years, increases in oil price have caused great concerns among market participants and policy makers. Thus, hedging oil price risk is of great interest for economists. In this subsection, we investigate how useful the stock markets are to hedge crude oil risk by addressing the following two questions: (1) Which model can generate the best strategy, multivariate GARCH, or the simple OLS? (2) Which is the better hedging instrument: stocks in oil-importing countries or those in oil-exporting countries?

As shown in Johnson (1960) and Baillie and Myers (1991), the dynamic optimal hedging ratio (OHR) is given by

$$\delta_t^* = h_{cs,t}/h_{s,t}, \tag{10}$$

where $\delta_t^*$ is the OHR at week $t$; $h_{cs,t}$ and $h_{s,t}$ are, respectively, the conditional covariance between crude oil and stock returns and conditional variance of stock returns implied by multivariate GARCH model. The OHR implies that for the purpose of minimizing the portfolio risk, a long position of one dollar taken in crude oil spot should be hedged by a short position of $\delta_t^*$ dollars in stock market. For comparison, we use the OLS as the benchmark strategy. The OLS is actually a regression in which the dependent variable is oil return and the independent variable is stock index return. Thus, the OLS-based OHR is the estimate of coefficient of stock index return. Then, the return of the hedged portfolio, $r_{H,t}$, can be written as,

$$r_{H,t} = r_{c,t} - \delta_t^* r_{s,t}, \tag{11}$$

where $r_{c,t}$ and $r_{s,t}$ are the returns of crude oil and stock returns at week $t$, respectively.

Following the literature (see, e.g., Ku et al. 2007; Chang et al. 2011: among others), we employ the percentage reduction in variance to measure the hedging effectiveness, which is defined as:

$$\mathrm{HE} = \frac{\mathrm{var}_{\mathrm{unhedged}} - \mathrm{var}_{\mathrm{hedged}}}{\mathrm{var}_{\mathrm{unhedged}}}, \tag{12}$$

where $\mathrm{var}_{\mathrm{unhedged}}$ is the variance of unhedged portfolio returns, i.e., the variance of crude oil returns; $\mathrm{var}_{\mathrm{hedged}}$ is the variance of hedged portfolio returns, i.e., the variance of $r_{H,t}$.

Traditionally, the inference of a better hedging strategy is drawn based on simple comparison of magnitude of hedging effectiveness generated from different strategies. To draw statistical inference, we formally test whether there is a significant difference in variances of hedged portfolios generated by two different strategies. We use the squared portfolio returns as a proxy of variance of hedged portfolio and use the SPA test again. The null hypothesis is that the hedging strategy generated by a benchmark model cannot be outperformed by $K$ alternative strategies generated by competing models. In this case, the loss function is the squared returns of the hedged portfolio, i.e., $X_t^{(i)} = (r_{c,t} - \delta_t^{(i)} r_{s,t})^2$, $(i = 1, 2, \ldots, K)$, where $\delta_t^{(i)}$ is the OHR generated by model $i$.

Table 9 shows the results of the comparison of different hedging strategies, including both hedging effectiveness and the corresponding bootstrapped $p$ values (numbers in parentheses). The first row displays the hedging instruments (stock indices in 16 countries), and the first column shows six hedging strategies. Thus, for example, the number in the second row and the second column is the hedging effectiveness of OLS if we use stock index in Saudi Arabia to hedge crude oil. The number in the parentheses of the second row and the second column is related to null hypothesis that if we use Saudi Arabia's stock index to hedge crude oil, OLS cannot be outperformed by its competitors (i.e., multivariate GARCH-based strategies).

We can see that if we use stock index in different countries to hedge crude oil risk, the optimal strategies implied by the highest hedging effectiveness are different. For example, if we use Saudi Arabia's stock index as a hedging instrument, the optimal strategy is obtained by the diagonal BEKK model; if we use the USA stock index, the optimal choice is from the DCC–GARCH model; and if we use Canada stock index, the RS–DCC performs best. Overall, for most countries, the DCC–GARCH and RS–DCC strategies that consider the time-varying correlations between crude oil and stock returns always have the highest hedging effectiveness. The better hedging performance of RS–DCC also confirms the important role of regime switching in

**Table 9** Comparison results of hedging effectiveness

| | S. Arabia | Russia | Canada | Norway | Venezuela | Kuwait | Mexico | USA | China | France | Germany | Spain | UK | Japan | Korea | India |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| OLS | 5.604 | 31.87* | 46.62 | **44.66** | 5.041 | 2.680 | 24.49** | 22.86 | 6.700 | **28.00** | 25.01 | **19.25** | 39.06 | 11.49 | 20.53 | **12.58** |
| | (0.573) | (0.073) | (0.670) | (1) | (0.603) | (0.142) | (0.037) | (0.126) | (0.433) | (1) | (0.738) | (1) | (0.279) | (0.145) | (0.224) | (1) |
| BEKK | 9.333 | 40.95 | 47.55 | 41.10 | 4.082 | **5.787** | 26.05** | 31.97 | 10.43 | 26.43 | 24.45 | 16.75 | 39.74 | 15.92 | 26.05 | 12.27 |
| | (0.995) | (0.778) | (0.670) | (0.328) | (0.119) | (1) | (0.037) | (0.637) | (0.957) | (0.694) | (0.738) | (0.331) | (0.279) | (0.329) | (0.224) | (0.944) |
| Diag | **9.615** | 40.54 | 47.73 | 41.86 | 2.200* | 5.469 | 30.19** | 32.01 | 10.92 | 26.41 | 25.51 | 14.62** | 40.85 | 15.74 | 27.62 | 12.38 |
| | (1) | (0.778) | (0.670) | (0.345) | (0.073) | (0.960) | (0.037) | (0.637) | (0.996) | (0.694) | (0.738) | (0.014) | (0.279) | (0.329) | (0.310) | (0.944) |
| Scalar | 1.452 | 40.81 | 48.11 | 41.78 | 2.080 | 5.680 | 30.20** | 32.80 | 10.95 | 26.60 | 26.92 | 15.77 | 41.77 | 15.90 | **28.08** | 12.51 |
| | (0.364) | (0.778) | (0.670) | (0.457) | (0.208) | (0.960) | (0.037) | (0.637) | (0.996) | (0.777) | (0.738) | (0.133) | (0.279) | (0.329) | (1) | (0.944) |
| CCC | 7.241 | 31.82** | 41.68 | 40.92 | **5.989** | 2.005 | 20.36** | 12.29** | 7.462 | 18.02* | 15.66* | 11.68** | 26.54 | 10.30* | 17.77* | 9.916 |
| | (0.929) | (0.043) | (0.315) | (0.345) | (1) | (0.142) | (0.037) | (0.021) | (0.321) | (0.091) | (0.054) | (0.014) | (0.117) | (0.090) | (0.094) | (0.796) |
| DCC | 9.518 | 41.71 | 48.85 | 42.70 | 5. 727 | 2.758 | **38.82** | **34.11** | 10.92 | 27.95 | 28.34 | 15.58 | **44.46** | **17.86** | 26.46 | 11.31 |
| | (0.995) | (0.875) | (0.921) | (0.503) | (0.794) | (0.142) | (1) | (1) | (0.996) | (0.777) | (0.738) | (0.141) | (1) | (1) | (0.310) | (0.944) |
| RS–DCC | 9.400 | **44.39** | **49.89** | 42.66 | 5.032 | 3.189 | 35.69 | 32.18 | **11.62** | 26.31 | **29.81** | 19.02 | 36.09 | 15.21 | 18.84 | 7.807 |
| | (0.922) | (1) | (1) | (0.480) | (0.986) | (0.142) | (0.437) | (0.662) | (1) | (0.694) | (1) | (0.608) | (0.218) | (0.299) | (0.155) | (0.530) |

This table shows the hedging effectiveness of different strategies in the sense of hedging crude oil using stock in different countries. The hedging effectiveness is calculated by the percentage of variance reduction. The numbers in bold are related to the strategy which has the greatest hedging effectiveness. The numbers in parentheses are the $p$ values obtained from SPA tests based on 10,000 bootstraps. *, **, and *** denote significance at the 10, 5, and 1 % levels, respectively correlations. The $p$ values from the SPA tests indicate that in most cases, the DCC–GARCH or RS–DCC cannot be significantly outperformed by its competitors, that is, these two strategies are always the better ones than the other multivariate GARCH and OLS strategies.

More importantly, we find that using stock index in several oil-exporting countries (e.g., Russia, Canada, Norway, and Mexico) always lead to greater hedging effectiveness than using stock indices in the oil-importing countries, regardless of which hedging strategy is employed. Thus, crude oil risk can be better hedged by investing in stocks of oil-exporting countries which are less affected by geopolitical events (e.g., Canada, Russia, Norway, and Mexico) than in those of oil-importing countries. The plausible explanations are twofold: First, crude oil is of greater importance for these oil-exporting economies than oil-importing economies. GDP of some industrialized oil-importing countries are more related to service industry which utilizes much less crude oil than manufacturing. Wang et al. (2013) find that oil-exporting countries are more dependent on crude oil than oil-importing countries according to oil expenditure (revenue)-to-GDP ratios. Therefore, correlations between crude oil and stock prices in oil-exporting countries are greater which implies greater hedging performance. Second, unlike oil-exporting countries in the Middle East, less geopolitical events which may cause structural breaks in oil–stock price linkages broke out in these four countries. Therefore, returns of hedged portfolio are less frequently affected by exogenous events and have smaller variances which imply greater hedging effectiveness in the sense of variance reduction.

## 5 Conclusion

In this paper, we investigate the volatility spillovers and dynamic correlations between crude oil and stock markets across seven oil-importing countries and nine oil-exporting countries. In addition, we examine the impact of volatility spillovers on the forecasting accuracy of oil and stock market volatilities as well as implication of dynamic correlations in using stock market to hedge crude oil risk.

First, we employ multivariate GARCH-class models and show the in-sample evidence based on the estimates of model parameters. We use the BEKK–GARCH model to investigate the volatility spillovers and find the existence of unidirectional volatility spillovers from crude oil market to several stock markets of oil-exporting countries (Russia, Norway, and Venezuela) and from several developed stock markets of oil-importing countries (the USA, UK, and Germany) to oil market. We use the CCC- and DCC-GARCH models to investigate the dynamic correlations between crude oil market and stock market. Our findings indicate that the conditional correlations between crude oil and stock returns in both oil-importing and oil-exporting countries are always positive since 2001. This is due to that oil price changes in recent years are mainly driven by aggregate demand, rather than by oil supply changes. Moreover, the correlations between oil return and stock return in oil-exporting countries are always stronger than those in oil-importing countries. Some exogenous events such as recent financial crisis and the second Gulf War can lead to abrupt rise or fall in the correlations.

Second, we examine the impact of volatility spillovers on the out-of-sample performance of the GARCH-class models in terms of their volatility forecasting accuracy. Our results based on the SPA tests indicate that multivariate GARCH models always have significantly greater accuracy than the standard GARCH(1,1) model in forecasting stock market volatility in most countries of interests, that is, oil price can provide useful information about stock price dynamics, further confirming the in-sample results. However, in forecasting crude oil market volatility, the univariate GARCH(1,1) cannot be significantly outperformed by the multivariate models. Thus, stock market volatility may not affect oil price volatility in the out-of-sample period. This evidence is not consistent with our in-sample result. We should be cautious about whether stock market volatility has explanatory power for oil volatility.

Finally, we investigate implication of dynamic correlations between crude oil and stock markets in risk management. Our objective was to find which model is the best one in modeling correlations between stock and crude oil returns. We explore the strategy of hedging crude oil risk using stock markets. Our out-of-sample findings indicate that the DCC and RS–DCC are the better strategies than the simple OLS and other multivariate GARCH-based strategies. Crude oil risk can be better hedged by investing in stocks of oil-exporting countries which are less affected by geopolitical events (e.g., Canada, Russia, Norway, and Mexico) than in those of oil-importing countries.

Our results have some important implications for market participants and policy makers. First, since oil price volatility can affect stock market volatility, stock market participants, especially for traders in oil-exporting countries, should pay attention to past oil market dynamics to perform risk management more effectively. Volatility is a key input in the formulas of derivative pricing. Thus, participants in stock-related derivative market should also pay attention on oil market dynamics because oil market volatility may be helpful for future stock-related derivative pricing. Second, in recent years, the major determinant of oil price changes is aggregate demand rather than oil supply. For this reason, stock and oil markets are always positively correlated. The policy makers in some countries (e.g., China) cannot totally attribute the bearish stock markets in recent years to the negative effects of increases in oil prices. Finally, if crude oil future contracts are not available (e.g., China and Korea), stock index futures may be good choices for hedging crude oil risk. Stock indices in several oil-exporting countries (e.g., Russia and Canada), which are less affected by geopolitical events, provide more effective instrument than stock indices in the oil-importing countries for hedging crude oil risk.

We would like to conclude this paper by outlining some points that deserve further investigation. First, the mean spillovers and seasonality in oil demand and supply may need to take into account for improving the model ability to fit into the data. Second, the investigation of the model performance in forecasting value at risk seems to be relevant. Third, the tail dependence between crude oil and stock returns may be of greater interest for market participants. Finally, the incorporation of some stylized facts such as the asymmetric responses of stock prices to oil price changes (see Aloui and Jammazi (2009) and references therein) may be more helpful to improve model performance. Nevertheless, qualitatively and quantitatively, we have obtained several interesting findings on the volatility relationships between crude oil and stock markets, which have important implications for market participants and policy makers.

**Acknowledgments** We would like to thank the editor, Robert Kunst, and two referees for making many constructive and useful comments and suggestions that helped us to improve the paper. The suggested additional analyses and changes proved to be important in making our findings more comprehensive, convincing, and better understood. This paper is supported by the National Science Foundation of China (No. 71401077).

## References

Akram QF (2004) Oil prices and exchange rates: Norwegian evidence. Econom J 7:476–504

Aloui C, Jammazi R (2009) The effects of crude oil shocks on stock market shifts behavior: a regime switching approach. Energy Econ 31:789–799

Amano RA, van Norden S (1998) Oil prices and the rise and fall of the US real exchange rate. J Int Money Finance 17:299–316

Apergis N, Miller SM (2009) Do structural oil-market shocks affect stock prices? Energy Econ 31:569–575

Arouri MEH (2011) Does crude oil move stock markets in Europe? a sector investigation. Econ Model 28:1716–1725

Arouri MEH, Lahiani A, Nguyen DK (2011) Return and volatility transmission between world oil prices and stock markets of GCC countries. Econ Model 28:1815–1825

Arouri MEH, Jouini J, Nguyen DK (2012) On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. Energy Econ 34:611–617

Ashley R, Granger CWJ, Schmalensee R (1980) Advertising and aggregate consumption: an analysis of causality. Econometrica 48:1149–1167

Baillie RT, Myers R (1991) Bivariate GARCH estimation of the optimal commodity futures hedge. J Appl Econom 6:109–124

Barsky RB, Kilian L (2004) Oil and macroeconomy since the 1970s. J Econ Perspect 18:115–134

Billio M, Caporin M (2005) Multivariate Markov switching dynamic conditional correlation GARCH representations for contagion analysis. Stat Methods Appl 14:145–161

Bjørnland HC (2009) Oil price shocks and stock market booms in an oil-exporting country. Scott J Polit Econ 56:232–254

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. J Econom 31:307–327

Bollerslev T (1990) Modelling the coherence in short-run nominal exchange rate: a multivariate generalized ARCH approach. Rev Econ Stat 72:498–505

Bollerslev T, Wooldridge JM (1992) Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econom Rev 11:143–172

Bollerslev T, Engle RF, Nelson D (1994) ARCH models. In: Engle RF, McFadden DL (eds) Handbook of econometrics, vol. IV. Elsevier Science B.V, Amsterdam, pp 2961–3038

Bollerslev T, Engle RF, Wooldridge JM (1988) A capital asset model with time-varying covariances. J Polit Econ 96:116–131

Caporin M, McAleer M (2012) Do we really need both BEKK and DCC? a tale of two covariance models. J Econ Surv 26:736–751

Chang C-L, McAleer M, Tansuchat R (2010) Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. Energy Econ 32:1445–1455

Chang C-L, McAleer M, Tansuchat R (2011) Crude oil hedging strategies using dynamic multivariate GARCH. Energy Econ 33:912–923

Chen S-S (2009) Oil price pass-through into inflation. Energy Econ 31:126–133

DeMiguel V, Garlappi L, Nogales F, Uppal R (2009) a generalized approach to portfolio optimization: improving performance by constraining portfolio norms. Manage Sci 55:798–812

Diebold FX, Lopez JA (1996) Forecast evaluation and combination. In: Maddala GS, Rao CR (eds) Handbook of statistics: statistical methods in finance, vol. 14. North-Holland, Amsterdam, pp 241–268

Elder J, Serletis A (2010) Oil price uncertainty. J Money Credit Bank 42:1137–1159

Engle RF (1982) Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50:987–1007

Engle RF (2002) Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J Bus Econ Stat 20:339–350

Engle RF, Kroner KF (1995) Multivariate simultaneous generalized ARCH. Econ Theory 11:122–150

Fan Y, Xu J-H (2011) What has driven oil prices since 2000? a structural change perspective. Energy Econ 33:1082–1094

Ferderer JP (1996) Oil price volatility and the macroeconomy. J Macroecon 18:1–26

Filis G, Degiannakis S, Foros C (2011) Dynamic correlation between stock market and oil prices: the case of oil-importing and oil-exporting countries. Int Rev Financ Anal 20:152–164

Hamilton JD (1983) Oil and the macroeconomy since World War II. J Polit Econ 91:228–248

Hamilton JD (1996) This is what happened to the oil price–macroeconomy relationship. J Monet Econ 38:215–220

Hamilton JD (2003) What is an oil shock? J Econom 113:363–398

Hamilton JD (2008) Macroeconomics and ARCH. NBER working paper 14151

Hamilton JD (2009) Understanding crude oil prices. Energy J 30:179–206

Hansen PR (2005) A test for superior predictive ability. J Bus Econ Stat 23:365–380

Hansen PR, Lunde A (2006) Consistent ranking of volatility models. J Econom 131:97–121

Inoue A, Kilian L (2004) In-sample or out-of-sample tests of predictability: Which one should we use? Econom Rev 23:371–402

Johnson LL (1960) The theory of hedging and speculation in commodity futures. Rev Econ Stud 27:139–151

Jorion P (1992) Portfolio optimization in practice. Financ Anal J 48:68–74

Jung H, Park C (2011) Stock market reaction to oil price shocks: a comparison between an oil-exporting economy and an oil-importing economy. J Econ Theory Econom 22:1–29

Kilian L (2009) Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am Econ Rev 99:1053–1069

Kilian L, Park C (2009) The impact of oil price shocks on the U.S. stock market. Int Econ Rev 50:1267–1287

Koopman SJ, Jungbacker B, Hol E (2005) Forecasting daily variability of the S&P 100 stock index using historical, realized and implied volatility measurements. J Empir Finance 12:445–475

Ku Y-H, Chen H-C, Chen K-H (2007) On the application of the dynamic conditional correlation model in the estimating optimal time-varying hedge ratios. Appl Econ Lett 14:503–509

LeBlanc M, Chinn MD (2004) Do high oil prices presage inflation? Bus Econ 39:38–48

Ljung M, Box G (1978) On a measure of lack of fit in time series models. Biometrika 65:297–303

Lopez JA (2001) Evaluation of predictive accuracy of volatility models. J Forecast 20:87–109

Malik F, Hammoudeh S (2007) Shock and volatility transmission in the oil, US and Gulf equity markets. Int Rev Econ Finance 16:357–368

Nomikos NK, Pouliasis PK (2011) Forecasting petroleum futures markets volatility: the role of regimes and market conditions. Energy Econ 33:321–337

Park J, Ratti RA (2008) Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Econ 30:2587–2608

Patton AJ (2011) Volatility forecast comparison using imperfect volatility proxies. J Econ 160:246–256

Politis DN, Romano JP (1994) The stationary bootstrap. J Am Stat Assoc 89:1303–1313

Sadorsky P (1999) Oil price shocks and stock market activity. Energy Econ 21:449–469

Sadorsky P (2012) Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ 34:248–255

Sadorsky P (2014) Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. Energy Econ 43:72–81

Wang Y, Wu C (2012a) Energy prices and exchange rates of the U.S. dollar: further evidence from linear and nonlinear causality analysis. Econ Model 29:2289–2297

Wang Y, Wu C (2012b) Forecasting energy market volatility using GARCH models: Can multivariate models beat univariate models? Energy Econ 34:2167–2181

Wang Y, Wu C, Yang L (2013) Oil price shocks and stock market activities: evidence from oil-importing and oil-exporting countries. J Comp Econ 41:1220–1239

Wei C (2003) Energy, the stock market, and the putty-clay investment model. Am Econ Rev 93:311–323