# Correlation transmission between crude oil and Indian markets

Dilip Kumar
*Institute for Financial Management and Research, Chennai, India, and*
S. Maheswaran
*Centre for Advanc Financial Studies,*
*Institute for Financial Management and Research, Chennai, India*

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## Abstract

**Purpose** – In this paper, the authors aim to investigate the return, volatility and correlation spillover effects between the crude oil market and the various Indian industrial sectors (automobile, financial, service, energy, metal and mining, and commodities sectors) in order to investigate optimal portfolio construction and to estimate risk minimizing hedge ratios.

**Design/methodology/approach** – The authors compare bivariate generalized autoregressive conditional heteroskedasticity models (diagonal, constant conditional correlation and dynamic conditional correlation) with the vector autoregressive model as a conditional mean equation and the vector autoregressive moving average generalized autoregressive conditional heteroskedasticity 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.

**Findings** – The authors' results indicate that the dynamic conditional correlation bivariate generalized autoregressive conditional heteroskedasticity model is better able to capture time-dynamics in comparison to other models, based on which the authors find evidence of return and volatility spillover effects from the crude oil market to the Indian industrial sectors. In addition, the authors 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). The authors also estimate risk minimizing hedge ratios and oil-stock optimal portfolio holdings.

**Originality/value** – This paper has empirical originality in investigating the return, volatility and correlation spillover effects from the crude oil market to the various Indian industrial sectors using BVGARCH models with the error terms assumed to follow the Student's t distribution.


**Keywords** Crude oil prices, Volatility, Indian industrial sectors, Hedge ratios, Portfolio construction, Oils, Oil industry, India

**Paper type** Research paper

## 1. Introduction

Crude oil is a global commodity and acts as the lifeblood of every economy. The impact of crude oil price changes on stock price changes is an important area of study for finance researchers and practitioners around the globe. Changes in crude oil prices may indirectly impact a firm's cash flows, earnings and its cost of capital by impacting input costs and 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. History witnesses substantial fluctuations in crude oil prices since the mid-1980s. It is shown in Figure 1 that crude oil prices show a continuous rise from \$18.2/barrel in January 2002 to \$145.31/barrel in July 2008 followed by a heavy decline to \$34.03 till February 2009. Such changes in crude oil prices can be related to the various industrial sectors in India (as shown in Figure 1) and the world (not shown in

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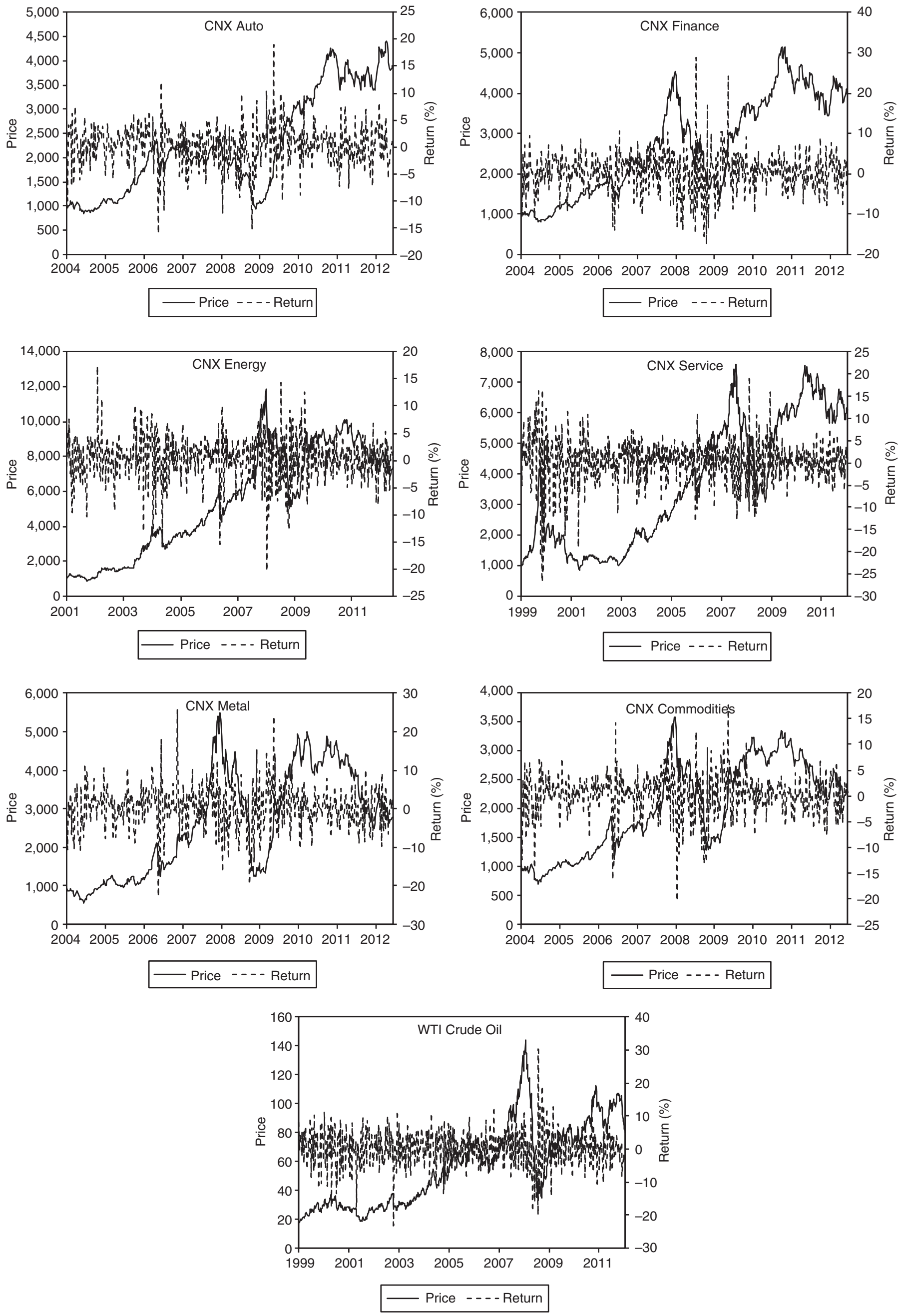


**Figure 1.**
Price and return plots

the figure) which suggests that there are similar movements in stock prices as shown by crude oil prices. 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 for and supply of various products and services in an economy. This makes it clear that the volatility in crude oil prices is likely to have a significant impact on the world economy (Kilian, 2008), because in one way or another, every industrial sector in the world relies on crude oil. The study of the spillover of shocks from the crude oil market to the various industrial sectors 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 toward 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 a stock portfolio can be hedged by taking a short position in oil and vice versa.

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 model of order 1 (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 is better able to capture 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.

The remainder of this paper is organized as follows: Section 2 discusses the literature review on the issue. Section 3 introduces the methodology we will use in this study. Section 4 describes the data and discusses the preliminary results. Section 5 reports the empirical results. Section 6 deals with the discussion of results and Section 7 concludes with a summary of our main findings.

## 2. Review of literature

The linkage between the crude oil market and the stock market is a significant area of study. 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. Crude oil plays a crucial role in giving direction to the global economy. Hence, it is natural to ask whether crude oil price changes exhibit a spillover effect on the stock market. 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 improves its risk-return characteristics. Kling (1985) examines the impact of oil shocks on the US stock market behavior and finds that stock market returns fall with a rise in crude oil prices. 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, the UK and the USA and find that the reaction of the USA and Canadian stock prices to oil price shocks can be completely accounted for by its impact on real cash flows. Huang *et al.* (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. Sadorsky (2001) finds that exchange rates and crude oil prices significantly impact stock returns in the Canadian oil and gas industry. 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. On the other hand, oil price shocks mainly reduce demand in the automobile industry. They suggest that oil price shocks influence economic activities beyond what is explained by direct input cost effects, possibly by delaying the purchasing decisions of durable goods. El-Sharif *et al.* (2005) examine the impact of crude oil price changes on the oil and gas sector returns from the UK and obtain a similar inference as found by Sadorsky (2001). Nandha and Faff (2008) investigate the adverse effect of oil price shocks on 35 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. Bhar and Nikolova (2009) examine the impact of global oil prices on stock returns and volatility of BRIC equity markets and find that such impact depends on the extent to which these countries are net importers or net exporters of oil. 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) applies multivariate GARCH models to capture conditional correlations and to examine the volatility spillovers between crude oil prices and the stock prices of clean energy companies and technology companies and finds that the DCC-MGARCH model best fits the data and, furthermore, that the stock prices of clean energy companies correlate more highly with technology companies than with crude oil.

## 3. Methodology

### *3.1 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 VAR(1). The VAR(1) model can capture the dynamics in market returns and reflect the quick response of markets to new information. Hence, the return for market $i$ at time $t$ is modeled as:

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

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 BVGARCH models (Diag, CCC and DCC). 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:

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

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

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 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:

$$H_t = D_t P_t D_t \tag{3}$$

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

$$D_t = \mathrm{diag}(\sqrt{\mathrm{h}_{11}}, \sqrt{\mathrm{h}_{22}}) \tag{4}$$

and

$$P_t = \mathrm{diag}((Q_t)^{-1/2}) Q_t \mathrm{diag}((Q_t)^{-1/2}) \tag{5}$$

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

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

where $\bar{Q}$ is a $(2 \times 2)$ 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:

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

The diagonal BVGARCH model assumes the DCC between asset returns to be zero, i.e. $\rho_{i,j,t} = 0$ for all $i$ and $j$. On the other hand, the CCC considers $P_{i,j} = \rho_{i,j}$ and $P_t = P$.

*3.2 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 $j$.

*3.3 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:

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

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

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 $(1-w_{i,j,t})$.

*3.4 Hedging effectiveness (HE)*

The HE across the proposed portfolios can be determined by analyzing the realized hedging errors as suggested by Ku *et al.* (2007) and is given as:

$$\mathrm{HE} = \left(\frac{Variance_{unhedged} - Variance_{hedged}}{Variance_{unhedged}}\right) \tag{10}$$

where $Variance_{hedged}$ indicates the variance of the returns of the stock-oil portfolio and $Variance_{unhedged}$ indicates the variance of returns of the portfolio of stocks alone. The higher HE of a given portfolio indicates the greater portfolio risk reduction due to hedging which in turn implies it is a better hedging strategy.

## 4. Data and preliminary analysis

In order to study the volatility and the correlation spillover effects from the crude oil market to the Indian industrial sectors, we use weekly data[1] of WTI crude oil prices and six industrial sectoral indices (CNX Auto (free-float market capitalization index of 15 stocks and reflects the performance of automobiles sector)), CNX Finance (free-float market capitalization index of most liquid and large capitalized 15 stocks from the Indian financial market which includes banks, financial institutions and housing finance and other financial services companies), CNX Energy (free-float market capitalization index of 10 stocks belonging to petroleum, gas and power sub-sectors), CNX Service (free-float market capitalization index of 30 stocks which includes companies belonging to services sector like computers – software, IT education and training, banks, telecommunication services, financial institutions, power, media, courier, shipping, etc.), CNX Metal (free-float market capitalization index of 15 stocks belonging to the metal and the mining sector) and CNX Commodities (free-float market capitalization index of 30 stocks which includes firm from sectors like oil, petroleum products, cement, power, chemical, sugar, metals and mining). The data for WTI crude oil spot prices is obtained from the Energy Information Administration of America. The data for Indian sectoral indices are obtained from the web site of the National Stock Exchange (www.nseindia.com).

Table I presents the details of the sample periods for the Indian sectoral indices under study. Since our core aim is to study the volatility and correlation spillover effects from the crude oil market to the major Indian industrial sectors, the sample period of the crude oil prices correspond to the period of study for each of the sectoral indices. The weekly data are associated with Wednesday. If Wednesday is a holiday, Tuesday data points are used. We have used the sector or market name to represent the index, i.e. auto for CNX Auto, finance for CNX Finance, energy for CNX Energy, service for CNX Service, metal for CNX Metal, commodities for CNX Commodities and oil for WTI crude oil.

Table II 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 percent level of significance.

Figure 1 presents the time plots of returns and prices for all the 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.

| | Sample period | No. of observations |
|---|---|---|
| CNX Auto | Jan 7, 2004 to June 30, 2012 | 442 |
| CNX Finance | Jan 7, 2004 to June 30, 2012 | 442 |
| CNX Energy | Jan 3, 2001 to June 30, 2012 | 599 |
| CNX Service | June 2, 1999 to June 30, 2012 | 682 |
| CNX Metal | Jan 7, 2004 to June 30, 2012 | 442 |
| CNX Commodities | Jan 7, 2004 to June 30, 2012 | 442 |

**Table I.**
The sample periods for the Indian sectoral indices

| | 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 |
| SD | 3.987 | 5.136 | 4.038 | 4.895 | 5.775 | 4.354 | 5.180 |
| Minimun | −16.169 | −17.409 | −20.240 | −26.515 | −22.847 | −20.418 | −23.263 |
| Maximum | 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 |

**Notes:** SD, standard deviation of returns; ARCH-LM, the Lagrange multiplier test for conditional heteroskedasticity with 10 lags; JB Stat, the Jarque Bera statistics; $Q$(20), Ljung-Box test up to 20 lags. *,** Significant at 1 and 5 percent levels of significance, respectively

**Table II.**
Descriptive statistics of returns

## 5. Empirical results

In this section, we first report the maximum likelihood estimates of the BVGARCH 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 sectors. Finally, we estimate the optimal weights and hedge ratios for the oil-stock portfolio.

### *5.1 The BVGARCH model*

We first compare the maximum likelihood estimates of BVGARCH models with VAR(1) as a conditional mean equation and VARMA-GARCH(1, 1) as a conditional variance equation. Tables III-V report the parameter estimates and the diagnostic results of the BVGARCH model under the assumption that the error terms follow the Student's $t$-distribution ( Diag, CCC and DCC) for all the oil-stock sector pairs. The coefficient $\mu_{12}$ 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 BVGARCH 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 (Nandha and Faff, 2008).

The ARCH ($\alpha_{ii}$) coefficient which measure the short-term shock persistence and the GARCH ($\beta_{ii}$) coefficient which measures the long-term volatility persistence are important in investigating the dynamic nature of conditional volatility. Both ARCH and GARCH coefficients for the stock sectors ($\alpha_{11}$ and $\beta_{11}$, respectively) and the crude oil prices ($\alpha_{22}$ and $\beta_{22}$, respectively) are statistically significant at conventional levels of significance for all the BVGARCH models. The statistical significance of ARCH coefficients indicate that current conditional volatility of both stock and oil returns are

| | Auto and Oil | | | Finance and Oil | | |
|---|---|---|---|---|---|---|
| | Diag | CCC | DCC | Diag | CCC | DCC |
| $\mu_{10}$ | 0.450* | 0.429** | 0.441* | 0.510** | 0.493** | 0.479** |
| $\mu_{11}$ | 0.030 | 0.021 | 0.067* | −0.091*** | −0.086*** | −0.084*** |
| $\mu_{12}$ | −0.007 | −0.002 | −0.030* | 0.051 | 0.047 | 0.032 |
| $\mu_{20}$ | 0.367*** | 0.346 | 0.452* | 0.312 | 0.332 | 0.367*** |
| $\mu_{21}$ | 0.065 | 0.051 | 0.072 | 0.007 | −0.006 | −0.014 |
| $\mu_{22}$ | −0.029 | −0.029 | −0.039** | −0.011 | −0.007 | −0.024 |
| $\omega_{10}$ | 2.702** | 1.823 | 2.037* | 0.600** | 0.465 | 0.599* |
| $\omega_{20}$ | 1.122*** | 0.894 | 1.444* | 0.932*** | 0.668 | 0.262*** |
| $\alpha_{11}$ | 0.161* | 0.156* | 0.153* | 0.075* | 0.081* | 0.044* |
| $\alpha_{12}$ | 0.112*** | 0.080 | 0.168* | −0.044 | −0.053 | −0.007 |
| $\alpha_{21}$ | −0.018 | −0.036 | −0.044 | −0.042 | −0.055 | −0.061* |
| $\alpha_{22}$ | 0.098* | 0.095* | 0.115* | 0.092* | 0.086** | 0.040* |
| $\beta_{11}$ | 0.642* | 0.595* | 0.737* | 0.903* | 0.857* | 0.922* |
| $\beta_{12}$ | 27.036 | 1.352 | −0.243* | 2.885 | 0.358 | −0.847* |
| $\beta_{21}$ | −7.201 | 0.222 | 0.156** | −5.045 | 1.109 | 1.187* |
| $\beta_{22}$ | 0.860* | 0.861* | 0.815* | 0.876* | 0.748* | 0.827* |
| $v$ | 13.743* | 14.612* | 14.526** | 17.338** | 21.197*** | 17.156** |
| $\rho_{21}$ | | 0.068 | | | 0.133** | |
| $\theta_1$ | | | 0.072* | | | 0.016* |
| $\theta_2$ | | | 0.831* | | | 0.492* |
| Log L | −2510.615 | −2511.400 | −2504.542 | −2610.283 | −2604.360 | −2603.886 |
| SIC | 11.559 | 11.543 | 11.516 | 12.061 | 11.970 | 11.954 |
| $\text{JBStat}_1$ | 50.956* | 55.375* | 34.650* | 20.077* | 16.802* | 29.602* |
| $Q(20)_1$ | 14.897 | 14.734 | 15.001 | 19.933 | 19.888 | 19.318 |
| $Qs(20)_1$ | 8.812 | 8.106 | 8.925 | 20.809 | 22.786 | 17.724 |
| $\text{ARCH}(10)_1$ | 0.482 | 0.390 | 0.480 | 1.103 | 1.203 | 1.046 |
| $\text{JBStat}_2$ | 1.574 | 1.868 | 2.051 | 1.813 | 1.439 | 1.465 |
| $Q(20)_2$ | 28.197 | 28.816*** | 26.753 | 28.753*** | 28.706*** | 28.401 |
| $Qs(20)_2$ | 16.083 | 16.463 | 14.689 | 16.936 | 17.713 | 19.460 |
| $\text{ARCH}(10)_2$ | 0.609 | 0.647 | 0.506 | 0.705 | 0.660 | 0.698 |

**Notes:** Subscript 1 represents stock and subscript 2 represents oil. *,**,*** Significant at 1, 5 and 10 percent levels of significance, respectively

**Table III.** Parameter estimates of BVGARCH models for auto and oil and finance and oil

affected by their own past shocks which affect the dynamics in returns, as well. The values of ARCH coefficients are smaller than the corresponding values of GARCH coefficients indicating that long-run persistence in the sector stock indices and oil is higher than the short-run persistence.

For the diagonal BVGARCH model, we observe significant short-run volatility spillover from the oil market to only the automobile sector ($\alpha_{12}$). Moreover, we do not find any significant long-run persistence volatility spillover from the oil market to other sector stocks. On the other hand, for the CCC-GARCH model, we do not find any significant short-run or long-run persistence volatility spillover from the crude oil market to any of the Indian industrial sectors. However, we observe significant positive conditional correlation ($\rho_{21}$) between the crude oil market and stock sectors, such as the financial sector, energy sector, metal and mining sector and the commodities market. We also observe negative CCC between oil and service sector.

The highest value of log-likelihood function and lowest value of SIC for DCC-GARCH model indicates that the DCC-GARCH model outperforms the other

| | Energy and Oil | | | Service and Oil | | |
|---|---|---|---|---|---|---|
| | Diag | CCC | DCC | Diag | CCC | DCC |
| $\mu_{10}$ | 0.396* | 0.396* | 0.359* | 0.416* | 0.426* | 0.414* |
| $\mu_{11}$ | 0.025 | 0.027 | 0.042 | −0.019 | −0.015 | −0.006 |
| $\mu_{12}$ | 0.012 | 0.011 | 0.012 | 0.041 | 0.039 | 0.039 |
| $\mu_{20}$ | 0.325*** | 0.316*** | 0.320*** | 0.362*** | 0.371** | 0.331*** |
| $\mu_{21}$ | 0.090*** | 0.074 | 0.085** | 0.089** | 0.085** | 0.089** |
| $\mu_{22}$ | −0.024 | −0.023 | −0.033 | −0.014 | −0.013 | −0.010 |
| $\omega_{10}$ | 0.793** | 0.251 | 0.889* | 0.493** | 0.424*** | 0.334* |
| $\omega_{20}$ | 1.257*** | 0.739 | 1.563* | 1.061*** | 1.000 | 1.059* |
| $\alpha_{11}$ | 0.139* | 0.142* | 0.133* | 0.104* | 0.106* | 0.113* |
| $\alpha_{12}$ | 0.018 | −0.007 | 0.061** | −0.036 | −0.040 | −0.065* |
| $\alpha_{21}$ | 0.000 | −0.023 | 0.023 | −0.032 | −0.006 | −0.044 |
| $\alpha_{22}$ | 0.074* | 0.066* | 0.074* | 0.068* | 0.058** | 0.062* |
| $\beta_{11}$ | 0.807* | 0.745* | 0.824* | 0.876* | 0.867* | 0.838* |
| $\beta_{12}$ | 4.545*** | 0.529 | −0.114* | 4.483 | −2.057 | 0.597* |
| $\beta_{21}$ | 6.100 | 0.386 | 0.007 | −9.810 | −10.971 | 1.589* |
| $\beta_{22}$ | 0.877* | 0.864* | 0.863* | 0.893* | 0.854* | 0.814* |
| $v$ | 8.292* | 8.827* | 8.899* | 12.491* | 12.587* | 12.737* |
| $\rho_{21}$ | | 0.151* | | | −0.005 | |
| $\theta_1$ | | | 0.092* | | | 0.018* |
| $\theta_2$ | | | 0.736* | | | 0.480** |
| Log L | −3404.981 | −3397.450 | −3396.076 | −3979.262 | −3976.866 | −3972.948 |
| SIC | 11.503 | 11.484 | 11.477 | 11.948 | 11.793 | 11.707 |
| $JBStat_1$ | 273.950* | 189.170* | 258.810* | 73.293* | 70.576* | 69.355* |
| $Q(20)_1$ | 36.507** | 35.731** | 37.171** | 27.519 | 27.446 | 27.136 |
| $Qs(20)_1$ | 10.705 | 11.010 | 10.595 | 10.086 | 10.122 | 10.633 |
| $ARCH(10)_1$ | 0.410 | 0.438 | 0.381 | 0.449 | 0.455 | 0.479 |
| $JBStat_2$ | 70.119* | 92.056* | 71.038* | 52.247* | 66.440* | 73.210* |
| $Q(20)_2$ | 28.270 | 27.456 | 27.715 | 32.031** | 31.228*** | 31.123*** |
| $Qs(20)_2$ | 10.317 | 9.857 | 11.050 | 11.907 | 10.939 | 12.093 |
| $ARCH(10)_2$ | 0.282 | 0.272 | 0.311 | 0.394 | 0.346 | 0.370 |

**Notes:** Subscript 1 represents stock and subscript 2 represents oil. *,**,*** Significant at 1, 5 and 10 percent levels of significance, respectively

**Table IV.**
Parameter estimates of BVGARCH models for energy and oil and service and oil

BVGARCH model in capturing the cross-sectional dynamics in volatility between the oil market and stock sector returns (Arouri *et al.*, 2011; Sadorsky, 2012). 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. These findings are not surprising because the energy sector contains firms from the petroleum, gas and power sub-sectors that mainly depend on crude oil byproducts for their operations. At the same time, changes in crude oil prices may also affect the consumer demand for automobiles. This indicates that short-term volatility shocks in the crude oil 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). 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. These findings are also expected, because

| | Metal and Oil | | | Commodities and Oil | | |
|---|---|---|---|---|---|---|
| | Diag | CCC | DCC | Diag | CCC | DCC |
| $\mu_{10}$ | 0.340 | 0.361 | 0.321 | 0.445* | 0.421** | 0.382* |
| $\mu_{11}$ | 0.052 | 0.062 | 0.065 | 0.035 | 0.041 | 0.047 |
| $\mu_{12}$ | 0.108** | 0.102*** | 0.109** | 0.026 | 0.027 | 0.033 |
| $\mu_{20}$ | 0.344*** | 0.352*** | 0.354*** | 0.365*** | 0.374*** | 0.361*** |
| $\mu_{21}$ | 0.061 | 0.060 | 0.059*** | 0.069 | 0.050 | 0.053 |
| $\mu_{22}$ | −0.038 | −0.038 | −0.041 | −0.033 | −0.035 | −0.037 |
| $\omega_{10}$ | 1.388 | 0.980 | 0.842* | 1.236* | 0.654 | 0.681* |
| $\omega_{20}$ | 1.190 | 0.709 | 0.751* | 1.128*** | 0.646 | 0.714* |
| $\alpha_{11}$ | 0.080*** | 0.113** | 0.129* | 0.238* | 0.236* | 0.242* |
| $\alpha_{12}$ | 0.039 | −0.003 | −0.055 | 0.034 | 0.010 | −0.022 |
| $\alpha_{21}$ | −0.015 | −0.034 | −0.047** | −0.014 | −0.037 | −0.059** |
| $\alpha_{22}$ | 0.110** | 0.116* | 0.122* | 0.106* | 0.096* | 0.102* |
| $\beta_{11}$ | 0.862* | 0.744* | 0.700* | 0.692* | 0.654* | 0.651* |
| $\beta_{12}$ | 4.847 | 0.441 | 0.663* | 16.449 | 0.338 | 0.362* |
| $\beta_{21}$ | −1.675 | 0.215 | 0.244* | −3.217 | 0.284 | 0.319* |
| $\beta_{22}$ | 0.851* | 0.802* | 0.794* | 0.855* | 0.836* | 0.828* |
| $v$ | 9.594* | 10.570* | 10.692* | 11.681* | 12.766* | 13.295** |
| $\rho_{21}$ | | 0.287* | | | 0.214* | |
| $\theta_1$ | | | 0.058* | | | 0.070* |
| $\theta_2$ | | | 0.351* | | | 0.338* |
| Log L | −2672.760 | −2655.434 | −2654.241 | −2525.669 | −2517.623 | −2515.947 |
| SIC | 12.205 | 12.201 | 12.119 | 11.616 | 11.566 | 11.540 |
| $\text{JBStat}_1$ | 151.480* | 248.300* | 273.590* | 33.278* | 36.936* | 36.417* |
| $Q(20)_1$ | 20.514 | 19.660 | 19.718 | 30.880*** | 29.696*** | 29.630*** |
| $Qs(20)_1$ | 10.035 | 8.603 | 8.662 | 12.744 | 13.279 | 13.805 |
| $\text{ARCH}(10)_1$ | 0.373 | 0.361 | 0.374 | 0.524 | 0.561 | 0.618 |
| $\text{JBStat}_2$ | 1.965 | 2.562 | 2.550 | 1.535 | 2.005 | 1.853 |
| $Q(20)_2$ | 27.411 | 27.083 | 26.541 | 27.816 | 28.212 | 27.351 |
| $Qs(20)_2$ | 16.474 | 17.741 | 17.096 | 15.904 | 17.010 | 16.455 |
| $\text{ARCH}(10)_2$ | 0.618 | 0.655 | 0.594 | 0.575 | 0.615 | 0.543 |

**Notes:** Subscript 1 represents stock and subscript 2 represents oil. *,**,*** Significant at 1, 5 and 10 percent levels of significance, respectively

**Table V.** Parameter estimates of BVGARCH models for metal and oil

changing crude oil prices are likely to influence the sentiment of investors which in turn may influence their decisions to invest in financial products. 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. The byproducts of crude oil are major inputs to most of the industries of metal and mining sector, energy sector, commodities sector and some industries in the service sector and hence changes in crude oil prices may impact the volatility dynamics in these sectors. The estimated coefficients $\theta_1$ and $\theta_2$ for DCC model are positive and statistically significant for all the cases at 1 percent level of significance. In addition, the $(\theta_1 + \theta_2) < 1$, 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 ($v$) indicates that the

BVGARCH model under the Student's $t$-distribution capture the leptokurtic behaviur of the estimated residuals. The insignificant values of $Q(20)$ and $Q$'s(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 percent level of significance. The insignificant value of the ARCH-LM statistic up to ten lags indicates that the DCC-GARCH model is also able to capture the heteroskedasticity in the series.

### *5.2 Time varying conditional correlation*

Figure 2 presents the time-varying DCC 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. For the automobile sector and oil pair, we find

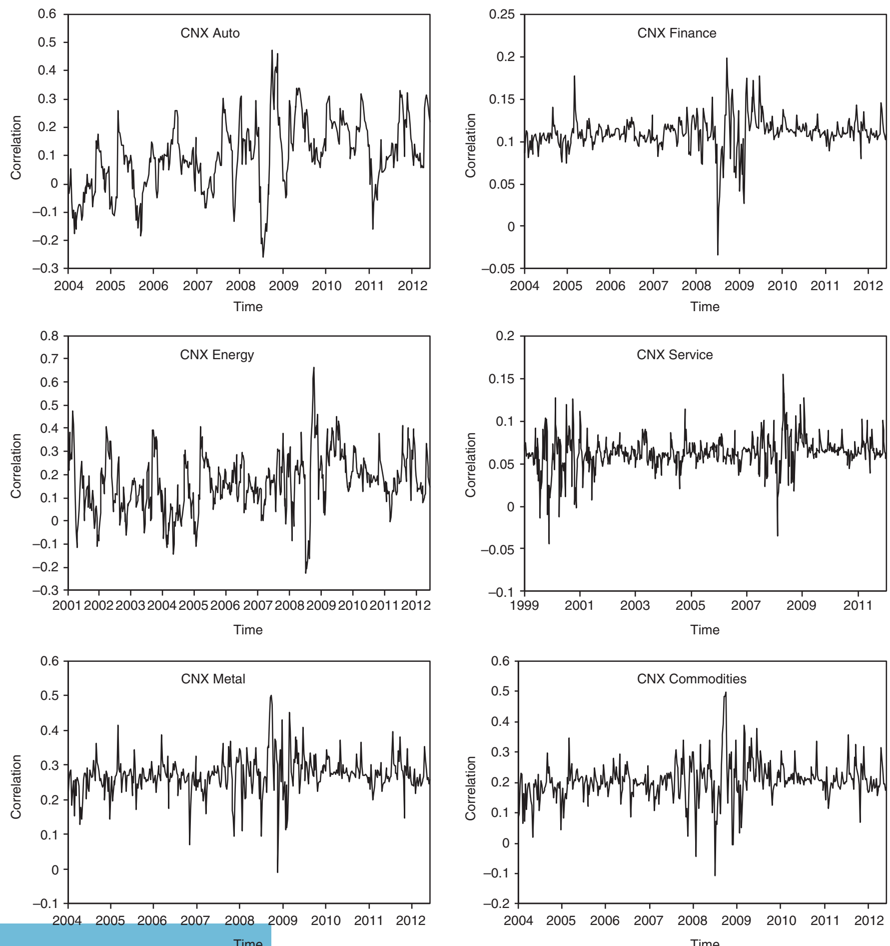


**Figure 2.**
Time varying conditional correlations estimated using DCC bivariate GARCH model

negative conditional correlation for most of the time, which confirms that automobile sectoral returns and crude oil returns are negatively related.

### *5.3 Hedge 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. 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).

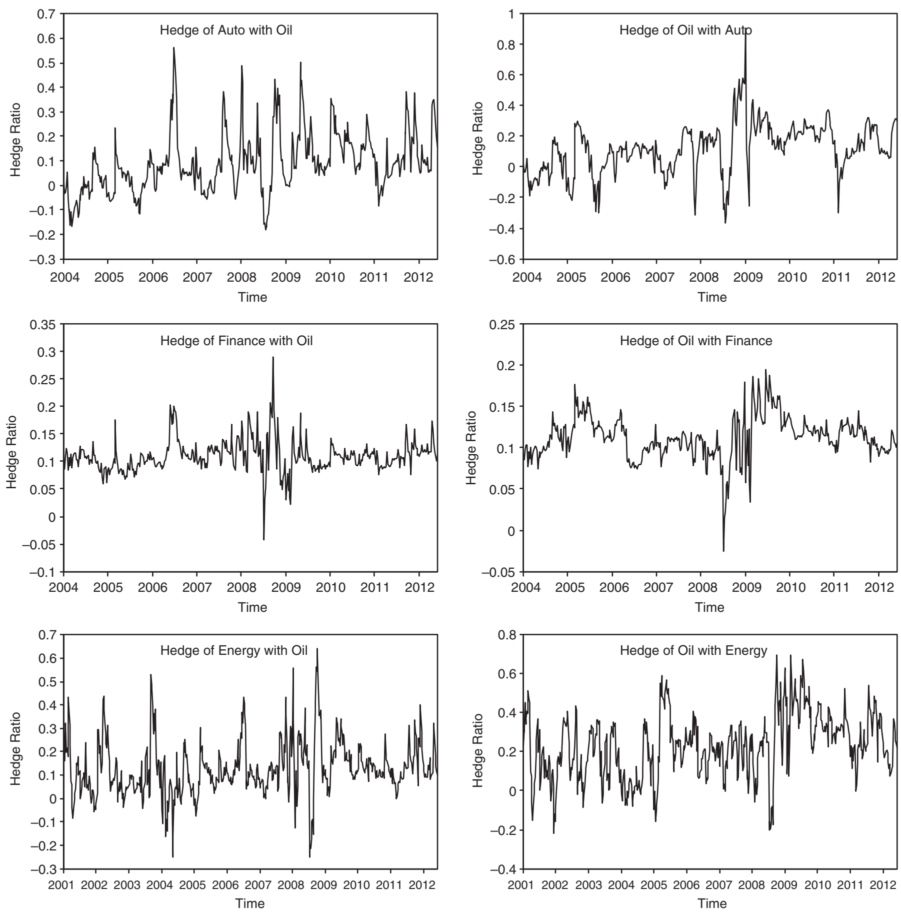


**Figure 3.**
Time varying hedge ratios estimated using DCC model

*(continued)*

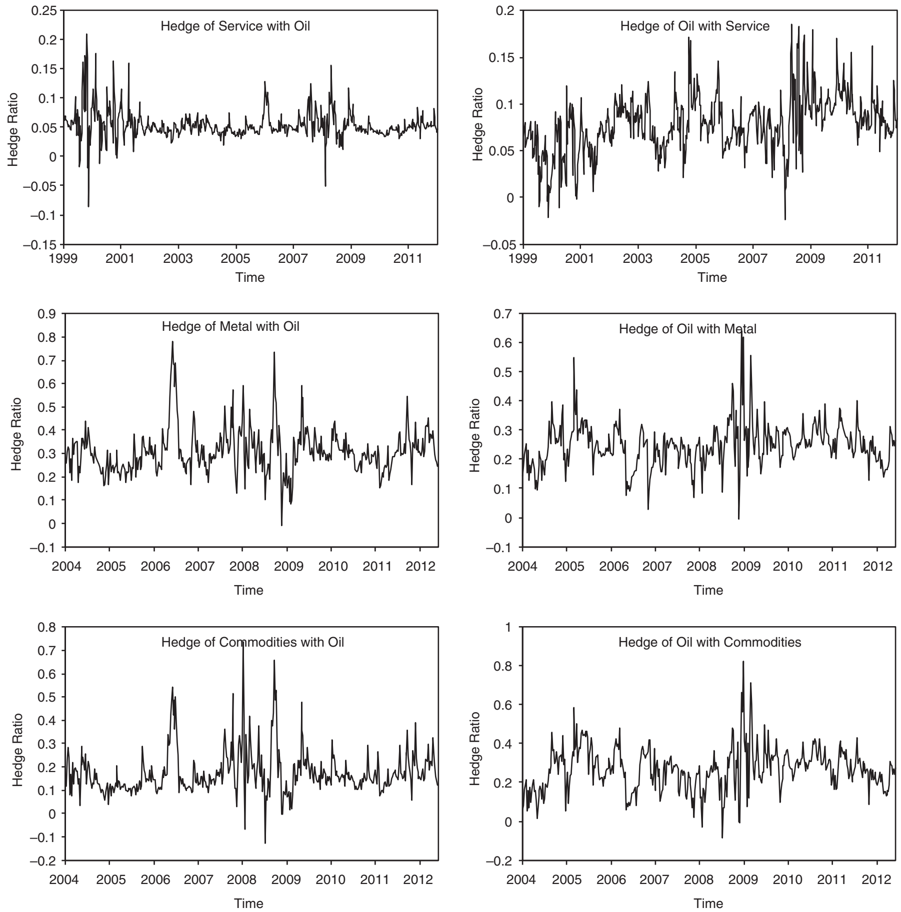


**Figure 3.**

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).

Table VI presents the summary statistics of the hedge ratios for all stock/oil and oil/stock pairs. The average value of the hedge ratio for the auto-oil pair is 0.092 which indicates that a \$1 long position in automobile sector stocks can be hedged with 9.2 percent of a short position in the crude oil market stocks. Similarly for the other cases also, a \$1 position in the first asset can be hedged with the average value of the hedge ratio percentage of a short position in the second asset. The cheapest hedge (the lowest value of the hedge ratio) among all the cases is to go long \$1 in the service sector stocks and go short 5.4 cents in oil and the most expensive hedge (the highest value of the hedge ratio) can be observed by going long \$1 in metal sector stocks and shorting 31 cents of oil.

*5.4 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

| | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| Auto/Oil | 0.092 | 0.075 | 0.125 | −0.181 | 0.565 |
| Finance/Oil | 0.110 | 0.107 | 0.029 | −0.043 | 0.291 |
| Energy/Oil | 0.129 | 0.238 | 0.117 | −0.252 | 0.640 |
| Service/Oil | 0.054 | 0.078 | 0.024 | −0.087 | 0.210 |
| Metal/Oil | 0.310 | 0.299 | 0.096 | −0.009 | 0.780 |
| Commodities/Oil | 0.174 | 0.152 | 0.093 | −0.128 | 0.736 |
| Oil/Auto | 0.118 | 0.123 | 0.161 | −0.366 | 0.907 |
| Oil/Finance | 0.113 | 0.112 | 0.025 | −0.026 | 0.195 |
| Oil/Energy | 0.232 | 0.688 | 0.164 | −0.222 | 0.699 |
| Oil/Service | 0.078 | 0.601 | 0.030 | −0.024 | 0.185 |
| Oil/Metal | 0.248 | 0.248 | 0.074 | −0.007 | 0.641 |
| Oil/Commodities | 0.268 | 0.269 | 0.110 | −0.088 | 0.822 |

**Table VI.** Summary statistics of the hedge ratio (long/short)

suggested by Kroner and Ng (1998) using Equations (8) and (9). Table VII 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 1 represent the percentage of unit weight to be invested in stocks. The optimal average weight for oil ranges from 34.3 percent (energy) to 57 percent (metal).

*5.5 HE*

Table VIII reports the unhedged portfolio variance, hedged portfolio variance and HE ratios based on Equation (10) for the whole sample data, and also for the in-sample and out-of-sample data. The out-of-sample analysis deals with the last 100 observations (from August 4, 2010 to June 27, 2012) of the data set. The dynamic weights for the constituents of the portfolio for the in-sample and out-of-sample analysis are obtained from Equations (8) and (9). The results indicate that including crude oil in a portfolio as a part of the hedging strategy significantly reduces portfolio risk. It can be seen that the HE due to the introduction of crude oil in an optimal portfolio ranges from 31.6 percent for the energy sector to 48.6 percent for the services sector for the whole sample. On the other hand, for the in-sample optimal portfolio, the HE ranges from 32.8 percent for the energy sector to 50.3 percent for the services sector. The HE over the out-of-sample period is lower when compared to the respective in-sample value but high enough to recommend going with the stock-oil portfolio. The HE over the out-of-sample period ranges from 17.7 percent for the services sector to 38.8 percent for the metal and mining sector. In addition, we find a significant variance reduction across all the sectors for the whole sample, as well as in the in-sample and out-of-sample analysis.

| | Mean | Median | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| 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 VII.** Summary statistics of portfolio weights for pairs of oil and stock sectors

| | Auto | Finance | Energy | Service | Metal | Commodities |
|---|---|---|---|---|---|---|
| *Whole sample* | | | | | | |
| $\text{Variance}_{\text{Unhedged}}$ | 15.570 | 26.082 | 16.309 | 23.980 | 33.230 | 18.677 |
| $\text{Variance}_{\text{Hedged}}$ | 10.164 | 14.357 | 11.150 | 12.338 | 17.872 | 12.061 |
| HE | 0.347 | 0.450 | 0.316 | 0.486 | 0.462 | 0.354 |
| *In-sample* | | | | | | |
| $\text{Variance}_{\text{Unhedged}}$ | 17.095 | 29.432 | 17.897 | 26.574 | 37.545 | 21.236 |
| $\text{Variance}_{\text{Hedged}}$ | 10.730 | 15.863 | 12.029 | 13.199 | 19.834 | 13.283 |
| HE | 0.372 | 0.461 | 0.328 | 0.503 | 0.472 | 0.374 |
| *Out-of-sample* | | | | | | |
| $\text{Variance}_{\text{Unhedged}}$ | 10.442 | 14.726 | 8.142 | 8.928 | 18.176 | 9.825 |
| $\text{Variance}_{\text{Hedged}}$ | 8.255 | 9.281 | 6.639 | 7.350 | 11.126 | 7.852 |
| HE | 0.209 | 0.370 | 0.185 | 0.177 | 0.388 | 0.201 |

**Note:** HE is the hedging effectiveness

**Table VIII.**
Hedging effectiveness

## 6. Discussion of results

Our findings suggest that past own short-run shocks and long-run volatility significantly impact the future volatility of the oil market and the Indian industrial sectors. Our results also indicate significant negative return spillover from the oil market to the automobile sector, positive return spillover from the oil market to the metal and mining sector. We find a negative short-run shock spillover from the oil market to the service sector and a positive short-run shock spillover from the oil market to the automobile sector and the energy sector. Our findings also indicate significant negative long-run volatility spillover effects from the crude oil market to the automobile sector, the financial sector and the energy sector and positive long-run volatility spillover effects from the crude oil market to the service sector, metal and mining sector and the commodities market. Our findings are consistent with the finding of Nandha and Faff (2008), Hammoudeh *et al.* (2009), Arouri *et al.* (2011, 2012). Our findings of a spillover effect from the oil market to the automobile sector are different from what was found by Arouri *et al.* (2011) for the European automobile sector. The reason for this difference is that there exists legislation in Europe governing the automobile sector which encourages the use of fuel efficient vehicles and the effective management of oil price risk by companies in the automobile industry in Europe.

The study of time varying conditional correlation and risk minimizing hedge ratios indicates a wide variation in the conditional correlation and risk minimizing hedge ratios between crude oil and stock sector pairs. We observe fluctuations over a wide range in the values of conditional correlation varying from extreme positive to extreme negative during the period of the global financial crisis (2008-2009) for all the stock-oil pairs. The results also provide evidence of considerable variability of the hedge ratios during the period of the dot-com bubble crisis (1999-2000) and the global financial crisis (2008-2009) for all the cases under study. These findings are in confirmation with the findings of Sadorsky (2012) who also observes a wide variation in the conditional correlation and hedge ratios during the crisis period.

Although it is true that the HE over the out-of-sample period is lower when compared to the respective in-sample value, it is high enough to recommend going with the stock-oil portfolio. In addition, we find a significant variance reduction across all the sectors for the whole sample, as well as in the in-sample and out-of-sample analysis. Moreover, we find that allowing for DCC helps significantly in terms of improving the HE of the stock-oil portfolios.

## 7. Conclusion

Based on the empirical analysis undertaken in this paper, we have examined the return and volatility spillover between the crude oil market and the Indian industrial sectors using BVGARCH models (Diag, CCC and DCC) with the VAR(1) model as a conditional mean equation and the 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 the DCC-BVGARCH model outperforms 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 metal and mining sector and 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 DCC 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 (2008-2009). The DCCs between crude oil and the Indian energy sector 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. In particular, allowing for DCCs can help substantially in improving HE.

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, 11, 12.9, 5.4 , 31 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.

Our findings indicate that crude oil exhibits the characteristics of a valuable asset class, the inclusion of which in a portfolio can improve its risk-adjusted performance. This may be relevant for implementing trading strategies and in the evaluation of investment and asset allocation decisions by portfolio managers, financial analysts and institutional investors such as pension funds.

### Note

1. Because daily observations may be associated with the biases due to non-trading, the bid-ask spread, asynchronous prices (Lo and MacKinlay, 1988).

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**Corresponding author**
Dilip Kumar can be contacted at: dksic212@gmail.com or dilip.kumar@ifmr.ac.in