Conditional Correlations and Volatility Spillovers Between Crude Oil and Stock Index Returns*

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Abstract

This paper investigates the conditional correlations and volatility spillovers between the crude oil and financial markets, based on crude oil returns and stock index returns. Daily returns from 2 January 1998 to 4 November 2009 of the crude oil spot, forward and futures prices from the WTI and Brent markets, and the FTSE100, NYSE, Dow Jones and S&P500 stock index returns, are analysed using the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), VARMA-AGARCH model of McAleer, Hoti and Chan (2008), and DCC model of Engle (2002). Based on the CCC model, the estimates of conditional correlations for returns across markets are very low, and some are not statistically significant, which means the conditional shocks are correlated only in the same market and not across markets. However, the DCC estimates of the conditional correlations are always significant. This result makes it clear that the assumption of constant conditional correlations is not supported empirically. Surprisingly, the empirical results from the VARMA-GARCH and VARMA-AGARCH models provide little evidence of volatility spillovers between the crude oil and financial markets. The evidence of asymmetric effects of negative and positive shocks of equal magnitude on the conditional variances suggests that VARMA-AGARCH is superior to VARMA-GARCH and CCC. The estimation and analysis of the volatility and conditional correlations between crude oil returns and stock index returns can provide useful information for investors, oil traders and government agencies that are concerned with the crude oil and stock markets, especially regarding optimal hedging across the two markets.

Keywords: Multivariate GARCH, volatility spillovers, conditional correlations, crude oil prices, spot, forward and futures prices, stock indexes.

JEL: C22, C32, G17, G32.

1. Introduction

Stock market and crude oil markets have developed a mutual relationship over the past few years, with virtually every production sector in the international economy relying heavily on oil as an energy source. Owing to such dependence, fluctuations in crude oil prices are likely to have significant effects on the production sector. The direct effect of an oil price shock may be considered as an input-cost effect, with higher energy costs leading to lower oil usage and decreases in productivity of capital and labour. Further to the direct impacts on productivity, fluctuations in oil prices also cause income effects in the household sector, with higher costs of imported oil reducing the disposable income of the household. Hamilton (1983) argues that a sharp rise in oil prices increases uncertainty in the operating costs of certain durable goods, thereby reducing demand for durables and investment.

The impact of oil prices on macroeconomic variables, such as inflation, real GDP growth rate, unemployment rate and exchange rates, is a matter of great concern for all economies. Due to the role of crude oil on demand and input substitution, more expensive fuel translates into higher costs of transportation, production and heating, which affect inflation and household discretionary spending. The literature has analysed the effects of major energy prices, economic recession, unemployment, and inflation (see, for example, Hamilton (1983), Mork, Olsen and Mysen (1994), Mork (1994), Lee et al. (1995), Sadorsky (1999), Lee et al. (2001), Hooker (2002), Hamilton and Herrera (2004), Cunado and Perez de Garcia (2005), Jimenez-Rodriguez and Sanchez (2005), Kilian (2008), Cologni and Manera (2008), and Park and Ratti (2008)). Moreover, higher prices may also reflect a stronger business performance and increased demand for fuel.

Chang et al. (2009) explained the effect of oil price shocks on stock prices through expected cost flows, the discount rate and the equity pricing model. However, the direction of the stock price effect depends on whether a stock is a producer or a consumer of oil or oil-related products. Figure 1 presents the plots of the Brent futures price and FTSE100 index from early 1998. Before 2003, the Brent futures price and FTSE100 index moved in opposite directions, but they moved together thereafter. However, the correlation between daily Brent futures prices and the FTSE100 index has been relatively weak at 0.162 over the past decade.

[Insert Figure 1 here]

Returns, risks and correlation of assets in portfolios of assets are key elements in empirical finance, especially in developing optimal hedging strategies, so it is important to model and forecast the correlations between crude oil and stock markets accurately. A volatility spillover occurs when changes in price or returns volatility in one market have a lagged impact on volatility in the financial, energy and stock markets (see, for example, Sadorsky (2004), Hammoudeh and Aleisa (2002), Hammoudeh et al. (2004), Å gren (2006), and Malik and Hammoudeh (2007)). Surprisingly, there does not seem to have been an analysis of the conditional correlations or volatility spillovers between shocks in crude oil returns and in index returns, despite these issues being very important for practitioners and investors alike.

The reaction of stock markets to oil price and returns shocks will determine whether stock prices rationally reflect the impact of news on current and future real cash flows. The paper models the conditional correlations and examines the volatility spillovers between two major crude oil return, namely Brent and WTI (West Texas Intermediate) and four stock index returns, namely FTSE100 (London Stock Exchange, FTSE), NYSE composite (New York Stock Exchange, NYSE), S&P500 composite index, and Dow Jones Industrials (DJ). Some of these issues have been examined empirically using several recent models of multivariate conditional volatility, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), VARMA-AGARCH model of McAleer, Hoti and Chan (2008), and DCC model of Engle (2002).

The remainder of the paper is organized as follows. Section 2 reviews the relationship between the crude oil market and stock market. Section 3 discusses various popular multivariate conditional volatility models that enable an analysis of volatility spillovers, and dynamic variances, covariances and correlations. Section 4 gives details of the data to be in the empirical analysis, descriptive statistics and unit root tests. The empirical results are analyzed in Section 5, and some concluding remarks are given in Section 6

2. Crude Oil and Stock Markets

There is a scant literature on the empirical relationship between the crude oil and stock markets. Jones and Kaul (1996) show the negative reaction of US, Canadian, UK and Japan stock prices to oil price shocks via the impact of oil price shocks on real cash flows. Ciner (2001) uses linear and nonlinear causality tests to examine the dynamic relationship between oil prices and stock markets, and concludes that a significant relationship between real stock returns and oil futures price is non-linear. Hammoudeh and Aleisa (2002) find spillovers from oil markets to the stock indices of oil-exporting countries, including Bahrain, Indonesia, Mexico and Venezuela. Kilian and Park (2009) report that only oil price increases, driven by precautionary demand for oil over concern about future oil supplies, affect stock prices negatively. Driesprong et al. (2008) find a strong relationship between stock market and oil market movements.

Several previous papers have applied vector autoregressive (VAR) models to investigate the relationship between the oil and stock markets. Kaneko and Lee (1995) find that changes in oil prices are significant in explaining Japanese stock market returns. Huang et al. (1996) show significant causality from oil futures prices to stock returns of individual firms, but not to aggregate market returns. In addition, they find that oil futures returns lead the petroleum industry stock index, and three oil company stock returns. Sadorsky (1999) indicates that positive shocks to oil prices depress real stock returns, using monthly data, and the results from impulse response functions suggest that oil price movements are important in explaining movements in stock returns.

Papapetrou (2001) reveals that the oil price is an important factor in explaining stock price movements in Greece, and that a positive oil price shock depresses real stock returns by using impulse response functions. Lee and Ni (2002) indicate that, as a large cost share of oil industries, such as petroleum refinery and industrial chemicals; oil price shocks tend to reduce supply. In contrast, for many other industries, such as the automobile industry, oil price shocks tend to reduce demand. Park and Ratti (2008) estimate the effects of oil price shocks and oil price volatility on the real stock returns of the USA and 13 European countries, and find that oil price shocks have a statistically significant impact on real stock returns in the same month, and real oil price shocks also have an impact on real stock returns across all countries. For emerging stock markets, Maghyereh (2004) finds that oil shocks have no significant impact on stock index returns in 22 emerging economies. However, Basher and Sadorsky (2006) show strong evidence that oil price risk has a significant impact on stock price returns in emerging markets.

Regarding the relationship between oil prices and stock markets, Faff and Brailsford (1999) find a positive impact on the oil and gas, and diversified resources, industries, whereas there is a negative impact on the paper and packing, banks and transport industries. Sadorsky (2001) shows that stock returns of Canadian oil and gas companies are positive and sensitive to oil price increases using a multifactor market model. In particular, an increase in the oil price factor increases the returns to Canadian oil and gas stocks. Boyer and Filion (2004) find a positive association between energy stock returns and an appreciation in oil and gas prices. Hammoudeh and Li (2005) show that oil price growth leads the stock returns of oil-exporting countries and oil-sensitive industries in the USA.

Nandha and Faff (2007) examine the adverse effects of oil price shocks on stock market returns using global industry indices. The empirical results indicate that oil price changes have a negative impact on equity returns in all industries, with the exception of mining, and oil and gas. Cong et al. (2008) argue that oil price shocks do not have a statistically significant impact on the real stock returns of most Chinese stock market indices, except for the manufacturing index and some oil companies. An increase in oil volatility does not affect most stock returns, but may increase speculation in the mining and petrochemical indexes, thereby increasing the associated stock returns. Sadorsky (2008) finds that the stock prices of small and large firms respond fairly symmetrically to changes in oil prices, but for medium-sized firms the response is asymmetric to changes in oil prices. From simulations using a VAR model, Henriques and Sadorsky (2008) show that shocks to oil prices have little impact on the stock prices of alternative energy companies.

In small emerging markets, especially in the Gulf Cooperating Council (GCC) countries, Hammoudeh and Aleisa (2004) show that the Saudi market is the leader among GCC stock markets, and can be predicted by oil futures prices. Maghyereh and Al-Kandari (2007) apply nonlinear cointegration analysis to examine the linkage between oil prices and stock markets in GCC countries. The empirical results indicate that oil prices have a nonlinear impact on stock price indices in GCC countries. Onour (2007) argues that, in the short run, GCC stock market returns are dominated by the influence of non-observable psychological factors. In the long run, the effects of oil price changes are transmitted to fundamental macroeconomic indicators which, in turn, affect the long run equilibrium linkages across markets.

Recent research has used multivariate GARCH specifications, especially BEKK, to model volatility spillovers between the crude oil and stock markets. Hammoudeh et al. (2004) find that there are two-way interactions between the S&P Oil Composite index, and oil spot and futures prices. Malik and Hammoudeh (2007) find that Gulf equity markets receive volatility from the oil markets, but only in the case of Saudi Arabia is the volatility spillover from the Saudi market to the oil market significant, underlining the major role that Saudi Arabia plays in the global oil market. Using a two-regime Markov-switching EGARCH model, Aloui and Jammazi (2009) examine the relationship between crude oil shocks and stock markets from December 1987 to January 2007. The paper focuses on the WTI and Brent crude oil markets and three developed stock markets, namely France, UK and Japan. The results show that the net oil price increase variable play a significant role in determining both the volatility of real returns and the probability of transition across regimes.

3. Econometric Models

In order to investigate the conditional correlations and volatility spillovers between crude oil returns and stock index returns, several multivariate conditional volatility models are used. This section presents the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer, Hoti and Chan (2009). These models assume constant conditional correlations, and do not suffer from the curse of dimensionality, as compared with the VECH and BEKK models (see McAleer (2005), McAleer et al. (2008) and Caporin and McAleer (2009, 2010) for further details). In order to to make the conditional correlations time dependent, Engle (2002) proposed the DCC model.

The typical CCC specification underlying the multivariate conditional mean and conditional variance in returns is given as follows:

$$y_t = E\left(y_t \middle| F_{t-1}\right) + \varepsilon_t$$

$$\varepsilon_t = D_t \eta_t$$

$$Var\left(\varepsilon_t \mid F_{t-1}\right) = \Omega_t = D_t \Gamma D_t \qquad (1)$$

where $y_t = \left(y_{1t},...,y_{mt}\right)'$, $\eta_t = \left(\eta_{1t},...,\eta_{mt}\right)'$ is a sequence of independently and identically distributed (iid) random vectors, F_t is the past information available to time *t*, $D_t = diag\left(h_{1t}^{1/2},...,h_{mt}^{1/2}\right)$, m is the number of returns, $t = 1,...,n$ (see Li, Ling and McAleer (2002), and Bauwens et al. (2006)), and

$$\Gamma = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1m} \\ \rho_{21} & 1 & \cdots & \vdots \\ \vdots & \vdots & \ddots & \rho_{m-1,m} \\ \rho_{m1} & \cdots & \rho_{m,m-1} & 1 \end{pmatrix}$$

which $\rho_{ij} = \rho_{ji}$ for $i, j = 1,...,m$. As $\Gamma = E\left(\eta_t\eta_t' \middle| F_{t-1}\right) = E\left(\eta_t\eta_t'\right)$, the constant conditional correlation matrix of the unconditional shocks, ε_t, for all *t* is, by definition, equal to the conditional covariance matrix of the standardized shocks, η_t.

The conditional correlations are assumed to be constant for all the models above. From (1), $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta' D_t$, and $E\left(\varepsilon_t\varepsilon_t' \middle| F_{t-1}\right) = \Omega_t = D_t\Gamma D_t$, where Ω_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1}\Omega_t D_t^{-1}$, which is assumed to be constant over time, and each conditional correlation coefficient is estimated from the standardized residuals in (1) and (2). The constant conditional correlation (CCC) model of Bollerslev (1990) assumes that the conditional variance for each return, h_{it}, $i = 1,..,m$, follows a univariate GARCH process, that is

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_{il}\varepsilon_{i,t-l}^2 + \sum_{j=1}^{s} \beta_{il} h_{i,t-l} \qquad (2)$$

where $\sum_{l=1}^{r}\alpha_{il}$ denotes the short run persistence, or ARCH effect, of shocks to return *i*, $\sum_{l=1}^{s}\beta_{il}$ represents the GARCH effect, and $\sum_{j=1}^{r}\alpha_{ij} + \sum_{j=1}^{s}\beta_{ij}$ denotes the long run persistence of shocks to returns.

In order to test for the existence of constant conditional correlations in the multivariate GARCH model, Tse (2000) suggested a Lagrange Multiplier test (hereafter LMC) based on the estimates of the CCC model. From (1), as the conditional covariances are given by

$$\sigma_{ijt} = \rho_{ijt}\sigma_{it}\sigma_{jt} ,$$

the equation for the time-varying correlations is defined as

$$\rho_{ijt} = \rho_{ij} + \delta_{ij} y_{i,t-1} y_{j,t-1} .$$

The null hypothesis of constant conditional correlations is $H_0 : \delta_{ij} = 0$ for $1 \le i < j \le K$. The LMC test is asymptotically distributed as χ^2_M , where $M = K(K-1)/2$. If the null hypothesis is rejected, the correlations between two series are dynamic rather than static.

Although the conditional correlations can be estimated in practice, the CCC model does not permit any interdependencies of volatilities across different assets and/or markets, and does not accommodate asymmetric behaviour. In order to incorporate interdependencies of volatilities across different assets and/or markets, Ling and McAleer (2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean in (1), and the following GARCH specification for the conditional variances:

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{3}$$

$$\varepsilon_t = D_t \eta_t$$

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \tag{4}$$

where $D_t = diag\left(h_{i,t}^{1/2}\right)$, $H_t = \left(h_{1t},...,h_{mt}\right)'$, $\Phi(L) = I_m - \Phi_1 L - \cdots - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - \cdots - \Psi_q L^q$ are polynomials in L, $\vec{\varepsilon} = \left(\varepsilon_{1t}^2,...\varepsilon_{mt}^2\right)'$, and W, A_l for $l = 1,..,r$ and B_l for $l = 1,..,s$ are $m \times m$ matrices and represent the ARCH and GARCH effects, respectively. Spillover effects, or the dependence of the conditional variance between crude oil returns and stock index returns, are given in the conditional variance for each returns in the portfolio. It is clear that when A_l and B_l are diagonal matrices, (4) reduces to (2), so the VARMA-GARCH model has CCC as a special case.

As in the univariate GARCH model, VARMA-GARCH assumes that negative and positive shocks of equal magnitude have identical impacts on the conditional variance. In order to separate the asymmetric impacts of positive and negative shocks, McAleer, Hoti and Chan (2009) proposed the VARMA-AGARCH specification for the conditional variance, namely

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_i I\left(\eta_{t-l}\right)\vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \tag{5}$$

where C_l are $m \times m$ matrices for $l = 1,..,r$, and $I_t = \mathrm{diag}\left(I_{1t},...,I_{mt}\right)$ is an indicator function, and is given as

$$I\left(\eta_{it}\right) = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases} \qquad (6).$$

If $m = 1$, (6) collapses to the asymmetric GARCH, or GJR, model of Glosten, Jagannathan and Runkle (1992). Moreover, VARMA-AGARCH reduces to VARMA-GARCH when $C_i = 0$ for all *i*. If $C_i = 0$ and A_i and B_j are diagonal matrices for all *i* and *j*, then VARMA-AGARCH reduces to CCC. The parameters of model (1)-(5) are obtained by maximum likelihood estimation (MLE) using a joint normal density. When η_t does not follow a joint multivariate normal distribution, the appropriate estimator is the Quasi-MLE (QMLE).

Unless η_t is a sequence of iid random vectors, or alternatively a martingale difference process, the assumption that the conditional correlations are constant may seen unrealistic. In order to make the conditional correlation matrix time dependent, Engle (2002) proposed a dynamic conditional correlation (DCC) model, which is defined as

$$y_t \mid \Im_{t-1} \sim (0, Q_t) \quad , \quad t = 1, 2, ..., n \tag{7}$$

$$Q_t = D_t \Gamma_t D_t, \tag{8}$$

where $D_t = \left[\mathrm{diag}\left(h_t\right)\right]^{1/2}$ is a diagonal matrix of conditional variances, and $\Im_t$ is the information set available to time *t*. The conditional variance, h_{it}, can be defined as a univariate GARCH model, as follows:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{ik} \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{il} h_{i,t-l} \ . \tag{9}$$

If η_t is a vector of i.i.d. random variables, with zero mean and unit variance, Q_t in (8) is the conditional covariance matrix (after standardization, $\eta_{it} = y_{it} \Big/ \sqrt{h_{it}}$). The η_{it} are used to estimate the dynamic conditional correlations, as follows:

$$\Gamma_t = \left\{(diag(Q_t)^{-1/2}\right\} Q_t \left\{(diag(Q_t)^{-1/2}\right\} \tag{10}$$

where the $k \times k$ symmetric positive definite matrix Q_t is given by

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 \eta_{t-1}\eta_{t-1}' + \theta_2 Q_{t-1} \tag{11}$$

in which θ_1 and θ_2 are non-negative scalar parameters to capture, respectively, the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation. As Q_t is conditional on the vector of standardized residuals, (11) is a conditional covariance matrix, and $\bar{Q}$ is the $k \times k$ unconditional variance matrix of η_t. For further details, and a critique of DCC and BEKK, see Caporin and McAleer (2009, 2010).

4. Data

For the empirical analysis, daily data are used for four indexes, namely FTSE100 (London Stock Exchange: FTSE), NYSE composite (New York Stock Exchange: NYSE), S&P500 composite (Standard and Poor's: S&P), and Dow Jones Industrials (Dow Jones: DJ), and three crude oil closing prices (spot, forward and futures) of two reference markets, namely Brent and WTI (West Texas Intermediate). Thus, there are six price indexes, namely Brent spot prices FOB (BRSP), Brent one-month forward prices (BRFOR), Brent one-month futures prices (BRFU), WTI spot Cushing prices (WTISP), WTI one-month forward price (WTIFOR), and WTI one month futures price (WTIFU). All 3,090 prices and price index observations are from 2 January 1998 to 4 November 2009. The data are obtained from DataStream database services, and crude oil prices are expressed in USD per barrel.

The returns of the daily price index and crude oil prices are calculated by a continuous compound basis, defined as $r_{ij,t} = \ln\left(P_{ij,t} / P_{ij,t-1}\right)$, where $P_{ij,t}$ and $P_{ij,t-1}$ are the closing price or crude oil price i of market j for days t and $t-1$, respectively. The daily prices and daily returns of each crude oil prices, and for the four set index, are given in Figures 1 and 2, respectively. The plots of the prices and returns in their respective markets clearly move in a similar manner. The descriptive statistics for the crude oil returns and set index returns are reported in Tables 1 and 2, respectively, and the respective data plots are given in Figures 2 and 3. The average returns of the set index are low, except for Dow Jones, but the corresponding standard deviation of returns is much higher. On the contrary, the average returns of crude oil are the same within their markets, and are higher than the average return of the set index. Based on the standard deviation, crude oil returns has a higher historical volatility than stock index returns.

[Insert Tables 1-2 here]

[Insert Figures 2-3 here]

Prior to estimating the conditional mean or conditional variance, it is sensible to test for unit roots in the series. Standard unit root testing procedures based on the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) tests are obtained from the EViews 6.0 econometric software package. Results of the tests for the null hypothesis that daily stock index returns and crude oil returns have a unit root are given in Table 2, and all reject the null hypothesis of a unit root at the 1% level of significance, both with a constant and with or without a deterministic time trend.

5. Empirical Results

This section presents the multivariate conditional volatility models for six crude oil returns, namely spot, forward and futures for the Brent and WTI markets, and four stock index returns, namely FTSE100, NYSE, Dow Jones and S&P, leading to 24 bivariate models. In order to check whether the conditional variances of the assets follow an ARCH process, univariate ARMA-GARCH and ARMA-GJR models are estimated. The ARCH and GARCH effects of all ARMA(1,1)-GARCH (1,1) models are statistically significant, as are the asymmetric effects of the ARMA-GJR(1,1) models. The empirical results of these univariate conditional volatility models are available from the authors on request.

Constant conditional correlations between the volatilities of crude oil returns and stock index returns, the Bollerslev and Wooldridge (1992) robust *t*-ratios using the CCC model based on ARMA(1,1)-CCC(1,1), and the LMC test statistics, are presented in Table 3. All estimates are obtained using the RATS 6.2 econometric software package. The conditional correlation matrices for the 24 pairs of returns can be divided into three groups, namely within crude oil markets, financial or stock markets, and across markets. The CCC estimates for pairs of crude oil returns within the crude oil market are high and statistically significant, as well as the estimates for pairs of stock index returns in financial markets. However, the CCC estimates for returns across markets are very low, and some are not statistically significant. Thus, the conditional shocks are correlated only in the same market, and not across markets.

[Insert Table 3 here]

The LMC test statistic is significant at the 5% level, so that the conditional correlations between any two series are time varying. The DCC estimates of the conditional correlations between the volatilities of crude oil returns and stock index returns, and the Bollerslev-Wooldridge robust *t*-ratios based on the ARMA(1,1)-DCC(1,1) models, are presented in Table 4. As the estimates of both $\hat{\theta}_1$, the impact of past shocks on current conditional correlations, and $\hat{\theta}_2$, the impact of previous dynamic conditional correlations, are statistically significant, this also indicates that the conditional correlations are not constant. The estimates $\hat{\theta}_1$ are generally low and close to zero, increasing to 0.021, whereas the estimates $\hat{\theta}_2$ are extremely high and close to unity, ranging from 0.973 to 0.991. Therefore, from (11), Q_t seems to be very close to Q_{t-1}, such as for the pair WTIFOR and FTSE.

[Insert Table 4 here]

The short run persistence of shocks on the dynamic conditional correlations is the greatest between BRFOR_FTSE, while the largest long run persistence of shocks on the conditional correlations is 0.998 for the pairs WTIFOR_FTSE and WTIFU_S&P. Thus, the conditional correlations between crude oil returns and stock index returns are dynamic. These findings are consistent with the plots of the dynamic conditional correlations between the standardized shocks for each pair of returns in Figure 4, which change over time and range from negative to positive. The greatest range of conditional correlations is between Brent forward returns and FTSE100. These results indicate that the assumption of constant conditional correlations for all shocks to returns is not supported empirically. However, the mean conditional correlations for each pair are nevertheless rather low and close to zero.

[Insert Table 5 here]

[Insert Figure 4 here]

Tables 6 and 7 present the estimates for VARMA-GARCH and VARMA-AGARCH, respectively. The two entries corresponding to each of the parameters are the estimates and the Bollerslev-Wooldridge robust *t*-ratios. Both models are estimated with the EViews 6.0 econometric software package and the Berndt-Hall-Hall-Hausman (BHHH) algorithm. Table 6 presents the estimates of the conditional variances of VARMA-GARCH (the estimates of the conditional means are available from the authors on request). In Panels 6a-6x, it is clear that the ARCH and GARCH effects of crude oil returns and stock index returns in the conditional covariances are statistically significant. Interestingly, Table 6 suggests there is no evidence of volatility spillovers in one or two directions (namely, interdependence), except for two cases, namely the ARCH and GARCH effects for WTIFOR_FTSE100 and WTIFU_FTSE100, with the past conditional volatility of FTSE100 spillovers for WTIFOR, and the past conditional volatility of WTIFU spillovers for FTSE100.

[Insert Table 6 here]

Table 7 presents the estimates of the conditional variances of VARMA-AGARCH (estimates of the conditional mean are available from the authors on request). The GARCH effect of each pair of crude oil returns and stock index returns in the conditional covariances are statistically significant. Surprisingly, Table 7 shows that there are only 3 of 24 cases for volatility spillovers from the past conditional volatility of the crude oil market on the stock market, namely WTIFOR_NYSE, WTIFOR_S&P and WTIFU_S&P. The estimated parameters are positive but also low, and the asymmetric effects of each pair are statistically insignificant. Therefore, VARMA-GARCH is generally preferred to VARMA-AGARCH.

[Insert Table 7 here]

In conclusion, from the VARMA-GARCH and VARMA-AGARCH models, there is little evidence of volatility spillovers between crude oil returns and stock index returns. These findings are consistent with the very low conditional correlations between the volatility of crude oil returns and stock index returns using the CCC model. These phenomena can be explained as follows. First, as the stock market index is calculated from the given company stock prices, which can be classified as producers and consumers of oil and oil-related companies, the impact of crude oil shocks on each stock index sector may balance out. For example, the energy sector, namely oil and gas drilling and exploration, refining and by-products, and petrochemicals, is typically positively affected by variations in oil prices, whereas the other sectors, such as manufacturing, transportation and financial sectors, are negatively affected by variations in oil prices.

Second, each common stock price in the stock index is not affected equally or contemporaneously by fluctuations in oil prices. The service sectors, namely media, entertainment, support services, hotel and transportation, are most negatively affected by fluctuations in oil prices, followed by the consumer goods sector, namely household goods and beverages, housewares and accessories, automobile and parts, and textiles. The next most negatively influenced sector is the financial sector, namely banks, life, assurance, insurance, real estate, and other finance. Consequently, the impacts of crude oil changes on stock index returns may not be immediate or explicit. Third, through advances in financial instruments, some firms may have found ways to pass on oil prices changes or risks to customers, or determined effective hedging strategies. Therefore, the effects of crude oil price fluctuations on stock prices may not be as large as might be expected.

6. Concluding Remarks

Virtually every production sector in the international economy relies heavily on oil as an energy source. Moreover, the impact of oil prices on macroeconomic variables is a matter of great concern for all international economies. In view of the Global Financial Crisis (GFC) of 2008-2009, and the intricate relationships between the financial and production sectors, a critical analysis of the spillover relationships between the stock market and crude oil markets is crucial for a deeper understanding of the impact of the financial and crude oil markets on the real economy.

The paper investigated conditional correlations and examined the volatility spillovers between crude oil returns, namely spot, forward and futures returns for the WTI and Brent markets, and stock index returns, namely FTSE100, NYSE, Dow Jones and S&P index, using four multivariate GARCH models, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), VARMA-AGARCH model of McAleer, Hoti and Chan (2008), and DCC model of Engle (2002), with a sample size of 3089 returns observations from 2 January 1998 to 4 November 2009.

The estimation and analysis of the spillover effects of volatility and conditional correlations between crude oil returns and stock index returns can provide useful information for investors, oil traders and government agencies that are concerned with the crude oil and stock markets. The empirical results also enable an evaluation of the impact of crude oil price fluctuations in spot, forward and futures returns on the financial returns in various stock markets.

Optimal hedging across the two markets relies on accurate estimation of conditional variances and covariances of stock and crude oil returns. In this respect, correct model specification is crucial for purposes of estimating dynamic variances, covariances and volatility spillovers. The paper estimated both constant and dynamic conditional correlations, and determined that dynamic models were essential for consistent estimation of variances, covariances and volatility spillovers.

Based on the CCC model, the estimated conditional correlations for returns across markets were very low, and some were not statistically significant, which means that the conditional shocks were correlated only in the same market, and not across markets. However, for the

DCC model, the estimates of the conditional correlations were always significant, which makes it clear that the assumption of constant conditional correlations was not supported empirically. This was highlighted by the dynamic conditional correlations between Brent forward returns and FTSE100, which varied dramatically over time. Therefore, these two markets would seem to be crucial for purposes of optimal hedging.

The empirical results from the VARMA-GARCH and VARMA-AGARCH models provided little evidence of dependence of volatility spillovers between the crude oil and financial markets. VARMA-GARCH model yielded only 2 of 24 cases, namely WTIFU_FTSE100 twice, whereas VARMA-AGARCH gave 3 of 24 cases, namely the past conditional volatility of FTSE100 spillovers to WTIFOR, and the past conditional volatility of WTIFU spillovers to FTSE100. The evidence of asymmetric effects of negative and positive shocks of equal magnitude on the conditional variance suggested that VARMA-AGARCH was superior to the VARMA-GARCH and CCC models.

Overall, the paper investigated which stock indexes and which crude oil prices were most useful for purposes of estimating dynamic spillovers, variances and covariances, and hence dynamic correlations, for purposes of determining optimal dynamic hedge ratios. In this respect, the use of appropriate multivariate conditional volatility models was shown to be essential for the estimation of dynamic optimal hedge ratios.

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Table 1. Descriptive Statistics

Returns	Mean	Max	Min	SD	Skewness	Kurtosis	Jarque-Bera
FTSE	-1.75e-06	0.093	-0.093	0.013	-0.125	8.741	4250.157
NYSE	7.58e-05	0.115	-0.102	0.013	-0.299	12.960	12812.11
S&P	2.44e-05	0.110	-0.095	0.014	-0.137	10.590	7423.755
DJ	-0.0001	0.132	-0.121	0.016	-0.244	9.227	5020.704
BRSP	0.0005	0.152	-0.170	0.023	-0.047	6.103	1240.415
BRFOR	0.0005	0.126	-0.133	0.023	-0.073	5.398	743.048
BRFU	0.0005	0.129	-0.144	0.024	-0.145	5.553	849.874
WTISP	0.0005	0.213	-0.172	0.027	-0.006	7.877	3062.127
WTIFOR	0.0005	0.229	-0.142	0.026	0.099	7.967	3179.933
WTIFU	0.0005	0.164	-0.165	0.026	-0.124	7.127	2199.531

Table 2. Unit Root Tests

	ADF			PP		
Returns	**None**	**Constant**	**Constant and Trend**	**None**	**Constant**	**Constant and Trend**
FTSE	**-27.327**	**-27.322**	**-27.318**	**-57.871**	**-57.862**	**-57.853**
NYSE	**-42.944**	**-42.940**	**-42.939**	**-59.142**	**-59.135**	**-59.134**
S&P	**-43.558**	**-43.552**	**-43.557**	**-60.770**	**-60.760**	**-60.772**
DJ	**-56.785**	**-56.780**	**-56.772**	**-57.002**	**-57.000**	**-56.992**
BRSP	**-54.904**	**-54.918**	**-54.909**	**-54.909**	**-54.922**	**-54.914**
BRFOR	**-57.211**	**-57.230**	**-57.222**	**-57.208**	**-57.229**	**-57.219**
BRFU	**-58.850**	**-58.869**	**-58.869**	**-58.821**	**-58.847**	**-58.838**
WTISP	**-56.288**	**-56.299**	**-56.290**	**-56.506**	**-56.539**	**-56.529**
WTIFOR	**-58.000**	**-58.013**	**-58.004**	**-58.181**	**-58.214**	**-58.204**
WTIFU	**-41.915**	**-41.934**	**-41.927**	**-56.787**	**-56.804**	**-56.794**

Note: Entries in bold are significant at the 5% level.

Table 3. Constant Conditional Correlations

	FTSE100		NYSE		DJ		S&P		BRSP		BRFOR		BRFU		WTISP		WTIFOR		WTIFU
	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}	LMC	ρ_{ij}
FTSE100	1																		
NYSE	**0.569** **(39.56)**	**171.5**	1																
DJ	**0.334** **(30.19)**	**-36.75**	**0.425** **(26.99)**	**93.23**	1														
S&P	**0.509** **(39.06)**	**-175.4**	**0.973** **(815.9)**	**-285.9**	**0.436** **(29.87)**	**-123.5**	1												
BRSP	**0.095** **(5.507)**	**7.51**	**0.047** **(2.417)**	**-19.76**	0.024 (1.300)	**-949.9**	0.012 (0.583)	**-105.5**	1										
BRFOR	**0.098** **(5.767)**	**40.44**	**0.043** **(2.588)**	**19.54**	0.029 (1.667)	**7.26**	0.008 (0.465)	**5.94**	**0.945** **(208.5)**	**-468.2**	1								
BRFU	**0.088** **(4.923)**	**-17.78**	**0.074** **(4.200)**	**-58.25**	0.025 (1.319)	**-99.77**	0.029 (1.673)	**-118.7**	**0.790** **(85.29)**	**-401.5**	**0.805** **(85.32)**	**-439.0**	1						
WTISP	**0.085** **(4.670)**	**-23.21**	**0.066** **(3.985)**	**30.12**	0.012 (0.687)	**6.22**	0.020 (1.102)	**-17.61**	**0.706** **(58.94)**	**-385.9**	**0.732** **(65.33)**	**-371.7**	**0.828** **(96.83)**	**-624.9**	1				
WTIFOR	**0.103** **(6.366)**	**5.90**	**0.092** **(5.038)**	**-40.09**	**0.043** **(2.182)**	**-42.43**	**0.047** **(2.328)**	**24.60**	**0.755** **(66.28)**	**-394.5**	**0.782** **(82.51)**	**-533.6**	**0.838** **(111.8)**	**-460.9**	**0.888** **(91.49)**	**-567.3**	1		
WTIFU	**0.099** **(5.683)**	**-73.94**	**0.082** **(4.490)**	**-4.45**	**0.035** **(2.331)**	**10.21**	**0.035** **(2.054)**	**12.01**	**0.724** **(62.10)**	**-346.2**	**0.750** **(78.53)**	**361.6**	**0.846** **(107.3)**	**-687.9**	**0.923** **(143.4)**	**-386.9**	**0.915** **(135.1)**	**-512.0**	1

Notes: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level. LMC is the Lagrange Multiplier test statistic for constant conditional correlations (see Tse (2000)).

Table 4. Dynamic Conditional Correlations

Returns	$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_1 + \theta_2$
BRSP_NYSE	**0.016** **(27.798)**	**0.977** **(228.17)**	0.993
BRSP_FTSE	**0.015** **(1.971)**	**0.981** **(87.34)**	0.996
BRSP_S&P	**0.014** **(2.350)**	**0.982** **(104.21)**	0.996
BRSP_DJ	**0.012** **(2.182)**	**0.982** **(91.63)**	0.994
BRFOR_NYSE	**0.017** **(2.143)**	**0.977** **(77.63)**	0.994
BRFOR_FTSE	**0.021** **(68.712)**	**0.973** **(294.77)**	0.994
BRFOR_S&P	**0.016** **(2.178)**	**0.979** **(80.85)**	0.995
BRFOR_ DJ	**0.012** **(2.740)**	**0.981** **(106.38)**	0.993
BRFU_NYSE	**0.020** **(7.161)**	**0.976** **(267.55)**	0.996
BRFU_FTSE	**0.020** **(2.914)**	**0.973** **(94.16)**	0.993
BRFU_S&P	**0.018** **(2.226)**	**0.978** **(87.66)**	0.996
BRFU_ DJ	**0.012** **(3.112)**	**0.985** **(186.65)**	0.997
WTISP_NYSE	**0.018** **(2.388)**	**0.977** **(91.03)**	0.995
WTISP _FTSE	**0.014** **(13.232)**	**0.982** **(497.96)**	0.996
WTISP _S&P	**0.015** **(2.256)**	**0.982** **(109.66)**	0.997
WTISP _ DJ	**0.011** **(2.625)**	**0.985** **(150.44)**	0.996
WTIFOR_NYSE	**0.017** **(3.727)**	**0.979** **(121.97)**	0.996
WTIFOR_FTSE	**0.007** **(1.991)**	**0.991** **(197.10)**	0.998
WTIFOR_S&P	**0.014** **(3.063)**	**0.983** **(151.20)**	0.997
WTIFOR_ DJ	**0.013** **(32.651)**	**0.981** **(302.59)**	0.994
WTIFU_NYSE	**0.013** **(20.736)**	**0.984** **(596.13)**	0.997
WTIFU_FTSE	**0.017** **(218.77)**	**0.976** **(215.27)**	0.993
WTIFU_S&P	**0.009** **(5.710)**	**0.989** **(474.21)**	0.998
WTIFU_ DJ	**0.001** **(3.076)**	**0.988** **(224.67)**	0.989

Notes: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 5. Descriptive Statistics for DCC

Returns	Mean	Max	Min	SD	Skewness	Kurtosis
BRSP_FTSE100	0.106	0.652	-0.314	0.158	0.956	4.694
BRSP_NYSE	0.057	0.422	-0.276	0.107	0.492	4.498
BRSP_S&P	0.019	0.354	-0.257	0.107	0.482	3.884
BRSP_ DJ	0.031	0.372	-0.174	0.092	0.822	4.028
BRFOR_FTSE100	0.114	0.684	-0.380	0.162	0.786	4.759
BRFOR_NYSE	0.059	0.457	-0.312	0.121	0.438	4.460
BRFOR_S&P	0.023	0.400	-0.305	0.121	0.433	3.931
BRFOR_ DJ	0.039	0.397	-0.190	0.100	0.804	4.008
BRFU_FTSE100	0.115	0.683	-0.380	0.159	0.663	4.862
BRFU_NYSE	0.100	0.566	-0.383	0.167	0.662	4.321
BRFU_S&P	0.050	0.525	-0.367	0.164	0.827	4.410
BRFU_ DJ	0.027	0.361	-0.278	0.120	0.378	3.292
WTISP_FTSE100	0.102	0.583	-0.237	0.134	1.027	4.513
WTISP_NYSE	0.085	0.504	-0.294	0.138	0.577	4.391
WTISP_S&P	0.036	0.436	-0.270	0.137	0.747	4.077
WTISP_ DJ	0.019	0.296	-0.222	0.097	0.521	3.553
WTIFOR_FTSE100	0.110	0.537	-0.140	0.124	1.261	4.809
WTIFOR_NYSE	0.111	0.619	-0.268	0.149	0.839	4.519
WTIRFOR_S&P	0.062	0.572	-0.250	0.148	1.014	4.435
WTIFOR_ DJ	0.049	0.381	-0.218	0.102	0.630	3.988
WTIFU_FTSE100	0.121	0.632	-0.319	0.136	0.790	5.148
WTIFU_NYSE	0.095	0.534	-0.249	0.141	0.757	4.225
WTIFU_S&P	0.039	0.436	-0.270	0.137	0.747	4.077
WTIFU_ DJ	0.019	0.296	-0.222	0.097	0.521	3.553

Table 6. VARMA-GARCH Spillovers - Equation (4)

Panel 6a BRSP_FTSE100					
Returns	ω	α_{BRSP}	α_{FTSE}	β_{BRSP}	β_{FTSE}
BRSP	**6.35E-06**	**0.035**	0.043	**0.951**	-0.032
	(2.730)	**(4.280)**	(1.268)	**(89.245)**	(-0.978)
FTSE100	**1.09E-06**	0.092	**-0.001**	0.903	**0.001**
	(2.700)	(-0.844)	**(7.526)**	(0.516)	**(82.771)**
Panel 6b BRSP_ NYSE					
	ω	α_{BRSP}	α_{NYSE}	β_{BRSP}	β_{NYSE}
BRSP	**9.75E-06**	**0.043**	0.045	**0.939**	-0.036
	(2.715)	**(3.743)**	(1.251)	**(61.06)**	(-0.953)
NYSE	**1.34E-06**	-0.0002	**0.078**	0.0003	**0.912**
	(1.534)	(-0.292)	**(6.845)**	(0.209)	**(82.582)**
Panel 6c BRSP_ S&P					
	ω	α_{BRSP}	$\alpha_{S\&P}$	β_{BRSP}	$\beta_{S\&P}$
BRSP	**9.69E-06**	**0.043**	0.040	**0.937**	-0.027
	(2.721)	**(3.721)**	(1.225)	**(59.357)**	(-0.845)
S&P	**6.85E-07**	-0.0006	**0.068**	0.001	**0.926**
	(1.404)	(-0.816)	**(6.330)**	(1.013)	**(92.731)**
Panel 6d BRSP_ DJ					
	ω	α_{BRSP}	α_{DJ}	β_{BRSP}	β_{DJ}
BRSP	**6.42E-06**	**0.038**	0.031	**0.947**	-0.018
	(2.629)	**(3.938)**	(1.472)	**(74.786)**	(-0.787)
DJ	**4.01E-06**	0.003	**0.082**	-0.005	**0.907**
	(3.570)	(1.518)	**(6.016)**	(-1.918)	**(67.082)**
Panel 6e BRFOR_FTSE100					
	ω	α_{BRFOR}	α_{FTSE}	β_{BRFOR}	β_{FTSE}
BRFOR	**5.97E-06**	**0.035**	0.038	**0.950**	-0.027
	(2.629)	**(4.218)**	(1.486)	**(83.824)**	(-1.070)
FTSE100	8.57E-07	**-0.002**	**0.097**	0.002	**0.899**
	(1.942)	**(-2.164)**	**(7.432)**	(1.426)	**(79.314)**
Panel 6f BRFOR_ NYSE					
	ω	α_{BRFOR}	α_{NYSE}	β_{BRFOR}	β_{NYSE}
BRFOR	**8.19E-06**	**0.040**	0.029	**0.941**	-0.019
	(2.686)	**(3.876)**	(1.067)	**(65.093)**	(-0.614)
NYSE	1.25E-06	-0.001	**0.079**	0.001	**0.912**
	(1.292)	(-0.783)	**(6.917)**	(0.419)	**(82.814)**

Panel 6g BRFOR_ S&P					
	ω	α_{BRFOR}	$\alpha_{S\&P}$	β_{BRFOR}	$\beta_{S\&P}$
BRFOR	**1.15E-05**	**0.046**	0.028	**0.925**	-0.010
	(2.491)	**(3.685)**	(1.056)	**(44.560)**	(-0.359)
S&P	6.73E-07	-0.001	**0.069**	0.002	**0.925**
	(1.235)	(-0.773)	**(6.378)**	(0.852)	**(91.513)**

Panel 6h BRFOR_ DJ					
	ω	α_{BRFOR}	α_{DJ}	β_{BRFOR}	β_{DJ}
BRFOR	**7.48E-06**	**0.040**	0.023	**0.938**	-0.008
	(2.552)	**(3.911)**	(1.372)	**(59.906)**	(-0.405)
DJ	**3.39E-06**	0.005	**0.081**	-0.004	**0.905**
	(2.624)	(1.275)	**(5.900)**	(-1.0642)	**(61.338)**

Panel 6i BRFU_FTSE100					
	ω	α_{BRFU}	α_{FTSE}	β_{BRFU}	β_{FTSE}
BRFU	**9.22E-06**	**0.045**	0.050	**0.936**	-0.041
	(2.781)	**(4.337)**	(1.931)	**(62.816)**	(-1.666)
FTSE100	7.36E-07	-0.002	**0.099**	0.003	**0.897**
	(1.717)	(-1.930)	**(7.490)**	(1.579)	**(77.307)**

Panel 6j BRFU_ NYSE					
	ω	α_{BRFU}	α_{NYSE}	β_{BRFU}	β_{NYSE}
BRFU	**1.09E-05**	**0.048**	0.046	**0.930**	-0.035
	(2.845)	**(3.982)**	(1.535)	**(52.592)**	(-1.087)
NYSE	9.81E-07	-0.001	**0.079**	0.002	**0.911**
	(1.451)	(-0.562)	**(6.931)**	(0.787)	**(79.700)**

Panel 6k BRFU_ S&P					
	ω	α_{BRFU}	$\alpha_{S\&P}$	β_{BRFU}	$\beta_{S\&P}$
BRFU	**1.07E-05**	**0.048**	0.040	**0.928**	-0.024
	(2.818)	**(3.973)**	(1.487)	**(51.084)**	(-0.851)
S&P	2.11E-07	-0.002	**0.070**	0.003	**0.924**
	(1.514)	(-1.048)	**(6.597)**	(1.296)	**(85.800)**

Panel 6l BRFU_ DJ					
	ω	α_{BRFU}	α_{DJ}	β_{BRFU}	β_{DJ}
BRFU	**7.62E-06**	**0.044**	0.027	**0.935**	-0.010
	(2.756)	**(4.121)**	(1.560)	**(63.100)**	(-0.512)
DJ	**3.20E-06**	0.006	**0.080**	-0.005	**0.904**
	(2.764)	(1.848)	**(5.845)**	(-1.393)	**(58.532)**

Panel 6m WTISP _FTSE100					
	ω	α_{WTISP}	α_{FTSE}	β_{WTISP}	β_{FTSE}
WTISP	4.29E-07	**0.098**	-0.001	**0.896**	0.002
	(0.862)	**(7.392)**	(-0.721)	**(77.035)**	(1.267)
FTSE100	**1.30E-05**	0.054	**0.049**	-0.039	**0.928**
	(2.724)	(1.253)	**(3.905)**	(-0.968)	**(52.795)**
Panel 6n WTISP_ NYSE					
	ω	α_{WTISP}	α_{NYSE}	β_{WTISP}	β_{NYSE}
WTISP	7.11E-07	**0.079**	-0.001	**0.9115**	0.002
	(1.163)	**(6.992)**	(-0.757)	**(80.704)**	(1.288)
NYSE	**1.61E-05**	0.059	**0.052**	-0.039	**0.9194**
	(2.715)	(1.235)	**(3.601)**	(-0.753)	**(42.657)**
Panel 6o WTISP_ S&P					
	ω	α_{WTISP}	$\alpha_{S\&P}$	β_{WTISP}	$\beta_{S\&P}$
WTISP	2.57E-08	**0.068**	-0.001	**0.925**	0.003
	(0.099)	**(6.554)**	(-0.961)	**(89.934)**	(1.505)
S&P	**1.63E-05**	0.0578	**0.053**	-0.029	**0.916**
	(2.689)	(1.384)	**(3.578)**	(-0.661)	**(39.664)**
Panel 6p WTISP_DJ					
	ω	α_{WTISP}	α_{DJ}	β_{WTISP}	β_{DJ}
WTISP	**9.58E-06**	**0.048**	0.018	**0.926**	0.017
	(2.276)	**(3.673)**	(0.768)	**(50.138)**	(0.596)
DJ	**2.51E-06**	0.0004	**0.083**	0.001	**0.904**
	(2.133)	(0.220)	**(5.845)**	(0.390)	**(58.177)**
Panel 6q WTIFOR_FTSE100					
	ω	α_{WTIFOR}	α_{FTSE}	β_{WTIFOR}	β_{FTSE}
WTIFOR	4.90E-07	**0.098**	**-0.002**	**0.897**	**0.003**
	(1.024)	**(7.623)**	**(-2.655)**	**(81.742)**	**(2.035)**
FTSE100	**1.28E-05**	0.045701	**0.056**	-0.023	**0.918**
	(2.729)	(1.411)	**(4.268)**	(-0.690)	**(48.917)**
Panel 6r WTIFOR_ NYSE					
	ω	α_{WTIFOR}	α_{NYSE}	β_{WTIFOR}	β_{NYSE}
WTIFOR	7.12E-07	**0.079**	-0.002	**0.910**	0.003
	(1.479)	**(6.767)**	(-1.916)	**(83.173)**	(1.515)
NYSE	**1.56E-05**	0.058	**0.036**	0.910	**-0.009**
	(2.825)	(1.022)	**(4.047)**	(-0.189)	**(41.583)**

Panel 6s WTIFOR_S&P					
	ω	α_{WTIFOR}	$\alpha_{\text{S\&P}}$	β_{WTIFOR}	$\beta_{\text{S\&P}}$
WTIFOR	8.98E-08	**0.069**	-0.002	**0.924**	0.003
	(0.663)	**(6.610)**	(-1.441)	**(88.676)**	(1.738)
S&P	**1.55E-05**	0.032	**0.059**	0.002	**0.907**
	(2.797)	(1.009)	**(4.009)**	(0.067)	**(39.771)**
Panel 6t WTIFOR_DJ					
	ω	α_{WTIFOR}	α_{DJ}	β_{WTIFOR}	β_{DJ}
WTIFOR	**1.03E-05**	**0.055**	0.007	**0.917**	0.024
	(2.461)	**(4.326)**	(0.464)	**(49.988)**	(1.041)
DJ	**3.05E-06**	0.003	**0.082**	-0.002	**0.904**
	(2.565)	(0.987)	**(5.827)**	(-0.497)	**(58.398)**
Panel 6u WTIFU_FTSE100					
	ω	α_{WTIFU}	α_{FTSE}	β_{WTIFU}	β_{FTSE}
WTIFU	**1.48E-05**	**0.056**	0.072	**0.915**	-0.0501
	(2.980)	**(4.009)**	(1.618)	**(46.339)**	(-1.240)
FTSE100	3.91E-07	**-0.002**	**0.097**	**0.003**	**0.898**
	(0.828)	**(-2.259)**	**(7.384)**	**(2.046)**	**(78.023)**
Panel 6v WTIFU_FTSE100					
	ω	α_{WTIFU}	α_{NYSE}	β_{WTIFU}	β_{NYSE}
WTIFU	**1.91E-05**	**0.061**	0.065	**0.902**	-0.037
	(3.063)	**(3.740)**	(1.231)	**(37.690)**	(-0.681)
NYSE	4.01E-07	-0.001	**0.079**	0.003	**0.910**
	(0.784)	(-1.357)	**(6.740)**	(1.343)	**(82.999)**
Panel 6w WTIFU_ S&P					
	ω	α_{WTIFU}	$\alpha_{\text{S\&P}}$	β_{WTIFU}	$\beta_{\text{S\&P}}$
WTIFU	**1.87E-05**	**0.062**	0.054	**0.899**	-0.018
	(3.031)	**(3.711)**	(1.174)	**(36.014)**	(-0.403)
S&P	-2.35E-07	-0.001	**0.068**	0.004	**0.925**
	(-1.613)	(-1.115)	**(6.513)**	(1.857)	**(89.724)**
Panel 6x WTIFU_ DJ					
	ω	α_{WTIFU}	α_{DJ}	β_{WTIFU}	β_{DJ}
WTIFU	**1.27E-05**	**0.060**	0.012	**0.907**	0.022
	(2.731)	**(3.754)**	(0.612)	**(40.670)**	(0.856)
DJ	**2.78E-06**	0.002	**0.081**	-0.001	**0.904**
	(2.158)	(0.936)	**(5.825)**	(-0.225)	**(58.051)**

Notes: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 7. VARMA-AGARCH Spillovers - Equation (5)

Panel 7a BRSP_FTSE100

Returns	ω	α_{BRSP}	α_{FTSE}	γ	β_{BRSP}	β_{FTSE}
BRSP	**6.93E-06**	0.009	0.039	**0.048**	**0.954**	-0.034
	(2.983)	(0.808)	(1.264)	**(3.308)**	**(90.985)**	(-1.122)
FTSE100	**9.24E-07**	-0.0003	0.008	**0.113**	0.001	**0.924**
	(2.422)	(-0.528)	(0.638)	**(5.107)**	(0.879)	**(104.812)**

Panel 7b BRSP_NYSE

Returns	ω	α_{BRSP}	α_{NYSE}	γ	β_{BRSP}	β_{NYSE}
BRSP	**8.99E-06**	0.012	0.034	**0.053**	**0.945**	-0.028
	(2.879)	(0.926)	(-0.831)	**(3.245)**	**(69.641)**	(1.081)
NYSE	1.43E-06	0.0002	-0.016	**0.143**	4.48E-05	**0.931**
	(8.792)	(0.296)	(-1.437)	**(9.623)**	(0.054)	**(95.219)**

Panel 7c BRSP_S&P

Returns	ω	α_{BRSP}	$\alpha_{S\&P}$	γ	β_{BRSP}	$\beta_{S\&P}$
BRSP	**8.25E-06**	0.010	0.024	**0.051**	**0.948**	-0.015
	(2.827)	(0.827)	(0.876)	**(3.155)**	**(71.001)**	(-0.533)
S&P	**4.71E-07**	-0.0001	**-0.023**	**0.131**	0.947	**0.001**
	(3.267)	(-0.306)	**(-2.544)**	**(8.463)**	(1.554)	**(128.707)**

Panel 7d BRSP_DJ

Returns	ω	α_{BRSP}	α_{DJ}	γ	β_{BRSP}	β_{DJ}
BRSP	**6.54E-06**	0.009	0.026	**0.048**	**0.952**	-0.016
	(2.807)	(0.745)	(1.340)	**(3.027)**	**(81.340)**	(-0.796)
DJ	**4.40E-06**	0.003	**0.032**	**0.093**	-0.003	**0.905**
	(3.820)	(1.224)	**(2.187)**	**(4.397)**	(-1.550)	**(68.889)**

Panel 7e BRFOR_FTSE100

Returns	ω	α_{BRFOR}	α_{FTSE}	γ	β_{BRFOR}	β_{FTSE}
BRFOR	**5.82E-06**	0.012	0.030	**0.038**	**0.954**	-0.022
	(2.727)	(1.180)	(1.283)	**(3.129)**	**(90.658)**	(-0.948)
FTSE100	7.64E-07	-0.001	0.009	**0.113**	0.002	**0.923**
	(1.757)	(-1.163)	(0.728)	**(5.197)**	(1.294)	**(105.044)**

Panel 7f BRFOR_NYSE

Returns	ω	α_{BRFOR}	α_{NYSE}	γ	β_{BRFOR}	β_{NYSE}
BRFOR	**7.15E-06**	0.012	0.018	**0.042**	**0.949**	-0.010
	(2.753)	(1.115)	(0.740)	**(3.080)**	**(77.262)**	(-0.360)
NYSE	**1.28E-06**	0.001	-0.017	**0.145**	5.54E-05	**0.930**
	(5.481)	(0.804)	(-1.653)	**(9.719)**	(0.042)	**(96.441)**

Panel 7g BRFOR_S&P

Returns	ω	α_{BRFOR}	$\alpha_{S\&P}$	γ	β_{BRFOR}	$\beta_{S\&P}$
BRFOR	**7.08E-06**	0.012	0.014	**0.043**	**0.9489**	-0.004
	(2.733)	(1.087)	(0.659)	**(3.116)**	**(74.963)**	(-0.185)
S&P	2.63E-07	0.0001	**-0.025**	**0.134**	0.002	**0.947**
	(1.926)	(0.223)	**(-2.790)**	**(8.504)**	(1.594)	**(126.729)**

Panel 7h BRFOR_DJ

Returns	ω	α_{BRFOR}	α_{DJ}	γ	β_{BRFOR}	β_{DJ}
BRFOR	**5.75E-06**	0.012	0.014	**0.041**	**0.951**	-0.002
	(2.581)	(1.027)	(0.939)	**(3.009)**	**(77.268)**	(-0.131)
DJ	**3.13E-06**	0.003	**0.029**	**0.096**	0.0001	**0.902**
	(2.384)	(0.797)	**(2.053)**	**(4.546)**	(0.035)	**(64.402)**

Panel 7i BRFU_FTSE100

Returns	ω	α_{BRFU}	α_{FTSE}	γ	β_{BRFU}	β_{FTSE}
BRFU	**7.60E-06**	**0.026**	0.045	0.024	**0.946**	-0.040
	(3.094)	**(2.125)**	(1.828)	(1.761)	**(79.696)**	(-1.686)
FTSE100	7.55E-07	-0.001	0.009	**0.114**	0.002	**0.922**
	(1.861)	(-0.889)	(0.715)	**(5.105)**	(1.2720)	**(102.996)**

Panel 7j BRFU_NYSE

Returns	ω	α_{BRFU}	α_{NYSE}	γ	β_{BRFU}	β_{NYSE}
BRFU	**1.03E-05**	**0.032**	0.041	0.024	**0.935**	-0.034
	(2.925)	**(2.271)**	(1.431)	(1.594)	**(56.689)**	(-1.100)
NYSE	**1.04E-06**	0.0004	-0.018	**0.145**	0.001	**0.930**
	(4.003)	(0.415)	(-1.763)	**(9.760)**	(0.555)	**(96.629)**

Panel 7k BRFU_S&P

Returns	ω	α_{BRFU}	$\alpha_{S\&P}$	γ	β_{BRFU}	$\beta_{S\&P}$
BRFU	**1.02E-05**	**0.033**	0.035	0.023	**0.933**	-0.023
	(2.886)	**(2.275)**	(1.365)	(1.554)	**(54.556)**	(-0.848)
S&P	1.12E-07	-4.81E-05	**-0.024**	**0.133**	0.002	**0.947**
	(0.932)	(-0.048)	**(-2.713)**	**(8.304)**	(1.633)	**(126.27)**

Panel 7l BRFU_DJ

Returns	ω	α_{BRFU}	α_{DJ}	γ	β_{BRFU}	β_{DJ}
BRFU	**7.39E-06**	0.027	0.026	0.025	**0.941**	-0.011
	(2.852)	(1.916)	(1.523)	(1.756)	**(64.493)**	(-0.553)
Dow Jones	**3.26E-06**	0.005	0.028	**0.097**	-0.001	**0.900**
	(2.730)	(1.462)	(1.906)	**(4.516)**	(-0.356)	**(60.504)**

Panel 7m WTISP_FTSE100

Returns	ω	α_{WTISP}	α_{FTSE}	γ	β_{WTISP}	β_{FTSE}
WTISP	**1.41E-05**	**0.028**	0.054	**0.055**	**0.929**	-0.042
	(3.098)	**(2.046)**	(1.270)	**(2.130)**	**(56.98)**	(-1.043)
FTSE100	5.65E-07	-0.001	0.008	**0.115**	0.002	**0.921**
	(1.265)	(-0.774)	(0.677)	**(5.262)**	(1.287)	**(103.8)**

Panel 7n WTISP_NYSE

Returns	ω	α_{WTISP}	α_{NYSE}	γ	β_{WTISP}	β_{NYSE}
WTISP	**1.77E-05**	**0.030**	0.061	**0.040**	**0.918**	-0.042
	(3.090)	**(1.995)**	(1.268)	**(2.150)**	**(45.855)**	(-0.822)
NYSE	**9.55E-07**	-0.0002	-0.016	**0.141**	0.001	**0.930**
	(2.426)	(-0.287)	(-1.397)	**(9.228)**	(0.826)	**(98.293)**

Panel 7o WTISP_S&P

Returns	ω	α_{WTISP}	$\alpha_{\text{S\&P}}$	γ	β_{WTISP}	$\beta_{\text{S\&P}}$
WTISP	**1.87E-05**	**0.032**	0.059	**0.042**	**0.910**	-0.028
	(3.083)	**(2.025)**	(1.380)	**(2.144)**	**(41.070)**	(-0.648)
S&P	2.15E-07	-0.0002	**-0.022**	**0.129**	0.002	**0.947**
	(1.831)	(-0.270)	**(-2.626)**	**(8.421)**	(1.701)	**(128.314)**

Panel 7p WTISP_DJ

Returns	ω	α_{WTISP}	α_{DJ}	γ	β_{WTISP}	β_{DJ}
WTISP	**1.11E-05**	0.030	0.013	0.034	**0.924**	0.021
	(2.564)	(1.915)	(0.585)	(1.872)	**(49.662)**	(0.760)
DJ	**2.89E-06**	-0.001	**0.029**	**0.098**	0.003	**0.901**
	(2.406)	(-0.273)	**(1.975)**	**(4.641)**	(1.004)	**(61.523)**

Panel 7q WTIFOR_FTSE100

Returns	ω	α_{WTIFOR}	α_{FTSE}	γ	β_{WTIFOR}	β_{FTSE}
WTIFOR	**1.14E-05**	0.016	0.042	**0.054**	**0.933**	-0.026
	(3.040)	(1.470)	(1.432)	**(3.185)**	**(65.867)**	(-0.879)
FTSE100	5.90E-07	-0.001	0.009	**0.113**	0.003	**0.922**
	(1.411)	(-1.406)	(0.746)	**(5.223)**	(1.716)	**(105.695)**

Panel 7r WTIFOR_NYSE

Returns	ω	α_{WTIFOR}	α_{NYSE}	γ	β_{WTIFOR}	β_{NYSE}
WTIFOR	**1.32E-05**	0.017	0.030	**0.055**	**0.927**	-0.011
	(3.072)	(1.456)	(0.957)	**(3.080)**	**(57.179)**	(-0.295)
NYSE	**2.16E-06**	-0.002	-0.001	**0.157**	**0.005**	**0.889**
	(3.641)	(-1.668)	(-0.079)	**(7.436)**	**(2.585)**	**(39.429)**

Panel 7s WTIFOR_S&P						
Returns	ω	α_{WTIFOR}	$\alpha_{\mathrm{S\&P}}$	γ	β_{WTIFOR}	$\beta_{\mathrm{S\&P}}$
WTIFOR	**1.32E-05**	0.018	0.024	**0.056**	**0.925**	0.001
	(3.030)	(1.459)	(0.866)	**(3.077)**	**(53.997)**	(0.033)
S&P	**6.75E-07**	-0.002	-0.018	**0.152**	**0.005**	**0.924**
	(2.014)	(-1.240)	(-1.460)	**(8.205)**	**(69.422)**	**(2.679)**
Panel 7t WTIFOR_DJ						
Returns	ω	α_{WTIFOR}	α_{DJ}	γ	β_{WTIFOR}	β_{DJ}
WTIFOR	**9.20E-06**	0.015260	0.007	**0.053**	**0.933**	0.016
	(2.730)	(1.377671)	(0.453)	**(3.149)**	**(67.590)**	(0.780)
DJ	**3.06E-06**	0.001	**0.029**	**0.098**	0.002	**0.901**
	(2.579)	(0.275)	**(1.984)**	**(4.597)**	(0.617)	**(60.798)**
Panel 7u WTIFU_FTSE100						
Returns	ω	α_{WTIFU}	α_{FTSE}	γ	β_{WTIFU}	β_{FTSE}
WTIFU	**1.40E-05**	0.023	0.073	**0.050**	**0.925**	-0.056
	(3.360)	(1.599)	(1.674)	**(3.017)**	**(56.133)**	(-1.421)
FTSE100	5.25E-07	-0.001	0.009	**0.113**	0.003	**0.922**
	(1.226)	(-1.399)	(0.747)	**(5.076)**	(1.767)	**(103.641)**
Panel 7v WTIFU_NYSE						
Returns	ω	α_{WTIFU}	α_{NYSE}	γ	β_{WTIFU}	β_{NYSE}
WTIFU	**1.74E-05**	0.026	0.065	**0.053**	**0.914**	-0.044
	(3.319)	(1.590)	(1.262)	**(2.900)**	**(45.754)**	(-0.847)
NYSE	**5.42E-07**	-0.0003	-0.017	**0.143**	0.002	**0.930**
	(3.889)	(-0.421)	(-1.607)	**(9.588)**	(1.913)	**(96.195)**
Panel 7w WTIFU_S&P						
Returns	ω	α_{WTIFU}	$\alpha_{\mathrm{S\&P}}$	γ	β_{WTIFU}	$\beta_{\mathrm{S\&P}}$
WTIFU	**1.73E-05**	0.028	0.053	**0.053**	**0.909**	-0.024
	(3.265)	(1.612)	(1.177)	**(2.842)**	**(42.314)**	(-0.554)
S&P	-8.61E-08	-0.0001	**-0.025**	**0.131**	**0.003**	**0.948**
	(-0.882)	(-0.195)	**(-2.874)**	**(8.4171)**	**(2.386)**	**(132.341)**
Panel 7x WTIFU_DJ						
Returns	ω	α_{WTIFU}	α_{DJ}	γ	β_{WTIFU}	β_{DJ}
WTIFU	**1.25E-05**	0.029	0.009	**0.049**	**0.914**	0.022
	(2.926)	(1.558)	(0.461)	**(2.627)**	**(43.890)**	(0.886)
DJ	**2.88E-06**	0.001	**0.029**	**0.097**	0.002	**0.901**
	(2.259)	(0.353)	**(1.968)**	**(4.603)**	(0.619)	**(61.100)**

Notes: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*-ratios. Entries in bold are significant at the 5% level

Figure 1. WTI Futures Prices and Dow Jones Index

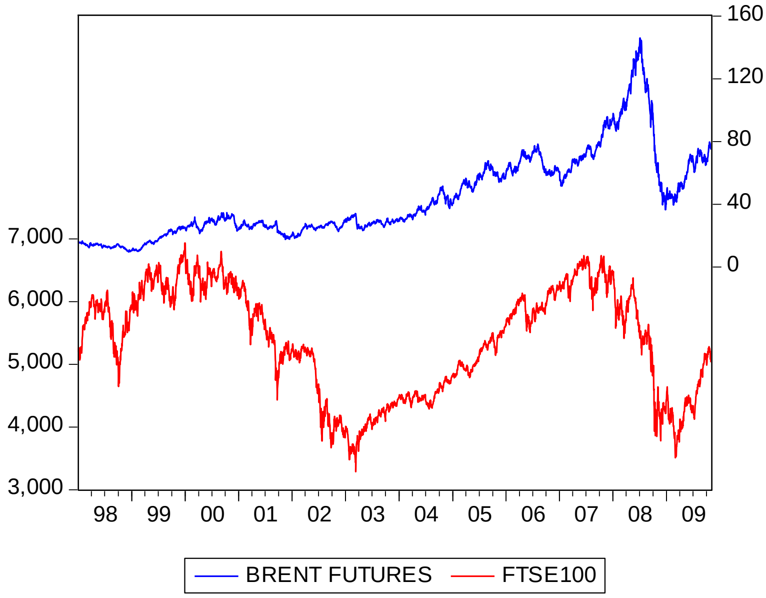

Figure 2. Stock Indexes

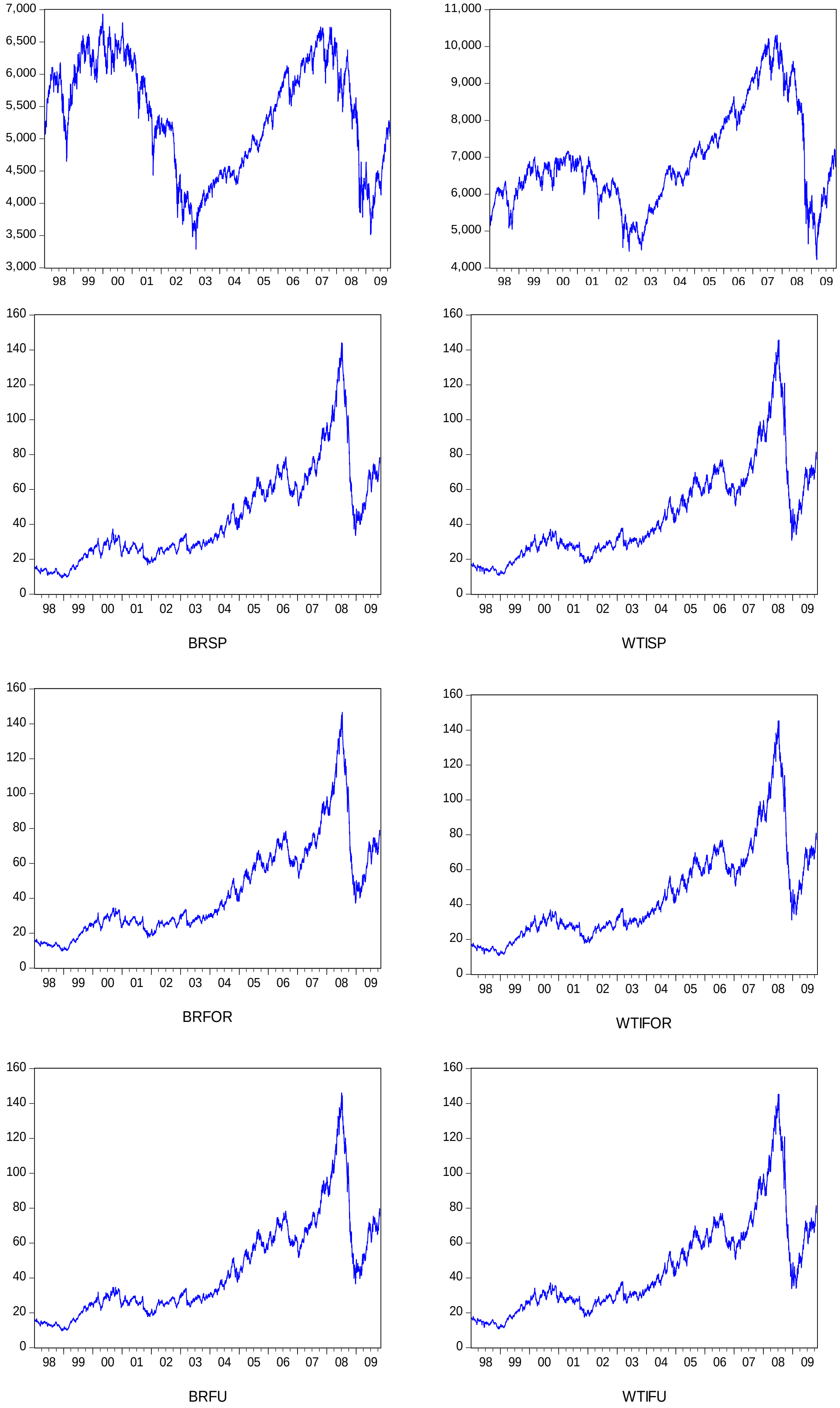

Figure 3a. Stock Index Returns

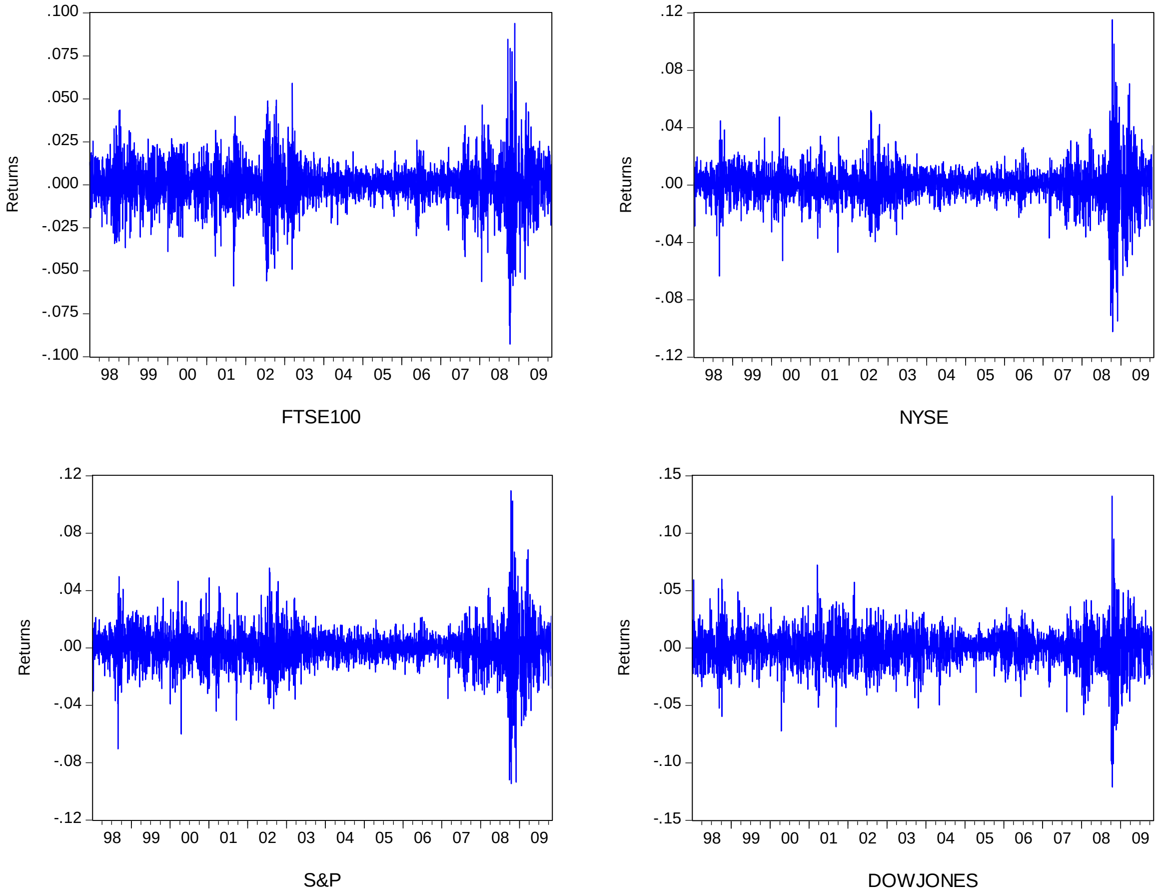

Figure 3b. Crude Oil Returns

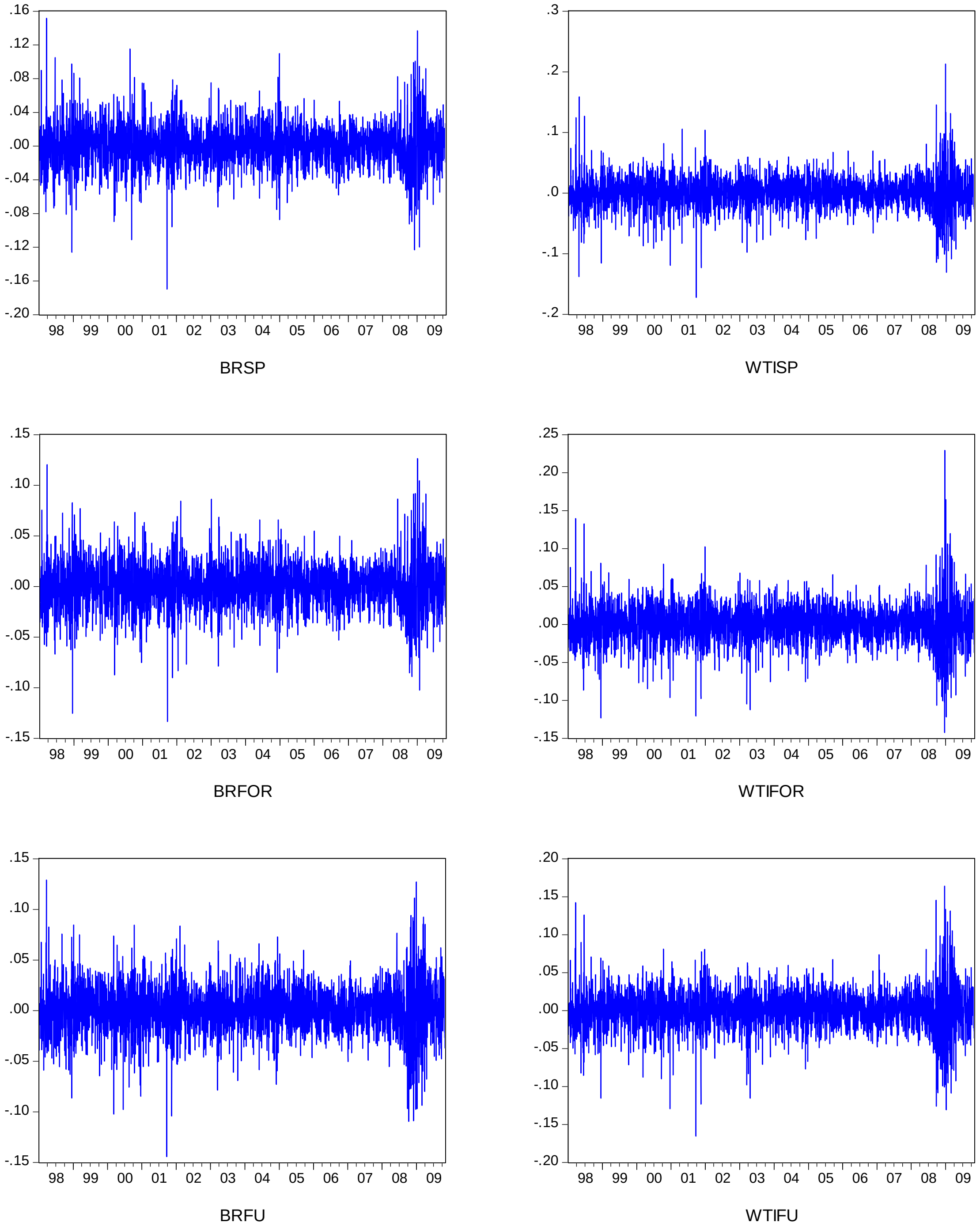

Figure 4. Dynamic Conditional Correlations

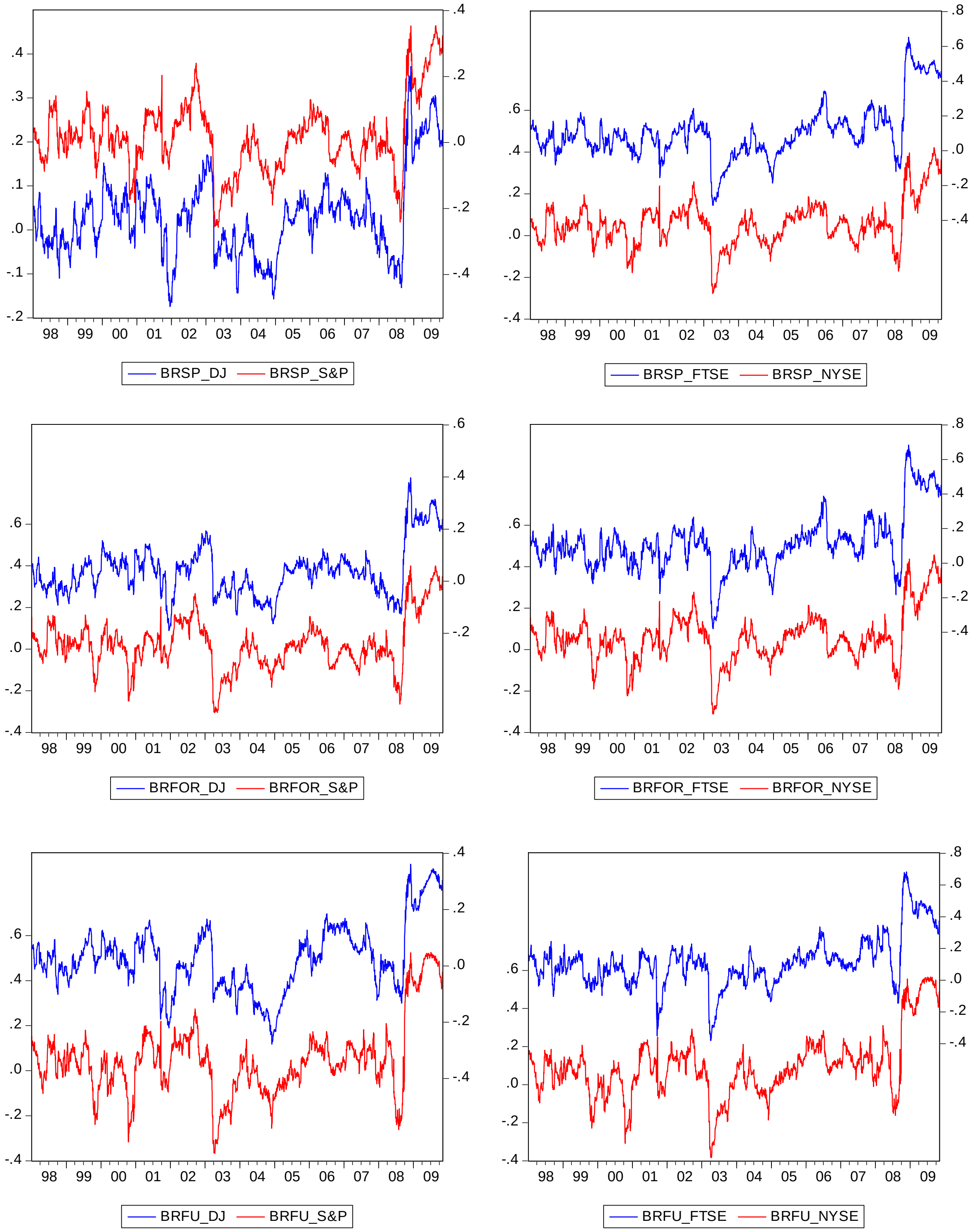

Figure 4. Dynamic Conditional Correlations (Cont.)