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# Quantitative Analysis of Crude Oil Market and Industrial Fluctuation in India

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***Abstract:***
*This paper investigates the quantitative analysis of crude oil market and industrial fluctuation in India in the context of automobile, financial Service, energy, metal, and commodities sectors in order to study the optimal portfolio construction and to estimate risk minimizing hedge ratios. We compare bivariate generalized autoregressive conditional heteroskedasticity models as a conditional mean equation and the vector autoregressive moving average GARCH model as a conditional variance equation with the error terms following the Student's t distribution so as to identify the model that would be appropriate for optimal portfolio construction and to estimate risk minimizing hedge ratios. Our findings indicate that the DCC-BVGARCH model outperforms other models and we find evidence of return and volatility spillover effects from the crude oil market to the Indian industrial sectors. In addition, we find that the conditional correlations between the crude oil market and the Indian industrial sectors change dynamically over time and that they reach their highest values during the period of the global financial crisis (2008-2009). We also estimate risk minimizing hedge ratios and oil-stock optimal portfolio holdings based on the results of econometric models.*

***Keywords:*** *Oil Prices; Volatility; Industrial Risk; Hedge ratios; Portfolio Analysis*

## 1. Introduction

Crude oil is a global commodity and life blood for the development through playing a crucial role in giving direction to global economy. Its impact on industrial fluctuation is an important area of research for economics and finance researchers and practitioners around the globe. The changes in crude oil prices may indirectly impact a firm's cash flows, return and the cost of capital by impacting input costs particularly energy costs which in turn significantly impact the valuation of the firm (Apergis and Miller, 2009). In addition, higher oil prices may reduce the purchasing power of disposable household income by increasing the prices of household products. On the macroeconomic front, such movements in the crude oil price may impact the GDP growth rate, inflation rate, exchange rates and the unemployment rate. Moreover, an increase in the oil price increases the transportation and production costs and thus adversely impacts the demand and supply of various products and services in an economy. The study of quantitative analysis of crude oil market and industrial fluctuation in India is important for policy makers, portfolio managers, risk managers, institutional investors and other market participants. Policy makers are concerned about the long run or the short run effect of crude oil price changes on the economy and try to maintain financial stability. Portfolio managers, risk managers and investors look for how asset prices behave in response to oil price shocks and whether these changes are permanent or transitory. Currently, emerging markets have become a prominent choice of major institutional investors such as pension funds with a view towards earning high returns on their investments in comparison to what can be earned by investing in the developed markets. This results in significant capital inflows from developed markets to emerging markets. In addition, emerging markets are more vulnerable to negative news and events occurring in the crude oil market which usually result in institutional investments flowing into or out of the market and is an important cause of volatility in stock markets. Our interest is to investigate the return, volatility and correlation spillovers from the crude oil market to the major Indian industrial sectors and to determine how a long position in the stock portfolio can be hedged by taking a short position in oil and vice versa.

Globalization of the economies around the world has played a crucial role in making prominent in the literature the issue of the spillover of shocks from one market to another. Satyanarayan and Varangis (1996), Geman and Kharoubi (2008), Arouri and Nguyen (2010) and Arouri et al. (2011) find that including crude oil in a portfolio improve its risk-return characteristics. Jones and Kaul (1996) apply a standard cash-flow valuation model to study the impact of oil price shocks on the stock markets of Canada, Japan, UK and the USA and find that the reaction of the US and Canadian stock prices to oil price shocks can be completely accounted for by its impact on real cash flows. Huang, Masulis, and Stoll (1996) apply the vector autoregressive (VAR) model to study the relationship between oil futures returns and the US stock return and find that oil futures return impact the individual oil company and exhibit weaker interactions with market indices. Sadorsky (1999) utilizes the vector autoregression technique to investigate the link between crude oil prices and stock prices and finds that oil prices and oil price volatility play an important role in influencing stock prices. Lee and Ni (2002) investigate the impact of oil price shocks on demand and supply in various industries and find that in the industries which have a large cost share of oil, such as petroleum refineries and industrial chemicals, oil price shocks mainly reduce supply. Nandha and Faff (2008) investigate the adverse effect of oil price shocks on thirty-five global industry indices and find that oil price increases have a negative impact on equity returns for all the sectors except mining, and oil and gas industries. Nandha and Brooks (2009) examine the impact of crude oil price changes on the transportation sector from 38 countries and find that oil price changes significantly impact the transportation sector of developed countries. Arouri et al. (2012) investigate volatility spillovers between oil and stock markets in Europe at both the aggregate as well as sectoral levels and find significant volatility spillovers between oil prices and the sectoral stock returns and suggest that these links are important for portfolio management in the presence of oil price risk. Sadorsky (2012) apply the multivariate GARCH models to model conditional correlations and to examine the volatility spillovers between crude oil prices and the stock prices of clean energy companies and technology companies and find that DCC-MGARCH model best fit the data and stock prices of clean energy companies correlate more highly with technology companies than with crude oil. The central aim of this paper is to investigate the return and volatility spillover from the crude oil market to the various industrial sectors in the Indian economy. Specifically, we undertake an extensive analysis to investigate how return and volatility shocks are transmitted from the oil market to the Indian sectoral stock indices. The study of the impact of oil price shocks on Indian industrial sectors has been a neglected area of research and hence, our study contributes in this context. We employ bivariate generalized autoregressive conditional heteroskedasticity (BVGARCH) models (Diagonal (Diag), constant conditional correlation (CCC) and dynamic conditional correlation (DCC)) with the vector autoregressive (VAR(1)) model as a conditional mean equation and the vector autoregressive moving average GARCH (VARMA-GARCH(1,1)) as a conditional variance equation with the error terms following the Student's t distribution. We find that the DCC-BVGARCH model shows an outstanding performance in capturing the dynamics of market interactions. We also estimate the time varying conditional correlation between the crude oil market and the Indian sectoral stock indices to examine their relationship over time. In addition, we apply our findings from the BVGARCH models to estimate the optimal hedge ratios and consequently, the optimal portfolio weights in the context of portfolio management.

## 2. Methodology

### *2.1. The bivariate VAR-GARCH model*

Suppose $r_{i,t}$ is the return for market *i* at time *t*. We model the spillover in mean returns by a vector autoregressive model of order 1 (VAR (1)). The VAR (1) acceptably captures the dynamics in market returns and reflects the quick response of markets to new information. Hence, the return for market *i* at time *t* is modeled as:

$$r_{i,t} = \mu_{i0} + \sum_{j=1}^{2} \mu_{ij}\, r_{j,t-1} + \varepsilon_{i,t}\ , \qquad \text{for } i,j = 1,2 \qquad (1)$$

in which $E[\varepsilon_{i,t}|\xi_{i,t-1}] = 0$, where $\xi_{i,t-1}$ contains all the information available at time *t - 1*. In equation (1), the conditional mean return in each market is a function of its own past returns and cross-market past returns. $\mu_{i,j}$ captures the lead/lag relationship among market returns for $i \neq j$. A significant value of coefficient $\mu_{i,j}$ implies that the current return in market *j* can help in predicting the future return of market *i*. In short, the VAR model used allows for cross-correlations and autocorrelations in returns. In order to capture the volatility spillover and to model conditional volatility, we utilize three bivariate Generalized Autoregressive Conditional Heteroskedasticity (BVGARCH) models (diagonal, constant conditional correlation and dynamic conditional correlation). For all these models, the conditional variance is taken as VARMA-GARCH (1, 1) as suggested by Ling and McAleer (2003) and is given as:

$$\varepsilon_{i,t} = z_{i,t}\sqrt{h_{i,t}}$$

$$h_{i,t} = \omega_{i0} + \sum_{j=1}^{2} \alpha_{ij}\varepsilon_{j,t-1}^{2} + \sum_{j=1}^{2} \beta_{ij} h_{j,t-1} \qquad , \text{ for } i,j = 1,2 \qquad (2)$$

where $z_{i,t}$ is the standardized residual and $h_{i,t}$ is the conditional variance. This VARMA-GARCH approach of Ling and McAleer (2003) allows us to examine the impact of large shocks in one variable on another variable.

The dynamic conditional correlation (DCC) model of Engle (2002) allows the conditional correlation matrix to vary over time and is estimated in two steps. In the first step, we deal with the estimation of the GARCH model parameters and in the second step, we estimate the time varying correlation. The DCC-GARCH model is defined as follows:

$$H_t = D_t\, P_t\, D_t \qquad (3)$$

where $H_t$ is the 2 x 2 conditional covariance matrix, $P_t$ is the conditional correlation matrix and $D_t$ is a diagonal matrix with time-varying standard deviations.

$$D_t = diag\left(\sqrt{h_{11}}, \sqrt{h_{22}}\right) \qquad (4)$$

and

$$P_t = diag\left((Q_t)^{-1/2}\right)\, Q_t\, diag\left((Q_t)^{-1/2}\right) \qquad (5)$$

where $Q_t$ is a (2 x 2) symmetric positive definite matrix, $Q_t = (q_t^{ij})$, and is given as:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z_{t-1}' + \theta_2 Q_{t-1} \qquad (6)$$

where $\bar{Q}$ is a (2 x 2) matrix of the unconditional correlation of standardized residuals. $\theta_1$ and $\theta_2$ are non-negative scalars and it is assumed that $\theta_1 + \theta_2 < 1$. The estimates of correlation are given as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,j,t}}}$$

The diagonal bivariate GARCH model assumes the dynamic conditional correlation between asset returns to be zero, i.e., $\rho_{i,j,t} = 0$ for all *i* and *j*. On the other hand, the constant conditional correlation considers $P_{i,j} = \rho_{i,j}$ and $P_t = P$.

*2.2. Hedge ratio*

In setting up the hedging process, we need to consider the estimation of the optimal hedge ratio. The estimates of the conditional variance and covariance can be used to compute the optimal hedge ratio which is based on the minimization of the variance of the portfolio return (Kroner and Sultan, 1993). The risk minimizing hedge ratio between asset i and asset j is given as:

$$\delta_{i,j,t} = \frac{h_{i,j,t}}{h_{j,j,t}} \tag{7}$$

where $h_{i,j,t}$ is the conditional covariance between asset *i* and *j* at time *t* and $h_{j,j,t}$ is the conditional variance of asset *j* at time *t*. It is to be noted that a long position in one dollar in asset *i* can be hedged by a short position in $\delta_{i,j,t}$ dollars of asset *j*.

*2.3. Optimal Portfolio Weights*

The existing literature provides evidence of a significant impact of the fluctuations in crude oil prices on stock markets. In this context, it is important to examine how oil price risk can be hedged substantially using the maximum likelihood estimates of VARMA-GARCH models. Suppose the investor is holding asset i and wants to hedge his exposure against unfavorable movements in asset j. Following Kroner and Ng (1998), the optimal portfolio weights can be constructed by minimizing the risk of the portfolio without impacting the expected return.

$$w_{i,j,t} = \frac{h_{j,j,t} - h_{i,j,t}}{h_{i,i,t} - 2h_{i,j,t} + h_{j,j,t}} \tag{8}$$

$$w_{i,j,t} = \begin{cases} 0, & if\ w_{i,j,t} < 0 \\ w_{i,j,t}, & if\ 0 \le w_{i,j,t} \le 1 \\ 1, & if\ w_{i,j,t} > 1 \end{cases} \tag{9}$$

where $w_{i,j,t}$ is the weight on the first asset in a one dollar portfolio of two assets (assets *i* and *j*) at time *t*. The weight on the second asset is given as ($1 - w_{i,j,t}$).

**3. Data and Preliminary Analysis**

In order to study the different parameters of Crude Oil Market and Industrial Fluctuation in India, its impact on cost and return of capital, portfolio construction, we apply the econometric models based on data from authentic sources. Table 1 reports the descriptive statistics of weekly returns based on all the sectoral indices and crude oil prices. The energy sector provides the highest mean weekly return when compared to the other sectors. However, the highest median weekly return is shown by the metal sector. The metal sector seems to be highly volatile followed by oil. Except for the financial sector, all the other indices and crude oil price returns are negatively skewed. In addition, all the indices exhibit significant leptokurtic behavior.

The Jarque-Bera statistic confirms the significant non-normality in all the series. The Box-Pierce Q-test strongly rejects the presence of no significant autocorrelations in the first 20 lags for all the return series at a conventional level of significance except for automobile sector. The ARCH-LM test provides evidence in support of the presence of conditional heteroskedasticity in the return series. ADF and KPSS tests confirm the stationarity of all the series at 1% level of significance.

Figure 1 presents the time plots of returns and prices for all time series under study. It can clearly be observed that all the indices display a great deal of momentum in their levels which includes a steep rise in index value from 2005 to the beginning of 2008 and a sudden drop from the beginning of 2008 to the end of 2008 and again a sudden rise in index value from 2009 onwards. We also observe volatility clustering during the period 2007-2009 for all the indices.

**4. Empirical Results**

We first report the maximum likelihood estimates of the bivariate GARCH class of models for oil-stock sector pairs. This will help us to investigate the volatility and the correlation spillover effects from crude oil prices to the Indian industrial sectors. Next we will investigate the time varying transmission of conditional correlation from the crude oil market to the Indian industrial fluctuation. Finally, we estimate the optimal weights and hedge ratios for the oil-stock portfolio.

*4.1. The Bivariate GARCH Model*

We first compare the maximum likelihood estimates of bivariate GARCH (BVGARCH) models with VAR (1) as a conditional mean equation and VARMA-GARCH (1,1) as a conditional variance equation. Tables 3 to 8 reports the parameter estimates and the diagnostic results of the bivariate GARCH model under the assumption that the error terms follow the Student's t distribution, constant conditional correlation (CCC) and dynamic conditional correlation (DCC)) for the all the stock sector-oil pairs. The coefficient □$_{12}$ represents the return spillover effect from the oil price returns to the stock sector returns. We find significant negative return spillover from oil price returns to Auto sector for DCC-GARCH model. We also find evidence of significant positive return spillover from oil price returns to metal sector returns for all the bivariate GARCH models considered in this study. This indicates that an increase in the crude oil price negatively impacts the return from the automobile sector and positively impacts the metal and mining stocks.

The ARCH (□$_{□□}$) coefficient which measure the short term shock persistence and the GARCH (□$_{□□}$) coefficient which measures the long-term persistence are important in investigating the dynamic nature of conditional volatility. Both ARCH and GARCH coefficients for the stock sectors (□$_{□□}$□and□□$_{□□}$□□respectively) and the crude oil prices (□$_{□□}$□and□□$_{□□}$□□respectively) are statistically significant at conventional levels of significance for all the bivariate GARCH models. The values of ARCH coefficients are smaller than the corresponding values of GARCH coefficients indicating that long-run persistence in the sectoral stock indices and oil is higher than the short-run persistence. For the diagonal bivariate GARCH model, we observe significant short-run volatility spillover from the oil market to only the automobile sector (□□□). We do not find any significant long-run persistence volatility spillover from the oil market to sector stocks. On the other hand, the CCC-GARCH model does not find any significant short-run or long-run persistence volatility spillover from the crude oil market to the various Indian industrial sectors. We find positive a significant conditional correlation (□□□) between the crude oil market and stock sectors, such as the financial sector, energy sector, metal and mining sector and the commodities market. We observe negative constant conditional correlation between oil and service sector. However, for the case of DCC-GARCH model, we find evidence of positive short run volatility spillover from the crude oil market to the automobile sector and the energy sector. This indicates that short term volatility shocks in the global market may also increase the volatility of the automobile sector and the energy sector in India with a bigger impact on the automobile sector than on the energy sector (because of the larger value of the coefficient for the automobile sector). Moreover, we find evidence of negative short run volatility spillover from the oil market to the service sector in India. On the flip side, the results indicate a positive long-run volatility spillover from the crude oil market to the service sector, metal and mining sector and the commodities market. We find that the magnitude of positive long-run volatility spillover is higher for the metal and mining sector followed by the service sector and the commodities market. In addition, we find evidence of a significant negative long-run volatility spillover from the crude oil market to the automobile sector, the financial sector and the energy sector. Here, the magnitude of negative long run volatility spillover is higher for the financial sector followed by the automobile sector and the energy sector. The estimated coefficients □□□and□□□□for DCC model are positive and statistically significant for all the cases at 1% level of significance. In addition, the (□□□□□□□) < 1, which indicates the mean reverting nature of dynamic condition correlations between the crude oil market and the stock sectors. The significant values of the degrees of freedom parameter (□) indicates that the bivariate GARCH model under the Student's t distribution capture the leptokurtic behaviour of the estimated residuals. The highest value of log-likelihood function for DCC-GARCH model indicates that the DCC-GARCH model outperforms the other bivariate GARCH model in capturing the cross-sectional dynamics in volatility between the oil market and stock sector returns. The insignificant values of Q(20) and Qs(20) for all the cases in the DCC GARCH model indicates the absence of serial correlation in standardized residuals and squared standardized residuals at 1% level of significance. The insignificant value of the ARCH-LM statistic up to 10 lags indicates that the DCC GARCH model is also able to capture the heteroskedasticity in the series.

*4.2. Time Varying Conditional Correlation*

Figure 2 presents the time-varying dynamic conditional correlation estimated from the DCC GARCH model for all the stock-oil pairs. We observe a wide variation in conditional correlations over the study period for all the pairs. This variation can be contrasted with the constant correlation obtained by using the CCC-GARCH model. Such a wide variation in the conditional correlation emphasizes the outstanding ability of the DCC-GARCH model in covering a range of conditional correlation values between negative and positive. This indicates that there is wider scope to examine the benefits of portfolio diversification in the stock-oil pairs. We also observe wider fluctuation in the values of conditional correlation varying from extreme positive to extreme negative during the period of global financial crisis (2008-2009) for all the stock-oil pairs. For the automobile sector and oil pair, we find negative conditional correlation for most of the time, which confirms that automobile sectoral returns and crude oil returns are negatively related.

*4.3. Hedging Ratio*

In this sub-section, we estimate the optimal hedge ratio based on the conditional variance and covariance estimates from the bivariate DCC-GARCH model using equation (7). Figure 3 reports the time varying risk minimizing hedge ratios for all the stock-oil as well as the oil-stock pairs under study. The hedge of asset *i* with asset *j* (as indicated in Figure 3) means that a long position in asset *i* can be hedged with a short position in asset *j*. We observe wide variation in the hedge ratio over time for all the stock-oil and oil-stock pairs. The results provide evidence of considerable variability of hedge ratios during the period of global financial crisis (2008-2009) for all the cases under study. For most of the cases, the maximum value of hedge ratio is observed during the 2008-2009 period except for the hedge of auto with oil, the hedge of service with oil and the hedge of metal with oil. For the case of the hedge of auto with oil and the hedge of metal with oil, the maximum value of the hedge ratio is observed in the period 2006-2007. Moreover, for the case of the hedge of service with oil, the maximum value of the hedge ratio is observed during the period of dot-com bubble crisis (1999-2000). On the other hand, minimum value of the hedge ratio is recorded during the period of global financial crisis for all the cases except for the hedge of service with oil. For the hedge of service with oil, the minimum value of hedge ratio is obtained during dot-com bubble crisis (1999-2000).

*4.4. Optimal Portfolio Weights*

In this sub-section, we construct optimal portfolio weights based on the conditional variances and covariances estimates from the bivariate DCC-GARCH model as suggested by Kroner and Ng (1998) using equations (8) and (9). Table 7 presents the summary statistics of the optimal portfolio weights in the stock in a stock-oil portfolio. The average weight for Auto/Oil portfolio is 0.612 indicating that for a $100 portfolio, on average $61.2 should be invested in automobile stocks and the remaining $38.8 should be invested in oil. Similarly, for other stock/oil pairs, the numbers mentioned in column one represent the percentage of unit weight to be invested in stocks. The optimal average weight for oil ranges from 34.3% (Energy) to 57% (Metal).

**5. Conclusion**

we have examined the crude oil prices and the Indian industrial fluctuation using BVGARCH models (Diagonal (Diag), constant conditional correlation (CCC) and dynamic conditional correlation (DCC)) with the vector autoregressive (VAR (1)) model as a conditional mean equation and the vector autoregressive moving average GARCH (VARMA-GARCH (1,1)) as a conditional variance equation under the assumption that the error terms follow the Student's t distribution. Our results indicate that DCC-BVGARCH model performs better than other models in capturing the interactive dynamics between crude oil and stock sectors. Our findings include evidence of a negative return spillover effect from oil prices to the Auto sector, a positive return spillover effect from oil prices to the Metal sector returns, a positive short run volatility spillover effect from the crude oil market to the automobile sector and the energy sector, a negative short run volatility spillover effect from the crude oil market to the service sector, a positive long-run volatility spillover effect from the crude oil market to the service sector, the commodities market and a negative long-run volatility spillover effect from the crude oil market to the automobile sector, the financial sector and the energy sector. We also estimate the dynamic conditional correlation and find that the conditional correlation varies substantially over time for all the oil-stock pairs. We find wide fluctuations in conditional correlations, reaching to their highest value for each oil-stock pair during the period of the global financial crisis. The dynamic conditional correlations between crude oil and the Indian esector are higher when compared with the other oil-stock pairs. The conditional volatility estimates from BVGARCH models are applied to estimate risk minimizing hedge ratios. Our findings indicate that on average, a $1 long position in automobile, finance, energy, service, metal and commodities sectors can be hedged by taking short position of 9.2 cents, 11 cents, 12.9 cents, 5.4 cents, 31 cents and 17.4 cents in crude oil, respectively. We also estimate optimal weights for constructing the optimal oil-stock portfolio. The results indicate that for every $100 of optimal stock/oil portfolio $61.2 should be invested in the auto sector and the remaining $38.8 invested in oil, $50.8 should be invested in the finance sector and remaining $49.2 invested in oil, $65.7 should be invested in the energy sector and remaining $34.3 invested in oil, $58.3 should be invested in the service sector and remaining $41.7 invested in oil, $43.0 should be invested in the metal sector and remaining $57.0% invested in oil and $62.2 should be invested in the commodities and remaining $37.8 invested in oil.

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**Annexure**

| | **Auto** | **Finance** | **Energy** | **Service** | **Metal** | **Commodities** | **Oil** |
|---|---|---|---|---|---|---|---|
| Mean | 0.313 | 0.315 | 0.324 | 0.264 | 0.239 | 0.184 | 0.231 |
| Median | 0.824 | 0.687 | 0.580 | 0.584 | 0.900 | 0.618 | 0.527 |
| Stdev | 3.987 | 5.136 | 4.038 | 4.895 | 5.775 | 4.354 | 5.180 |
| Min | -16.169 | -17.409 | -20.240 | -26.515 | -22.847 | -20.418 | -23.263 |
| Max | 19.026 | 28.959 | 17.279 | 18.915 | 25.860 | 17.697 | 30.305 |
| Quartile 1 | -1.788 | -2.378 | -1.721 | -1.992 | -2.877 | -1.755 | -3.069 |
| Quartile 3 | 2.669 | 3.268 | 2.657 | 2.988 | 3.448 | 2.818 | 3.620 |
| Skewness | -0.325$^{\#}$ | 0.167$^{\#}$ | -0.504$^{\#}$ | -0.763$^{\#}$ | -0.062$^{\#}$ | -0.557$^{\#}$ | -0.192$^{\#}$ |
| Kurtosis | 1.990$^{\#}$ | 3.302$^{\#}$ | 2.546$^{\#}$ | 3.847$^{\#}$ | 1.863$^{\#}$ | 2.329$^{\#}$ | 2.610$^{\#}$ |
| JB Stat | 82.409$^{\#}$ | 206.383$^{\#}$ | 189.643$^{\#}$ | 491.369$^{\#}$ | 65.700$^{\#}$ | 124.983$^{\#}$ | 200.241$^{\#}$ |
| ARCH LM | 20.619$^{*}$ | 34.950$^{\#}$ | 34.464$^{\#}$ | 171.798$^{\#}$ | 37.242$^{\#}$ | 47.394$^{\#}$ | 40.129$^{\#}$ |
| Q(20) | 22.833 | 41.929$^{\#}$ | 58.842$^{\#}$ | 27.577 | 31.745$^{*}$ | 55.145$^{\#}$ | 56.121$^{\#}$ |
| ADF | -6.472$^{\#}$ | -6.996$^{\#}$ | -7.519$^{\#}$ | -8.146$^{\#}$ | -6.311$^{\#}$ | -6.529$^{\#}$ | -7.350$^{\#}$ |
| KPSS | 0.079 | 0.077 | 0.263 | 0.070 | 0.139 | 0.101 | 0.086 |
| Corr. with oil | 0.107 | 0.111 | 0.169 | 0.063 | 0.270 | 0.205 | 1.000 |
| N | 442 | 442 | 599 | 682 | 442 | 442 | 682 |

$^{\#}$, $^{*}$ and $^{\dagger}$ means significant at 1%, 5% and 10% level of significance respectively. Where Stdev represents the standard deviation of returns and ARCH-LM indicates the Lagrange multiplier test for conditional heteroskedasticity with 10 lags, JB Stat indicates the Jarque Bera statistics, Q(20) statistic is the Ljung-Box test up to 20 lags.

*Table 1: Descriptive statistics of returns*

| | **Diag** | | **CCC** | | **DCC** | |
|---|---|---|---|---|---|---|
| | Coeff | (SE)/[p] | Coeff | (SE)/[p] | Coeff | (SE)/[p] |
| $\square_{10}$ | 0.450$^{\#}$ | (0.158) | 0.429$^{*}$ | (0.169) | 0.441$^{\#}$ | (0.040) |
| $\square_{11}$ | 0.030 | (0.050) | 0.021 | (0.050) | 0.067$^{\#}$ | (0.005) |
| $\square_{12}$ | -0.007 | (0.032) | -0.002 | (0.032) | -0.030$^{\#}$ | (0.003) |
| $\square_{20}$ | 0.367$^{\dagger}$ | (0.211) | 0.346 | (0.217) | 0.452$^{\#}$ | (0.072) |
| $\square_{21}$ | 0.065 | (0.055) | 0.051 | (0.056) | 0.072 | (0.049) |
| $\square_{22}$ | -0.029 | (0.049) | -0.029 | (0.051) | -0.039$^{*}$ | (0.018) |
| $\square_{10}$ | 2.702$^{*}$ | (1.050) | 1.823 | (1.543) | 2.037$^{\#}$ | (0.039) |
| $\square_{\square\square}$ | 1.122$^{\dagger}$ | (0.657) | 0.894 | (0.825) | 1.444$^{\#}$ | (0.258) |
| $\square_{\square\square}$ | 0.161$^{\#}$ | (0.058) | 0.156$^{\#}$ | (0.056) | 0.153$^{\#}$ | (0.005) |
| $\square_{\square\square}$ | 0.112$^{\dagger}$ | (0.059) | 0.080 | (0.067) | 0.168$^{\#}$ | (0.002) |
| $\square_{\square\square}$ | -0.018 | (0.049) | -0.036 | (0.058) | -0.044 | (0.037) |
| $\square_{\square\square}$ | 0.098$^{\#}$ | (0.033) | 0.095$^{\#}$ | (0.035) | 0.115$^{\#}$ | (0.009) |
| $\square_{\square\square}$ | 0.642$^{\#}$ | (0.095) | 0.595$^{\#}$ | (0.118) | 0.737$^{\#}$ | (0.004) |
| $\square_{\square\square}$ | 27.036 | (32.318) | 1.352 | (2.607) | -0.243$^{\#}$ | (0.014) |
| $\square_{\square\square}$ | -7.201 | (4.704) | 0.222 | (1.375) | 0.156$^{*}$ | (0.066) |
| $\square_{\square\square}$ | 0.860$^{\#}$ | (0.045) | 0.861$^{\#}$ | (0.073) | 0.815$^{\#}$ | (0.011) |
| $\square$ | 13.743$^{\#}$ | (5.210) | 14.612$^{\#}$ | (5.388) | 14.526$^{*}$ | (5.943) |
| $\square_{\square\square}$ | | | 0.068 | (0.062) | | |
| $\square_{\square}$ | | | | | 0.072$^{\#}$ | (0.008) |
| $\square_{\square}$ | | | | | 0.831$^{\#}$ | (0.008) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Log L | -2510.615 | | -2511.400 | | -2504.542 | |
| $JBStat_1$ | 50.956# | [0.000] | 55.375# | [0.000] | 34.650# | [0.000] |
| $Q(20)_1$ | 14.897 | [0.782] | 14.734 | [0.791] | 15.001 | [0.776] |
| $Qs(20)_1$ | 8.812 | [0.985] | 8.106 | [0.991] | 8.925 | [0.984] |
| $ARCH(10)_1$ | 0.482 | [0.902] | 0.390 | [0.951] | 0.480 | [0.903] |
| $JBStat_2$ | 1.574 | [0.455] | 1.868 | [0.393] | 2.051 | [0.359] |
| $Q(20)_2$ | 28.197 | [0.105] | 28.816† | [0.091] | 26.753 | [0.142] |
| $Qs(20)_2$ | 16.083 | [0.711] | 16.463 | [0.688] | 14.689 | [0.794] |
| $ARCH(10)_2$ | 0.609 | [0.807] | 0.647 | [0.774] | 0.506 | [0.886] |

#, * and † means significant at 1%, 5% and 10% level of significance, respectively.
Subscript 1 represents stock and subscript 2 represents oil.

*Table 2: Parameter estimates of BVGARCH models for Auto and Oil*

| | **Diag** | | **CCC** | | **DCC** | |
|---|---|---|---|---|---|---|
| | Coeff | (SE)/[p] | Coeff | (SE)/[p] | Coeff | (SE)/[p] |
| $\square_{10}$ | 0.510* | (0.200) | 0.493* | (0.204) | 0.479* | (0.199) |
| $\square_{11}$ | -0.091† | (0.048) | -0.086† | (0.048) | -0.084† | (0.050) |
| $\square_{12}$ | 0.051 | (0.043) | 0.047 | (0.049) | 0.032 | (0.043) |
| $\square_{20}$ | 0.312 | (0.204) | 0.332 | (0.215) | 0.367† | (0.206) |
| $\square_{21}$ | 0.007 | (0.048) | -0.006 | (0.045) | -0.014 | (0.047) |
| $\square_{22}$ | -0.011 | (0.051) | -0.007 | (0.051) | -0.024 | (0.044) |
| $\square_{10}$ | 0.600* | (0.299) | 0.465 | (0.350) | 0.599# | (0.062) |
| $\square_{\square\square}$ | 0.932† | (0.518) | 0.668 | (0.648) | 0.262† | (0.142) |
| $\square_{\square\square}$ | 0.075# | (0.024) | 0.081# | (0.026) | 0.044# | (0.002) |
| $\square_{\square\square}$ | -0.044 | (0.039) | -0.053 | (0.042) | -0.007 | (0.013) |
| $\square_{\square\square}$ | -0.042 | (0.035) | -0.055 | (0.046) | -0.061# | (0.023) |
| $\square_{\square\square}$ | 0.092# | (0.031) | 0.086* | (0.039) | 0.040# | (0.005) |
| $\square_{\square\square}$ | 0.903# | (0.026) | 0.857# | (0.093) | 0.922# | (0.003) |
| $\square_{\square\square}$ | 2.885 | (6.658) | 0.358 | (0.655) | -0.847# | (0.027) |
| $\square_{\square\square}$ | -5.045 | (3.218) | 1.109 | (0.765) | 1.187# | (0.060) |
| $\square_{\square\square}$ | 0.876# | (0.042) | 0.748# | (0.095) | 0.827# | (0.006) |
| $\square$ | 17.338* | (7.764) | 21.197† | (11.764) | 17.156* | (7.317) |
| $\square_{\square\square}$ | | | 0.133* | (0.060) | | |
| $\square_{\square}$ | | | | | 0.016# | (0.004) |
| $\square_{\square}$ | | | | | 0.492# | (0.145) |
| Log L | -2610.283 | | -2604.360 | | -2603.886 | |
| $JBStat_1$ | 20.077# | [0.000] | 16.802# | [0.000] | 29.602# | [0.000] |
| $Q(20)_1$ | 19.933 | [0.462] | 19.888 | [0.465] | 19.318 | [0.501] |
| $Qs(20)_1$ | 20.809 | [0.408] | 22.786 | [0.299] | 17.724 | [0.606] |
| $ARCH(10)_1$ | 1.103 | [0.358] | 1.203 | [0.287] | 1.046 | [0.403] |
| $JBStat_2$ | 1.813 | [0.404] | 1.439 | [0.487] | 1.465 | [0.481] |
| $Q(20)_2$ | 28.753† | [0.093] | 28.706† | [0.094] | 28.401 | [0.101] |
| $Qs(20)_2$ | 16.936 | [0.657] | 17.713 | [0.606] | 19.460 | [0.492] |

| | | | | | | |
|---|---|---|---|---|---|---|
| ARCH(10)$_2$ | 0.705 | [0.720] | 0.660 | [0.762] | 0.698 | [0.726] |
| #, * and † means significant at 1%, 5% and 10% level of significance, respectively. Subscript 1 represents stock and subscript 2 represents oil. | | | | | | |

*Table 3: Parameter estimates of BVGARCH models for Finance and Oil*

| | **Diag** | | **CCC** | | **DCC** | |
|---|---|---|---|---|---|---|
| | Coeff | (SE)/[p] | Coeff | (SE)/[p] | Coeff | (SE)/[p] |
| □$_{10}$ | 0.396$^{\#}$ | (0.126) | 0.396$^{\#}$ | (0.135) | 0.359$^{\#}$ | (0.129) |
| □$_{11}$ | 0.025 | (0.043) | 0.027 | (0.044) | 0.042 | (0.043) |
| □$_{12}$ | 0.012 | (0.026) | 0.011 | (0.026) | 0.012 | (0.027) |
| □$_{20}$ | 0.325$^{\dagger}$ | (0.185) | 0.316$^{\dagger}$ | (0.185) | 0.320$^{\dagger}$ | (0.175) |
| □$_{21}$ | 0.090$^{\dagger}$ | (0.047) | 0.074 | (0.048) | 0.085$^{*}$ | (0.042) |
| □$_{22}$ | -0.024 | (0.041) | -0.023 | (0.043) | -0.033 | (0.039) |
| □$_{10}$ | 0.793$^{*}$ | (0.343) | 0.251 | (0.420) | 0.889$^{\#}$ | (0.114) |
| □□□ | 1.257$^{\dagger}$ | (0.675) | 0.739 | (0.565) | 1.563$^{\#}$ | (0.201) |
| □□□ | 0.139$^{\#}$ | (0.040) | 0.142$^{\#}$ | (0.040) | 0.133$^{\#}$ | (0.013) |
| □□□ | 0.018 | (0.036) | -0.007 | (0.032) | 0.061$^{*}$ | (0.025) |
| □□□ | 0.000 | (0.044) | -0.023 | (0.043) | 0.023 | (0.035) |
| □□□ | 0.074$^{\#}$ | (0.027) | 0.066$^{\#}$ | (0.025) | 0.074$^{\#}$ | (0.010) |
| □□□ | 0.807$^{\#}$ | (0.052) | 0.745$^{\#}$ | (0.082) | 0.824$^{\#}$ | (0.010) |
| □□□ | 4.545 | (7.928) | 0.529 | (0.430) | -0.114$^{\#}$ | (0.041) |
| □□□ | 6.100 | (9.211) | 0.386 | (0.305) | 0.007 | (0.058) |
| □□□ | 0.877$^{\#}$ | (0.040) | 0.864$^{\#}$ | (0.040) | 0.863$^{\#}$ | (0.009) |
| □ | 8.292$^{\#}$ | (1.610) | 8.827$^{\#}$ | (1.725) | 8.899$^{\#}$ | (1.582) |
| □□□ | | | 0.151$^{\#}$ | (0.043) | | |
| □□ | | | | | 0.092$^{\#}$ | (0.029) |
| □□ | | | | | 0.736$^{\#}$ | (0.099) |
| Log L | -3404.981 | | -3397.450 | | -3396.076 | |
| JBStat$_1$ | 273.950$^{\#}$ | [0.000] | 189.170$^{\#}$ | [0.000] | 258.810$^{\#}$ | [0.000] |
| Q(20)$_1$ | 36.507$^{*}$ | [0.013] | 35.731$^{*}$ | [0.017] | 37.171$^{*}$ | [0.011] |
| Qs(20)$_1$ | 10.705 | [0.954] | 11.010 | [0.946] | 10.595 | [0.956] |
| ARCH(10)$_1$ | 0.410 | [0.942] | 0.438 | [0.928] | 0.381 | [0.955] |
| JBStat$_2$ | 70.119$^{\#}$ | [0.000] | 92.056$^{\#}$ | [0.000] | 71.038$^{\#}$ | [0.000] |
| Q(20)$_2$ | 28.270 | [0.103] | 27.456 | [0.123] | 27.715 | [0.116] |
| Qs(20)$_2$ | 10.317 | [0.962] | 9.857 | [0.971] | 11.050 | [0.945] |
| ARCH(10)$_2$ | 0.282 | [0.985] | 0.272 | [0.987] | 0.311 | [0.978] |
| #, * and † means significant at 1%, 5% and 10% level of significance, respectively. Subscript 1 represents stock and subscript 2 represents oil. | | | | | | |

*Table 4: Parameter estimates of BVGARCH models for Energy and Oil*

| | **Diag** | | **CCC** | | **DCC** | |
|---|---|---|---|---|---|---|
| | Coeff | (SE)/[p] | Coeff | (SE)/[p] | Coeff | (SE)/[p] |
| □$_{10}$ | 0.416$^{\#}$ | (0.145) | 0.426$^{\#}$ | (0.142) | 0.414$^{\#}$ | (0.135) |
| □$_{11}$ | -0.019 | (0.041) | -0.015 | (0.042) | -0.006 | (0.041) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\square_{12}$ | 0.041 | (0.029) | 0.039 | (0.030) | 0.039 | (0.029) |
| $\square_{20}$ | $0.362^{\dagger}$ | (0.185) | $0.371^{*}$ | (0.178) | $0.331^{\dagger}$ | (0.170) |
| $\square_{21}$ | $0.089^{*}$ | (0.042) | $0.085^{*}$ | (0.038) | $0.089^{*}$ | (0.035) |
| $\square_{22}$ | -0.014 | (0.040) | -0.013 | (0.039) | -0.010 | (0.038) |
| $\square_{10}$ | $0.493^{*}$ | (0.207) | $0.424^{\dagger}$ | (0.239) | $0.334^{\#}$ | (0.083) |
| $\square_{\square\square}$ | $1.061^{\dagger}$ | (0.542) | 1.000 | (0.636) | $1.059^{\#}$ | (0.177) |
| $\square_{\square\square}$ | $0.104^{\#}$ | (0.025) | $0.106^{\#}$ | (0.025) | $0.113^{\#}$ | (0.007) |
| $\square_{\square\square}$ | -0.036 | (0.027) | -0.040 | (0.027) | $-0.065^{\#}$ | (0.019) |
| $\square_{\square\square}$ | -0.032 | (0.032) | -0.006 | (0.039) | -0.044 | (0.033) |
| $\square_{\square\square}$ | $0.068^{\#}$ | (0.021) | $0.058^{*}$ | (0.023) | $0.062^{\#}$ | (0.007) |
| $\square_{\square\square}$ | $0.876^{\#}$ | (0.028) | $0.867^{\#}$ | (0.036) | $0.838^{\#}$ | (0.006) |
| $\square_{\square\square}$ | 4.483 | (13.306) | -2.057 | (5.830) | $0.597^{\#}$ | (0.081) |
| $\square_{\square\square}$ | -9.810 | (6.589) | -10.971 | (8.391) | $1.589^{\#}$ | (0.149) |
| $\square_{\square\square}$ | $0.893^{\#}$ | (0.033) | $0.854^{\#}$ | (0.063) | $0.814^{\#}$ | (0.008) |
| $\square$ | $12.491^{\#}$ | (3.430) | $12.587^{\#}$ | (3.248) | $12.737^{\#}$ | (3.022) |
| $\square_{\square\square}$ | | | -0.005 | (0.005) | | |
| $\square_{\square}$ | | | | | $0.018^{\#}$ | (0.006) |
| $\square_{\square}$ | | | | | $0.480^{*}$ | (0.233) |
| Log L | -3979.262 | | -3976.866 | | -3972.948 | |
| $JBStat_1$ | $73.293^{\#}$ | [0.000] | $70.576^{\#}$ | [0.000] | $69.355^{\#}$ | [0.000] |
| $Q(20)_1$ | 27.519 | [0.121] | 27.446 | [0.123] | 27.136 | [0.131] |
| $Qs(20)_1$ | 10.086 | [0.967] | 10.122 | [0.966] | 10.633 | [0.955] |
| $ARCH(10)_1$ | 0.449 | [0.922] | 0.455 | [0.918] | 0.479 | [0.904] |
| $JBStat_2$ | $52.247^{\#}$ | [0.000] | $66.440^{\#}$ | [0.000] | $73.210^{\#}$ | [0.000] |
| $Q(20)_2$ | $32.031^{*}$ | [0.043] | $31.228^{\dagger}$ | [0.052] | $31.123^{\dagger}$ | [0.054] |
| $Qs(20)_2$ | 11.907 | [0.919] | 10.939 | [0.948] | 12.093 | [0.913] |
| $ARCH(10)_2$ | 0.394 | [0.949] | 0.346 | [0.968] | 0.370 | [0.959] |

#, * and † means significant at 1%, 5% and 10% level of significance, respectively. Subscript 1 represents stock and subscript 2 represents oil.

*Table 5: Parameter estimates of BVGARCH models for Service and Oil*

| | **Diag** | | **CCC** | | **DCC** | |
|---|---|---|---|---|---|---|
| | Coeff | Std err | Coeff | Std err | Coeff | Std err |
| $\square_{10}$ | $0.445^{\#}$ | (0.154) | $0.421^{*}$ | (0.165) | $0.382^{\#}$ | (0.148) |
| $\square_{11}$ | 0.035 | (0.050) | 0.041 | (0.049) | 0.047 | (0.051) |
| $\square_{12}$ | 0.026 | (0.033) | 0.027 | (0.035) | 0.033 | (0.034) |
| $\square_{20}$ | $0.365^{\dagger}$ | (0.200) | $0.374^{\dagger}$ | (0.213) | $0.361^{\dagger}$ | (0.196) |
| $\square_{21}$ | 0.069 | (0.050) | 0.050 | (0.051) | 0.053 | (0.048) |
| $\square_{22}$ | -0.033 | (0.049) | -0.035 | (0.051) | -0.037 | (0.046) |
| $\square_{10}$ | $1.236^{\#}$ | (0.479) | 0.654 | (0.553) | $0.681^{\#}$ | (0.180) |
| $\square_{\square\square}$ | $1.128^{\dagger}$ | (0.671) | 0.646 | (0.584) | $0.714^{\#}$ | (0.207) |
| $\square_{\square\square}$ | $0.238^{\#}$ | (0.068) | $0.236^{\#}$ | (0.064) | $0.242^{\#}$ | (0.024) |
| $\square_{\square\square}$ | 0.034 | (0.057) | 0.010 | (0.056) | -0.022 | (0.039) |
| $\square_{\square\square}$ | -0.014 | (0.044) | -0.037 | (0.046) | $-0.059^{*}$ | (0.030) |

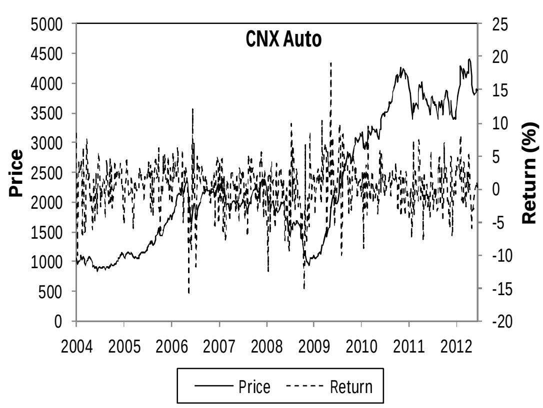
| | | | | | | |
|---|---|---|---|---|---|---|
| □□□ | 0.106# | (0.036) | 0.096# | (0.035) | 0.102# | (0.011) |
| □□□ | 0.692# | (0.064) | 0.654# | (0.092) | 0.651# | (0.018) |
| □□□ | 16.449 | (19.275) | 0.338 | (0.324) | 0.362# | (0.063) |
| □□□ | -3.217 | (2.198) | 0.284 | (0.210) | 0.319# | (0.058) |
| □□□ | 0.855# | (0.048) | 0.836# | (0.048) | 0.828# | (0.010) |
| □ | 11.681# | (4.007) | 12.766# | (4.721) | 13.295* | (5.238) |
| □□□ | | | 0.214# | (0.048) | | |
| □□ | | | | | 0.070# | (0.005) |
| □□ | | | | | 0.338# | (0.043) |
| Log L | -2525.669 | | -2517.623 | | -2515.947 | |
| $JBStat_1$ | 33.278# | [0.000] | 36.936# | [0.000] | 36.417# | [0.000] |
| $Q(20)_1$ | 30.880† | [0.057] | 29.696† | [0.075] | 29.630† | [0.076] |
| $Qs(20)_1$ | 12.744 | [0.888] | 13.279 | [0.865] | 13.805 | [0.840] |
| $ARCH(10)_1$ | 0.524 | [0.873] | 0.561 | [0.846] | 0.618 | [0.799] |
| $JBStat_2$ | 1.535 | [0.464] | 2.005 | [0.367] | 1.853 | [0.396] |
| $Q(20)_2$ | 27.816 | [0.114] | 28.212 | [0.104] | 27.351 | [0.126] |
| $Qs(20)_2$ | 15.904 | [0.723] | 17.010 | [0.652] | 16.455 | [0.688] |
| $ARCH(10)_2$ | 0.575 | [0.834] | 0.615 | [0.801] | 0.543 | [0.860] |

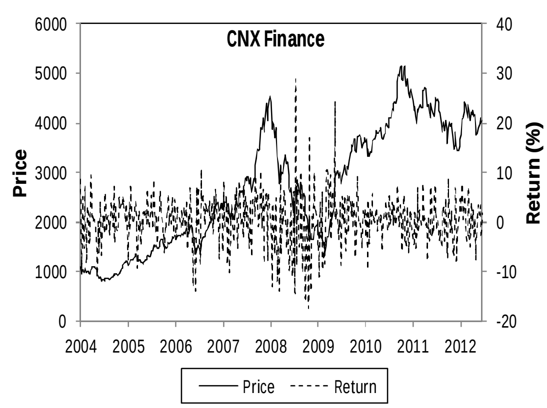
#, * and † means significant at 1%, 5% and 10% level of significance, respectively. Subscript 1 represents stock and subscript 2 represents oil.

*Table 6: Parameter estimates of BVGARCH models for Commodities and Oil*

| | **Mean** | **Median** | **St. dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| Auto/Oil | 0.612 | 0.625 | 0.145 | 0.095 | 1.000 |
| Finance/Oil | 0.508 | 0.504 | 0.089 | 0.250 | 0.695 |
| Energy/Oil | 0.657 | 0.312 | 0.157 | 0.155 | 0.932 |
| Service/Oil | 0.583 | 0.399 | 0.129 | 0.165 | 0.835 |
| Metal/Oil | 0.430 | 0.424 | 0.135 | 0.027 | 0.887 |
| Commodities/Oil | 0.622 | 0.656 | 0.178 | 0.047 | 0.966 |

*Table 7: Summary statistics of portfolio weights for pairs of oil and stock sectors*



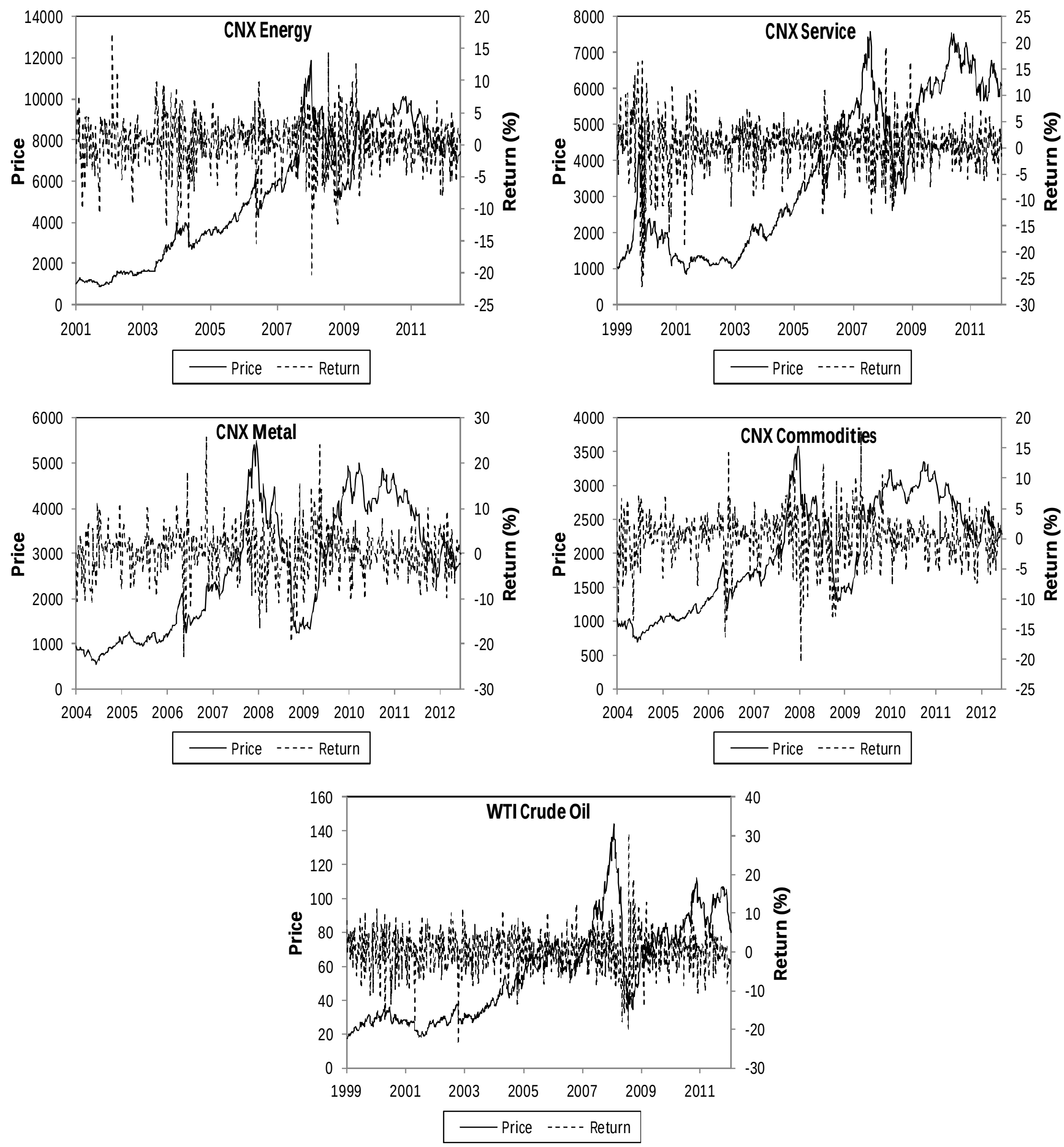
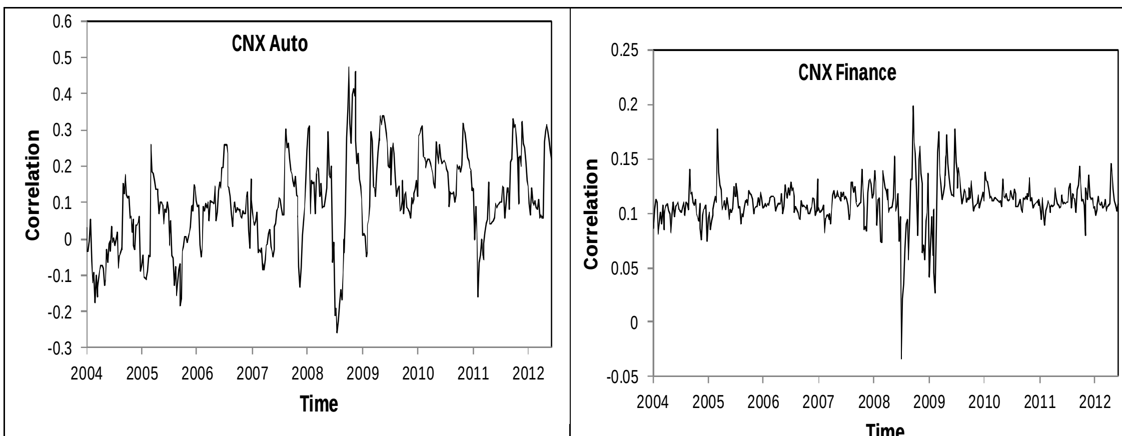



*Figure 1: Price and Return plots*



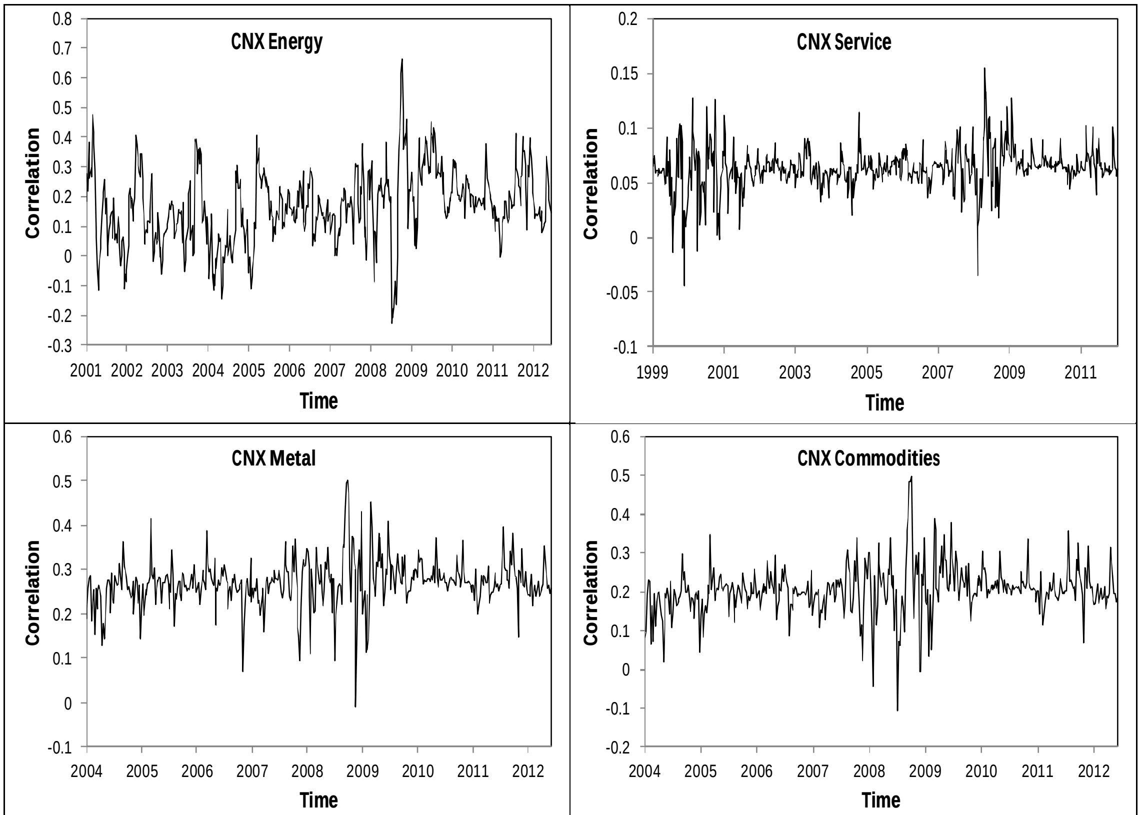
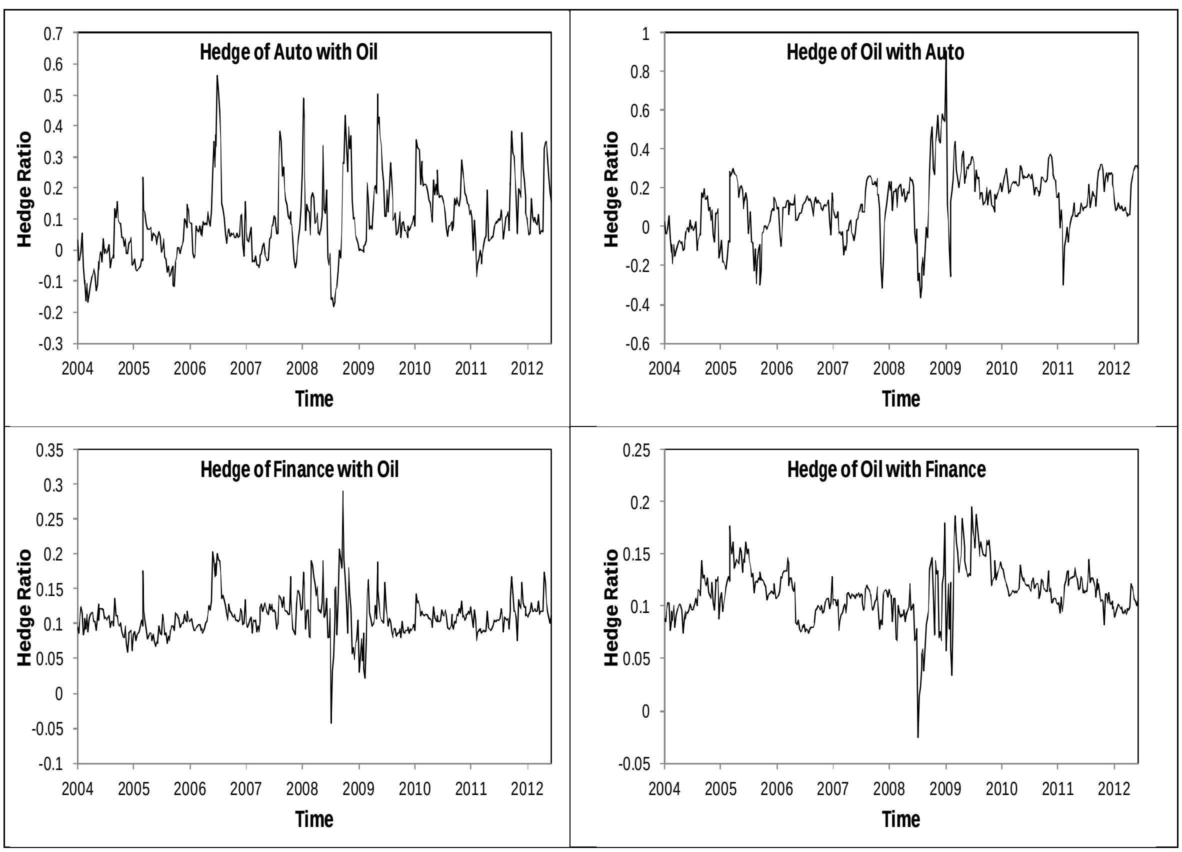



*Figure 2: Time varying conditional correlations estimated using DCC bivariate GARCH model.*



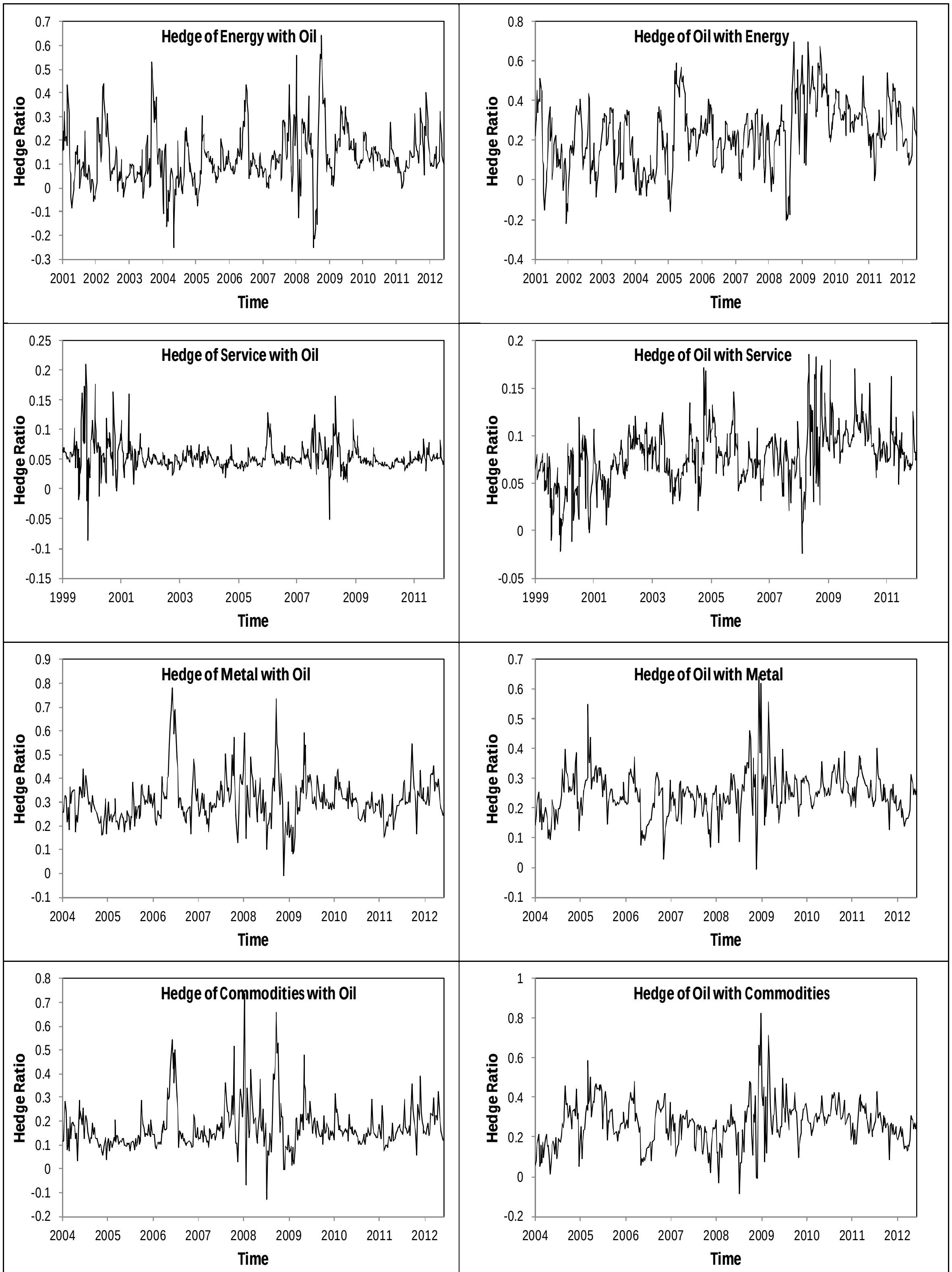



*Figure 3: Time varying hedge ratios estimated using DCC model*