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Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models

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ABSTRACT

Objective of this study is to empirically investigate the time varying co-movements between crude oil and Indian stock market returns both at aggregate and sector level. This study uses weekly closing prices for Brent Crude, BSE-Sensex and seven sector indices of Bombay Stock Exchange namely Automotive, Energy, Financial, Industrial, Metal, Oil & Gas and Power as data input. The data span of this study runs from January 1, 2006 to Feb 28, 2015, which encompasses the booming, recessionary and the recovering phase of global as well as Indian economy. The paper deploys VAR-DCC-GARCH framework. Three versions of GARCH namely standard, threshold and exponential and both symmetric and asymmetric versions of dynamic contemporaneous correlations have been used. Results of the study indicate that direct volatility spill over from oil market to Indian stock market is not significant at the aggregate level; however, it is significant in case of auto, power and finance sector. Parameter of dynamic correlations and volatility were significant thereby providing empirical evidence of the time varying differential dependence of Indian stock sector indices on oil price fluctuations. Outcomes of this study highlights that investors attempting to diversify their investments should always consider dynamic volatility and correlation linkages so as to maximize returns and minimize risk.

1. Introduction

Commonly referred as “Black Gold” – Crude Oil is probably the most essential natural resource and commodity. In June 2015, India became the world's third largest importer (according to EIA) of crude oil edging out Japan. It is a critical input to modern industry and owing to its volatility; Indian economy is deeply impacted. According to recent estimate by Central Bank of India, every 10 dollar per barrel drop in price of crude oil will improve India's annual current account balance by around USD 9 billion or 0.5% of GDP.

In a similar way, stock markets of a country are an integral part of the dynamics of economic activity. They are usually considered as an indicator of country's social mood, economic strength and development (Hamilton, 1983, 1996, 2004; Kilian, 2009; Mork et al., 1994). India being emerging economy is always a favorite destination for investment and so are its stock markets, especially post-recession. These markets present investors opportunity to diversify invest across various sectors ranging from consumer durables to metals.

Indian markets seem to share a deep nexus with international crude oil. Nearly all industries, consume oil as a natural resource in some way or the other. From the industries' perspective, it is expected that high oil prices lead to increase in the overall costs of goods, causing their profits to plunge which in turn will impact its performance in the stock market. From the investors' perspective, increasing oil prices leads to rise in inflation due to which Central Bank hikes the interest rate, leading to a shift in the investment from stock markets.

In spite of the fact that stock market, crude oil and their interactions play a significant role in shaping the economy, there are a limited number of studies (Maghyereh,2004; Gay, 2011; Bhar and Nikolova, 2009; Ono, 2011; Wang et.al, 2013) on the subject specifically in Indian context. Studies mentioned above focus largely on emerging markets as a whole and they also overlook volatility linkages.

Recently, there is a study by Jain and Biswal (2016) that investigated the dynamic linkages between crude oil and stock markets in Indian context and found significant results. However the limitation of that study is that it had considered volatility transmissions at market level and not at sector level. Different sectors of the economy might respond differently to crude oil price shocks depending upon whether oil and related products are an input or an output for that sector. For firms whose output is oil, an oil price rise will leads to increase in cash flows, while for those firms that use oil as an input, cash flows will fall. Therefore understanding the dynamics of time varying volatility between crude oil and different industries is very important as it helps in better understanding of investors related to portfolio diversification,

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hedging and better risk management practices.

Therefore, this study attempts to fill this gap and examines the time varying volatility linkage and dynamic correlation between oil returns and Indian sector stock returns. For this purpose the study uses Vector Auto Regression-Dynamic Conditional Correlation-Generalised Autoregressive Conditional Heteroskedasticity (VAR-DCC-GARCH) framework.

The remainder of the paper is organized as follows:Section 2 presents the related review of literature, Section 3 presents the empirical model used, Section 4 presents data and preliminary analysis, Section 5 highlights empirical findings and finally Section 6 concludes.

2. Literature review

Over the past two decades, there is a growing body of literature investigating the relationship between crude price and stock market movement. As mentioned by Arouri et al. (2012), initial studies in this domain tend to investigate the impact of crude price movements on macro economy. The seminal study in this area was done by Hamilton (1983) who investigated the impact of crude oil price shocks on Gross National Product. Following this, a number of researchers (Mork et al.,1994; Huang et al.,1996; Bernanke et al.,1997; Sadorsky, 1999; Brown and Yücel, 2002; Hamilton and Herrera, 2004; Barsky and Kilian, 2004; Blanchard and Gali, 2007; Apergis and Miller, 2009; Jbir and Zouari-Ghorbel, 2009; Tang et al, 2010; Chen et al., 2014) have examined the impact of oil price shocks on various macro economic factors (economic growth, inflation rate, interest rates, monetary policy, output, price level, unemployment and real investment) and favors the opinion that oil prices exert a significant impact on economic variables.

Macroeconomic variables of a country affect the investors' sentiment, determine their consumption and investment pattern and, thus, expected to affect stock market movements. Therefore the literature investigating the relationship between oil price and stock market returns have started emerging. The earlier study in this regard was done by Kaul & Jones (1996), who examined the impact of crude oil price changes on the stock market returns of Canada, the United States (US), the United Kingdom (UK) and Japan and concluded that stock market returns in these countries responds negatively to oil price changes. In the same year, another study was done by Huang et al. (1996) on US markets and they refuted the above argument and concluded that there is no link between oil prices and stock returns. Sadorsky (1999) reveals the negative association between oil prices and stock returns by using a VAR model. Thereafter, a number of researchers tried to examine this nexus under different settings by following different methodological approaches and varied proxies for oil price and stock returns so as to offer robust explanations for the relationship. The literature in this area could broadly be categorized under following clusters.

First set of studies are there which concluded that there is a negative relationship between oil prices and stock market returns (Gjerde and Sættem,1999; Papapetrou, 2001; Ciner, 2001; Sadorsky, 2001; Kilian and Park, 2009; Hammoudeh and Li, 2005; Ghouri, 2006; Miller and Ratti, 2009; Aloui and Jammazi, 2009; Chen, 2010; Basher and Sadorsky, 2006; Hammoudeh and Choi, 2007; Nandha and Hammoudeh, 2007; O'Neill et al., 2008; Lee and Chiou, 2011; Asteriou and Bashmakova, 2013; Cunado and Perez de Gracia, 2014 and Filis and Chatziantoniou, 2014). The justification provided by these researchers is that rising oil prices will increase the production cost, which in turn directly affect the cash flows of a company and hence its stock prices. Indirectly also rising oil price will increases inflation in a country, which is controlled by central banks by increasing interest rate and these increased interest rates are then used to discount the future cash flows of a company due to which the value of its stock decreases. Second set of studies establish a positive link between oil prices and stock returns (Chen et al., 1986; Faff and Brailsford, 1999; Sadorsky, 2001; Jimenez-Rodriguez and Sanchez, 2005; El-Sharif et al., 2005; Park and Ratti, 2008; Bjornland, 2009; Narayan and Narayan, 2010; Arouri and Rault, 2012). These studies were done mainly in context of oil exporting countries. The justification provided by these studies is that as the oil price increases, the revenues of oil exporting country will increase which, in turn, leads to high expenditure and investment, increased productivity, positive investor's sentiment and a bullish trend in stock market. In contrast to the above two sets, there is third set which concluded that there is no relationship between oil price and stock market movements (Jammazi and Aloui, 2010, 2008).

Additionally, there are another set of researchers who believe that the impact of oil prices on different sectors must depend upon whether that sector consumes oil or is a producer of oil and therefore they investigated the impact of oil prices on different sectors rather than aggregate stock market (Degiannakis et al., 2013; Scholtens and Yurtsever, 2012; Arouri, 2012; Broadstock et al., 2012; Narayan and Sharma, 2011; Arouri and Nguyen, 2010). Study done by Nandha and Faff (2008) on relationship between oil prices and thirty-five global industries concluded that the rise of oil prices has a negative impact on industries other than oil and gas. Nandha and Brooks (2009) also investigated the response of transportation sector returns from oil price change and found positive impact on European countries. However, Hammoudeh and Li (2005) and Nandha and Brooks (2009) establish that this effect is insignificant in case of US and Asian and Latin American countries. In context of Australian markets Faff and Brailsford (1999) find that oil prices have a positive impact on energy related industries and a negative impact on paper, packaging and transportation industries while Ratti and Hasan (2013) found significant impact on most sectors. Elyasiani et al. (2011) divides stock returns of thirteen US industries in four categories and found direct effect of oil price movements on oil-related and oil-substitute industries while indirect effect was found for the oil-users and financial industries.

Majority of these studies mentioned above have been conducted on developed countries and very few studies have been done in the context of oil importing developing countries. Gencer and Demiralay (2013) study the impact of oil price change on 18 selected sub-sector indices from Borsa Istanbul for the period between January 2002 and April 2013 by using multivariate GARCH (MGARCH) model. The results of the study suggest uni-directional volatility spill over from oil market to four out of eighteen sectors. Broadstock and Filis (2014) found insignificant effect of oil price change on Chinese stock returns, which indicates that China's stock market is insulated from international crude oil price movements.

So far as India is concerned, despite being a major oil importing developing country, this aspect of time varying volatility linkages between crude oil price stock market returns at aggregate and sector level remain unaddressed. Current study tries to fill this gap.

As far time series techniques are concerned, majority of the studies mentioned above have employed vector auto-regression (VAR), Cointegration, univariate and/or multivariate GARCH framework. Cointegration and VAR framework although examine the long run and short term association but ignores time varying volatility transmission among the variables. ARCH and GARCH class of models proposed by Bollerslev (1986) were among the major tools to capture this volatility transmission. But these were univariate in nature and in order to understand the volatility transmission among multiple asset classes, multivariate GARCH (MGARCH) model proposed by Engle (2002) is becoming increasingly popular in empirical research. However, one of the major limitations of MGARCH model is that it assumes the conditional correlation among various assets to be constant or time invariant. Some recent studies (Guesmi and Fattoum, 2014; Creti et al., 2013, 2014) pointed the limitations of considering co movement of stock market and oil price in a static manner. They concluded that the co-movement between crude oil and equity market is time varying in nature and therefore uses time varying multivariate DCC GARCH approach. In context of oil importing developing countries recently Bouri (2015) and Lin et al. (2014) examines the return and volatility linkages in case of Lebanon and Ghana stock market by using the recently developed VAR DCC GARCH models and found unidirectional volatility transmission from oil prices to these stock markets and these effects peaked during the crisis period and then ceased afterwards. However in Indian context no study has been done that considers the time varying dynamic co movement of aggregate stock market and different sectors with respect to oil price returns.

3. Material and methods

In this study the returns are first modeled in a vector auto regression framework (VAR) framework and then DCC GARCH has been used to estimate the time varying correlations. VAR modeling is done so that the residual after GARCH estimation reaches white noise.

In order to capture volatility transmission among financial markets, multivariate GARCH models (BEKK and VEC) proposed by (Baba et al.,1991; Engle and Kroner, 1995) are the prevailing methods which can efficiently estimate the conditional correlation between financial assets. However the number of parameters to be estimated in case of multivariate GARCH is large and rises exponentially with the rise in number of assets. Engle et al. (1990) and Bollerslev (1990) introduced the Constant Conditional Correlation (CCC) – GARCH model, which assumes all conditional correlations to be constant to produce a more parsimonious procedure. However, it is possible that the conditional correlations vary over time as they are updated by the conditional volatility. To solve the problem of increased dimensionality problem of the multivariate GARCH as well as the constant correlation problem of the CCC model, Engle and Sheppard (2001) introduced the Dynamic Conditional Correlation (DCC)-GARCH model, which relaxes the constant correlation assumption and allow for the time-varying correlation. In DCC-GARCH model the number of parameters to be estimated increases linearly rather than exponentially, as in case of multivariate GARCH, thereby solving the issue of dimensionality. Cappiello et al. (2006) introduced the asymmetric version of DCC GARCH so as to address the impact of asymmetric information on the time varying correlations. In this study six version of DCC GARCH (three symmetric and three asymmetric) has been used and therefore each bivariate system is modeled and estimated in six ways: VAR-DCC-GARCH, VAR-DCC-GJR/TGARCH, VAR-DCC-EGARCH, VAR-ADCC-GARCH, VAR-ADCC-GJR/TGARCH, and VAR-ADCC-EGARCH.

A bi-variate VAR of order (p) can be represented by

$$X_{s,t} = C_1 + \mu^{s}_{1,1} X_{s(t-1)} + \mu^{s}_{1,2} X_{s(t-2)} + \ldots\ldots..+\mu^{s}_{1,p} X_{s(t-p)} + \mu^{\circ}_{1,1} OIL_{(t-1)} + \mu^{\circ}_{1,2} OIL_{(t-2)} + \ldots\ldots..+ \mu^{\circ}_{1,p} OIL_{(t-p)} + \varepsilon_{s,t} \quad (1)$$

$$OIL_t = C_2 + \; + \mu^{\circ}_{2,1} OIL_{(t-1)} + \mu^{o}_{2,2} OIL_{(t-2)} + \ldots\ldots..+ \mu^{o}_{2,p} OIL_{(t-p)} + \mu^{\circ}_{2,1} X_{s(t-1)} + \mu^{\circ}_{2,2} X_{s(t-2)} + \ldots\ldots..+\mu^{o}_{2,p} X_{s(t-p)} + \varepsilon_{o,t} \quad (2)$$

Here, $X_{s,t}$ and OIL_t represent returns on stock sector and oil price index respectively and $X_{s,t-i}$ *and* OIL_{t-i}, (where i=1, 2,..., p) are lagged dependent variables for stock sector and oil returns. $\varepsilon_{o,t}$ and $\varepsilon_{s,t}$ are the residual terms of the VAR (p) model for oil and stock sector returns respectively.

In the present study, we use the Akaike's information criterion (AIC) in order to determine the optimal lag length (p) of the model. After estimating VAR (p) model, the residuals have been collected for further DCC GARCH modeling. In the first step, residuals are De-GARCHED in three ways (standard, threshold and exponential). In the second step time varying correlations were estimated by relying on lagged values of residuals and covariance matrices. In the present study both symmetric and asymmetric version (DCCGARCH (Engle, 2002) and ADCC GARCH (Cappiello et al., 2006) of modeling time varying correlations has been used.

The Covariance matrix in DCC GARCH (Engle, 2002) has been defined as

$$H_t = D_t R_t D_t \quad (3)$$

H_t is the conditional covariance matrix.

D_t is the k×k diagonal matrix of time varying standard deviations from univariate GARCH models with $(\sigma^2_{i,t})^{1/2}$ on the *i*th diagonal

$$Dt = \begin{bmatrix} \sqrt{\sigma^2_{o,t}} & 0 \\ 0 & \sqrt{\sigma^2_{s,t}} \end{bmatrix} \quad (4)$$

Rt is the time varying correlation matrix.

$$Rt = \begin{bmatrix} \varepsilon_{oo,t} & \varepsilon_{os,t} \\ \varepsilon_{so,t} & \varepsilon_{ss,t} \end{bmatrix} = \begin{bmatrix} 1 & \varepsilon_{os,t} \\ \varepsilon_{so,t} & 1 \end{bmatrix} \quad (5)$$

Further R has to be definite positive and all the parameters should be equal to or less than one. In order to ensure this R_t has been modeled as

$$R_t = Q^{*-1}_{os,t}\, Q_{os,t}\, Q^{*-1}_{os,t} \quad (6)$$

Where

$$Q_{os,t} = (1 - \theta_1 - \theta_2).\ Q^* + \ \theta_1(\varepsilon_{o,t-1}\varepsilon_{s,t-1}) + \theta_2(Q_{os,t-1}) \quad (7)$$

Where $Q_{os,t}$ is the unconditional variance between series and I and j and follows a GARCH process, Q* is the unconditional covariance between the series estimated in step 1 and the scalar parameters θ_1 and θ_2 are non-negative and satisfy $\theta_1+\theta_2 < 1$.

Following the methodology of Engle (2002), the parameters θ_1 and θ2 is estimated by maximizing the log-likelihood function. The log likelihood function can be expressed as:

$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi)) + log(|D$ <math > < mrow > < msub > < ! − −move before − − > < mi > t < /mi > < /msub > < msub > < mrow > < mi > R < /mi > < /mrow > < mrow > < mi > t < /mi > < /mrow > < /msub > < mi > D < /mi > < mmultiscripts > < mi > t < /mi > < none/ > < none/ > < mprescripts/ > < none/ > < /mmultiscripts > < /mrow > < /math > $Z|) + \varepsilon_t' D_t^{-1} R_t^{-1} D_t^{-1} \varepsilon_t$ (8)

$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi)) + 2\log(\lceil D_t \rceil) + \log(\lceil R_t \rceil) + \varepsilon_t' R_t^{-1} \varepsilon_t) \quad (9)$$

As the above model DCC model does not allow for asymmetries and asset specific news impact parameter, the modified model of Cappiello et al. (2006) for incorporating the asymmetrical effect and asset specific news impact can be written as: $Q_{os,t} = (1 - \theta_1 - \theta_2).\ Q^{-} - \theta_3.\ \overline{\xi_t} + \theta_1(\varepsilon_{o,t}\varepsilon'_{s,t-1}) + \theta_2(Q_{os,t-1})$where $\overline{\xi_t}$=E

$$+ \theta_3(\varphi_{t-1}\varphi'_{t-1})$$

$|\overline{\varphi_{ot}\varphi'_{st}}|$ and $\overline{\varphi_{0t}} = (I\,[\overline{\varepsilon_{0t}} < 0]\,o\overline{\varepsilon_{ot}})$, the latter being the element by element Hadamard product of the residuals if the oil price returns is negative and $\overline{\varphi_{0t}}$=0 otherwise. Here θ_3 is the asymmetric term which captures periods where both oil and stock market experience bad news making $|\overline{\varphi_{0t}\varphi'_{st}}| = I_t$. This model is estimated using Quasi Maximum Likelihood (QML) technique based on BHHH optimization algorithm.

4. Data and preliminary analysis

This study considers weekly closing prices for Brent crude, S & P BSE SENSEX and seven sector indices of Bombay Stock Exchange namely: Automotive, Energy, Financial, Industrial, Metal, Oil & Gas and Power; to explore the time varying correlations between crude oil and stock market returns in India. S & P BSE SENSEX is a free float market capitalization based index that represents the movement of stocks of the 30 most financially sound and actively traded firms. These 30 stocks belong to the different sectors of the economy therefore SENSEX, which indicates the average movement of these sectors, is the representative of Indian economy. Since Brent crude comprises significant share in the Indian crude basket, therefore, it has been taken as a proxy for the crude oil market movements. In this study weekly data has been used. As the Indian stocks and commodity market are not synchronous, daily data might be infeasible to use whereas the use of monthly data might do aggregation and mask crucial volatility transmission channels. Hence, to capture the dynamic interactions between oil and stock market weekly data is appropriate (Arouri and Nguyen, 2010).

Weekly data for Brent crude oil and S & P BSE SENSEX has been taken from the Bloomberg terminal whereas the data for various sectors is pooled from Bombay Stock Exchange website. The time span for the study runs from January 1, 2006 to February 28, 2015. This period is selected on the basis of data availability and, additionally, it covers booming, recessionary as well as recovering global as well as Indian economy. Fig. 1 provides plot of Brent spot price versus S & P BSE SENSEX and different sector indices from 2006 to 2015. Visual Inspection of the BSE SENSEX plot reveals that it displays significant upward movement during the entire time frame except for a downside trough during 2007-08. In 2008 the value of SENSEX declined from 20,000 to 8000 within few days. Crude oil prices also collapse significantly during 2008 and it is towards the end of 2009, that SENSEX and crude prices start rebounding. However in 2011, Brent crude prices escalate while SENSEX price declines. At the sector level, price of all sectors except auto exhibit a significant plunge during the global financial crises. Prices of auto sector reveal a continuous upward trend and progress quite independently of the movement of crude oil. Towards the end of 2014, when the prices of Brent plummet significantly, prices of energy, metal, oil and gas and power sector also plunge while others spiral up signifying that different sectors gets affected differently from the movement of crude prices.

Returns of SENSEX (SEN), Automotive (AUTO), Energy (EN), Financial (FIN), Industrial (IND), Metal (METAL), Oil and Gas (O & G) Power (POWER) and Brent crude oil (OIL) are calculated by taking the first differences of the logarithm of the two successive prices i.e. $r_t=\log(P_t/P_t-1)$. Time series graphs of the returns series have been plotted which depict vividly how volatility has varied across time (Fig. 2). The point worth noticing is that all series experience pronounced volatility clustering between August 2008 and August 2009, a time period representing the global recession.

Table 1 illustrates the descriptive statistics of return series of Crude Oil, S & P BSE SENSEX and various sector indices. As evident from Table 1, SEN, AUTO and FIN have the highest mean average returns while OIL shows a negative mean returns. METAL has the highest volatility followed by OIL, IND and POWER. Returns of all the series are negatively skewed and the kurtosis is much higher than 3 for all the cases. This is indicative of the deviation of the series from the normal distribution which is further confirmed by the Jarque–Bera statistics. JB statistics validates that series are not normally distributed. Further the stationarity of the variables has been examined using Augmented Dickey–Fuller (ADF) unit root test. The null hypothesis of unit root is accepted for all the series at the price levels while it is rejected for all the return series. The result of Ljung–Box Q-statistics and ARCH LM testing confirms the presence of serial correlation and heteroskedasticity in all return series. Unconditional correlations of SEN and sector index returns with OIL have been calculated. The result validates that OIL correlates positively with SEN and all sector index returns. SEN shows the highest correlation followed by METAL, EN and O & G while FIN exhibits the lowest correlation with OIL.

5. Empirical analysis

As discussed in the methodology section, before proceeding with the estimation of parameters of dynamic correlations and GARCH model, bivariate VAR of OIL with SEN and other sector index returns have been estimated. Table 2 presents the results of bivariate VAR modeling. Results indicate that volatility spillover from international crude oil returns (OIL) to Indian stock market returns (SEN) is insignificant. This result is coherent with the results reported by Ghosh and Kanjilal (2014), which established that the movements of crude oil price indirectly impact the stock market through macroeconomic factors. However volatility transmission from OIL to some stock sector returns is significant. As evident from Table 2, among sector indices movement in OIL significantly affect the AUTO, EN and POWER sector returns at 5% significance level while it affects FIN and O & G sector returns at 10% level of significance. IND and METAL remains unaffected by OIL. This volatility linkage for EN and O & G sector in India is direct and quite expected. Volatility in OIL affect the AUTO sector returns by raising the fuel prices and FIN sector through their effects on monetary policy and interest rates.

After VAR modeling, diagnostic tests on residuals to check for serial correlation and ARCH effect have been conducted. These tests reveal that residuals are free from serial correlation up-to 20 lags and ARCH effect is present as evident by Ljung Box Q-Statistic and ARCH LM statistic respectively in Table 2.

Having performed VAR modeling and diagnostic tests, the next step is to run different versions of DCC GARCH models on residuals of VAR equations. Table 3 presents the parameter estimates of different DCC GARCH models for SENSEX and crude oil returns. The result of univariate GARCH model (Table 3 Panel A) indicates that coefficients of both ARCH and GARCH are positive and significant at 5% significance level. Additionally, the sum of coefficients on the lagged squared error and lagged conditional variance are close to unity (0.96 and 0.95 respectively for OIL and SEN) implying that shocks to conditional variance are highly persistent. For GJR specification, the asymmetry term $\boldsymbol{\lambda}$ is positive but insignificant for SEN. However, for OIL, it is highly significant conveying that crude oil responds differently to positive and negative return shocks.

Results from EGARCH model for SEN delineate that size effect is positive and highly significant at 5% level indicating significant increase in volatility of Indian stock market returns following a shock. The sign effect α is negative and insignificant, indicating the absence of asymmetric effect. This is consistent with the results of GJR/TGARCH model. The positive and highly significant value of β validates that shocks are highly persistent in nature. For OIL out of various EGARCH parameters, only β is significant indicating long run persistence of shocks in returns of international crude oil market.

Panel B of Table 3 summarizes the results of DCC estimates for the combination of SEN and OIL. As evident, parameters theta 1 and theta 2, which is associated with the short run and long run persistence of shocks on the dynamic conditional correlation, are statistically significant at 5% level in all versions of symmetric GARCH. Theta 3 in Panel C of Table 3 corresponds to the asymmetry in the dynamic conditional correlation and is insignificant in all cases. These results are consistent and statistical insignificance of asymmetric term rules out the possibility of considering ADCC GARCH model for time varying correlation. Among the three versions of DCC GARCH model, AIC criteria suggests that DCC-GJR/TGARCH model outperforms other models and, therefore, considered for time varying correlation between SEN and OIL. Results of the diagnostic test (Ljung Box Q-Statistic and ARCH LM statistic) reveal that residuals are free from serial correlation and ARCH effect.

Fig. 3 displays the time varying conditional correlation between SENSEX and Crude. The graph is highly time varying both within a time-frame of a year (like 2007; 2008 and 2010) and across a span of years. As is evident from the figure, during mid of 2006 the correlation

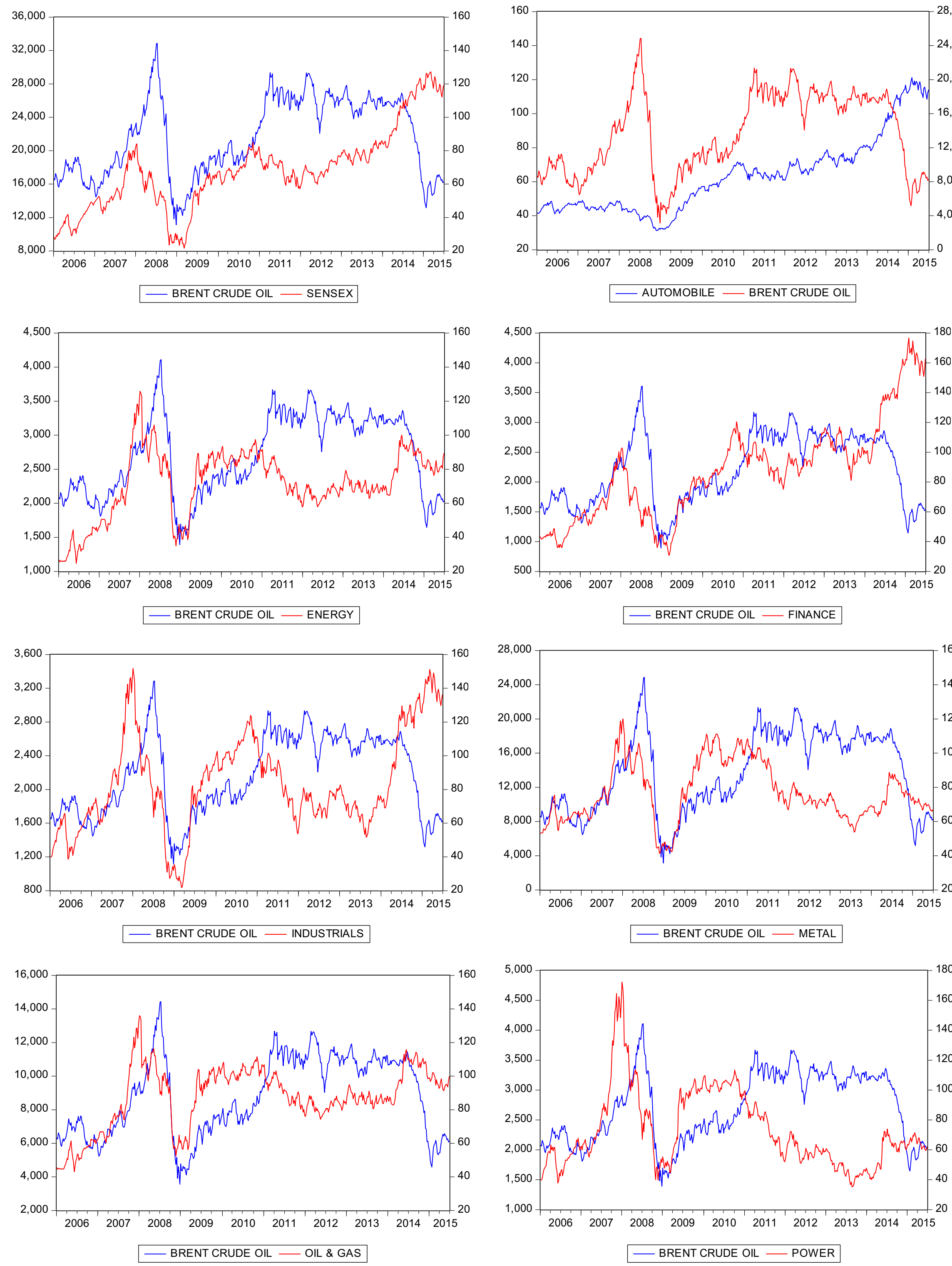

Fig. 1. Graph of Brent Crude Oil versus SENSEX and Sector Price Indices.

was more than 0.30 but by the end of 2006 it drops to 0.10. In 2007, it rises again and then falls significantly from end of 2007 (0.35) to mid 2008 (0.03). However during late 2008 it peaks to 0.41 and remains high during the crises. Post crises, correlation declines again and hovers in the range of 0.15–0.20 from 2012 onwards. In a nutshell, the correlation between OIL and SEN is time dependent and unstable; hence assuming a constant/static measure of correlation might be misleading.

5.1. Sector analysis

Having estimated dynamic correlation between OIL and SEN at the aggregate stock market level, we further investigate the linkage & time dependent movement of various sector returns with OIL. Result of DCC GARCH and ADCC GARCH are presented in Table 4.

As seen from Panel A of Table 4, the coefficients of both the lagged squared residual and lagged conditional variance are statistically significant for all sectors. Additionally both the estimates are positive

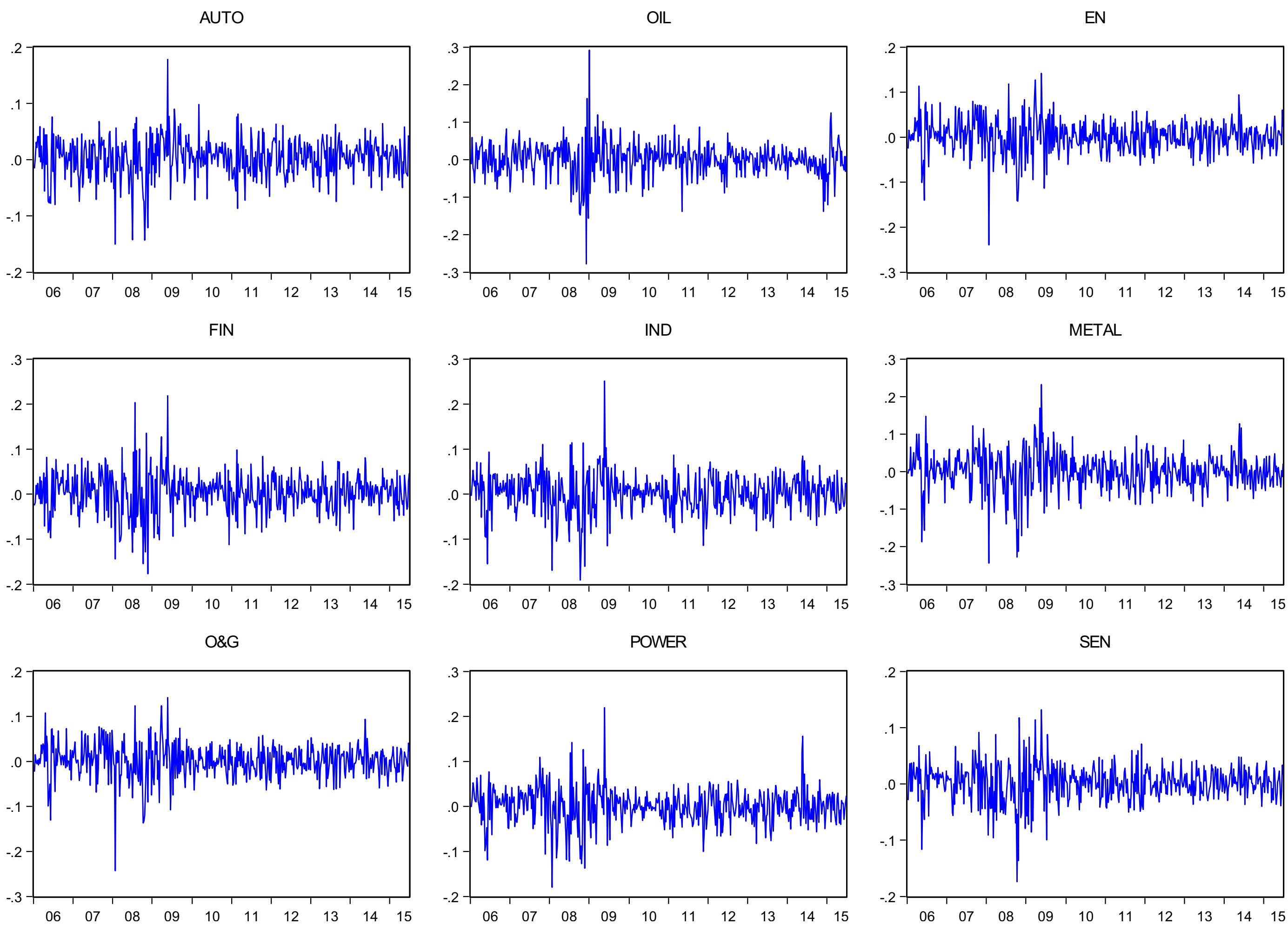

Fig. 2. Graphs of return Series of Crude oil, SENSEX and Various Sector Indices .

and their sum is less than 1, thereby validating stationarity of the covariance. Result of Diagnostic tests reveals that residuals are free from serial correlation and ARCH effect.

For the DCC model (Table 4 Panel B), the estimated coefficients theta1 and theta2 are found to be statistically significant for all sectors except EN and O & G, indicating that the conditional correlations are not constant over time. In case of EN and O & G, short run persistence parameter i.e. theta 1 highly significant but theta 2, parameter of long run persistence is insignificant. For the ADCC model (Table 4 Panel C), the asymmetry parameter theta 3 is significant only for METAL and O

Table 1
Descriptive statistics of Return series .

	OIL	SEN	AUTO	EN	FIN	IND	METAL	O & G	POWER
Mean	−5.92E−05	0.002145	0.002970	0.001725	0.002674	0.001932	0.000694	0.001594	0.000637
Median	0.001576	0.004328	0.005956	0.002172	0.004211	0.003998	0.002606	0.002394	0.002264
Maximum	0.292017	0.131709	0.178077	0.141555	0.218610	0.251261	0.232171	0.141555	0.219241
Minimum	−0.277616	−0.173808	−0.150281	−0.239152	−0.176596	−0.190658	−0.243808	−0.242683	−0.179795
Std. Dev.	0.046441	0.032855	0.035920	0.038614	0.045000	0.043841	0.052109	0.038115	0.041207
Skewness	−0.297196	−0.437277	−0.397801	−0.634571	−0.042001	−0.237208	−0.506992	−0.661430	−0.025364
Kurtosis	9.018631	6.046428	5.249653	7.086299	5.317548	6.303855	6.161638	7.268606	6.133766
Jarque-Bera	752.8810	206.7712	117.1999	376.8512	110.6989	229.3092	226.9132	411.0689	202.1913
Probability	[0.00000]*	[0.00000]*	[0.00000]*	[0.00000]*	[0.00000]*	[0.0000]*	[0.00000]*	[0.00000]*	[0.00000]*
ADF Test (Level)	−1.307633	−1.949758	−1.316705	−2.580045	−2.040343	−1.736759	−2.148266	−2.609647	−2.543985
p-value	[0.8848]	[0.6266]	[0.8825]	[0.2897]	[0.5772]	[0.7335]	[0.5170]	[0.2762]	[0.3067]
ADF Test (Returns)	−10.54619	−19.98760	−20.72805	20.19937	−22.26056	−19.94571	−19.08129	−20.24971	−19.98760
p-value	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*	[0.0000]*
Correlation Coefficients (OIL)	1.0000	0.322234	0.179111	0.233075	0.139560	0.209638	0.316859	0.229362	0.181780

Notes: between parentheses: p-values. the number of observations is 495 for each series. jb are the empirical statistics of the jarque–bera test for normality based on skewness and excess kurtosis.
adf test refers to the augmented dickey fuller test for the presence of unit root for levels (prices) and first log differences(returns).
* Denotes rejection of null of normal distribution and non stationarity at 5% significance level.

Table 2
VAR parameter estimates.

	AUTO (X_S)	EN (X_S)	FIN (X_S)	IND (X_S)	METAL (X_S)	O & G (X_S)	POWER (X_S)	SEN (X_S)
C_1	0.002365 [1.45308]	0.001784 [1.03979]	0.002498 [1.22115]	0.001374 [0.69966]	0.000573 [0.24789]	0.001654 [0.97453]	0.000124 [0.06705]	0.001854 [1.25319]
$X_{S,(t-1)}$	0.053590 [1.16584]	0.069330 [1.51108]	−0.017795 [−0.38768]	0.064930 [1.40377]	0.085289 [1.780]**	0.068657 [1.49585]	0.087700 [1.874]**	0.011332 [0.23678]
$X_{S,(t-2)}$	0.083392 [1.81971]	0.068402 [1.48476]	0.079215 [1.727]**	0.094375 [2.0421]*	0.093156 [1.941]**	0.064740 [1.40662]	0.040149 [0.85957]	0.173194 [3.6598]*
$X_{S,(t-3)}$	0.062825 [1.35948]	0.037424 [0.80978]	0.036086 [0.78307]	0.075143 [1.62956]	0.034074 [0.72191]	0.033950 [0.73519]	0.053276 [1.13829]	−0.062263 [−1.29989]
$X_{S,(t-4)}$		−0.177055 [−3.848]*				−0.171531 [−3.72790]*	0.017644 [0.37668]	
$X_{S,(t-5)}$							−0.034291 [−0.73518]	
$X_{S,(t-6)}$							0.076543 [1.6404]**	
$X_{S,(t-7)}$							−0.103898 [−2.21663]*	
$X_{S,(t-8)}$							0.081962 [1.7531]**	
$OIL_{(t-1)}$	0.010390 [0.29209]	0.073822 [1.920]**	0.071468 [1.60048]	0.082745 [1.90936]	0.165023 [3.1216]*	0.066401 [1.746]**	0.064891 [1.54662]	0.019735 [0.58877]
$OIL_{(t-2)}$	0.066379 [1.880]**	0.044408 [1.16098]	−0.014598 [−0.32862]	0.026485 [0.61079]	0.005660 [0.10610]	0.048257 [1.27703]	0.054631 [1.30034]	−0.030088 [−0.89919]
$OIL_{(t-3)}$	−0.029321 [−0.82772]	0.052362 [1.37629]	−0.009223 [−0.20760]	−0.029056 [−0.67018]	−0.035586 [−0.66942]	0.049220 [1.31012]	−0.014883 [−0.35516]	0.017084 [0.50931]
$OIL_{(t-4)}$		−0.038290 [−0.99826]				−0.037348 [−0.98602]	−0.095791 [−2.28192]*	
$OIL_{(t-5)}$							−0.008268 [−0.19638]	
$OIL_{(t-6)}$							−0.004204 [−0.19638]	
$OIL_{(t-7)}$							−0.004815 [−0.11595]	
$OIL_{(t-8)}$							−0.006304 [−0.15199]	
	OIL	**OIL**	**OIL**	**OIL**	**OIL**	**OIL**	**OIL**	**OIL**
C_2	−0.000757 [−0.36443]	−0.000327 [−0.15738]	−0.000349 [−0.16829]	−0.000342 [−0.16465]	−0.000200 [−0.09636]	−0.000310 [−0.14940]	−0.000192 [−0.09365]	−0.000375 [−0.17958]
$OIL_{(t-1)}$	−0.036837 [−0.62799]	−0.032395 [−0.69559]	−0.026900 [−0.59335]	−0.036865 [−0.80412]	−0.047991 [−1.01220]	−0.030807 [−0.66205]	−0.027694 [−0.59754]	- 0.031433 [−0.66437]
$OIL_{(t-2)}$	0.148927 [2.5466]*	0.056464 [1.21811]	0.064477 [1.42964]	0.058484 [1.27494]	0.045085 [0.94230]	0.056614 [1.22401]	0.061278 [1.32041]	0.062482 [1.32290]
$OIL_{(t-3)}$	0.109519 [1.857]**	0.129725 [2.8136]*	0.138347 [3.0673]*	0.133520 [2.9111]*	0.124744 [2.6164]*	0.129852 [2.82385]*	0.110716 [2.39175]*	0.128117 [2.7058]*
$OIL_{(t-4)}$		−0.076023 [−1.635]**				−0.075269 [−1.62353]	−0.055016 [−1.18645]	
$OIL_{(t-5)}$							−0.007374 [−0.15857]	
$OIL_{(t-6)}$							0.073219 [1.59044]	
$OIL_{(t-7)}$							0.013341 [0.29083]	
$OIL_{(t-8)}$							0.089724 [1.9582]**	
$X_{S,(t-1)}$	−0.039495 [−0.87003]	0.013931 [0.25055]	−0.054343 [−1.16611]	−0.014652 [−0.29943]	0.019675 [0.45785]	0.005889 [0.10482]	−0.003962 [−0.07667]	−0.023341 [−0.34550]
$X_{S,(t-2)}$	0.051660 [1.14687]	0.102287 [1.832]**	0.098323 [2.1117]*	0.069541 [1.42246]	0.055147 [1.28168]	0.111697 [1.98276]**	0.106296 [2.06019]*	0.044492 [0.66607]
$X_{S,(t-3)}$	0.137368 [3.0388]*	0.062795 [1.12124]	0.049240 [1.05243]	0.065919 [1.35131]	0.046620 [1.10128]	0.066680 [1.17974]	0.065604 [1.26893]	0.104282 [1.54240]
$X_{S,(t-4)}$		−0.004098 [−0.07350]				−0.008301 [−0.14738]	−0.059987 [−1.15938]	
$X_{S,(t-5)}$							0.067796 [1.31582]	
$X_{S,(t-6)}$							−0.076121 [−1.47692]	
$X_{S,(t-7)}$							0.014393 [0.27798]	
$X_{S,(t-8)}$							0.140757 [2.72567]*	
Ljung–Box statistics (20)	1.266600 [0.8670]	5.865975 [0.2094]	2.846438 [0.5838]	6.643821 [0.1560]	3.557020 [0.4693]	4.773578 [0.3113]	3.269466 [0.5138]	2.662128 [0.6159]

(continued on next page)

Table 2 *(continued)*

	AUTO (X_s)	EN (X_s)	FIN (X_s)	IND (X_s)	METAL (X_s)	O & G (X_s)	POWER (X_s)	SEN (X_s)
ARCH Test	179.5713 [0.0000]*	230.9279 [0.0000]*	222.4941 [0.0000]*	199.8126 [0.0000]*	196.7659 [0.0000]*	230.3541 [0.0000]*	343.7383 [0.0000]*	226.1685 [0.0000]*

Notes: for var estimates between parentheses are t-values. * and ** denotes rejection of null hypothesis at 5% and 10% significance level.
for ljung box and arch test value in parenthesis are p-values. ljung–box statistics correspond to a test of the null of no autocorrelation with h=20.arch lagrange multiplier statistics correspond to a test of the null of no arch effect.

& G at 5% significance level while it is significant for EN and IND at 10% level of significance.

Analysis of GJR/TGARCH model at the sector level (Table 5 Panel A) indicates that the asymmetric coefficient **λ** is significant only for AUTO and FIN at 5% significance level. GARCH and ARCH effect is found to be significant for all the sectors except for FIN where ARCH effect is insignificant. The diagnostic tests on residuals reveals that all the models are correctly specified.

For the DCC models, (Table 5 Panel B) the parameter theta 2 is positive and highly significant at 1% level, however theta 1 is insignificant for EN and O & G sector. This result of DCC GJR/TGARCH is similar to result of DCC GARCH. In case of Asymmetric GJR DCC GARCH model (Table 5 Panel C), theta 3 is found positive and significant for EN, IND and METAL sector. However for EN theta1 is insignificant and for O & G optimization failed when asymmetric version of DCC is employed.

Results of EGARCH model (Table 6 Panel A) indicate that size effect is significant for all the cases except for AUTO, indicating that significant volatility increases in all sectors in response to shocks occurring in the market. α coefficient is insignificant in all the sectors except for AUTO and FIN sector and negative value indicates that bad news generates more volatility in these sectors as compared to good news. This result of sign coefficient is consistent with the asymmetry coefficient of GGJR/TGARCH model. β parameter is highly positive and significant for all sectors indicating that shocks are highly persistent in all the sectors. The value of LM statistic and Ljung Box Q-Statistic indicates that diagnostic tests on residuals are satisfactory in all the sectors.

Estimation of DCC model (Table 6 Panel B) indicates long run persistence of shocks to the conditional correlations is positive and highly significant for all the sectors whereas short run persistence of shocks to the conditional correlations is lowest for AUTO and insignificant for EN and O & G. The result for EN and O & G is consistent in all symmetric versions of DCC GARCH. The coefficient of asymmetric version theta 3 (Table 6 Panel C) was significant for all sectors except for FIN and POWER. In case of EN, in the ADCC model the coefficient of theta2 is greater than one which violates the stability condition.

The decision on the best model is based on the Akaike Information Criteria (AIC). Results indicate that for AUTO, EN, METAL and O & G DCC GJR/TGARCH model outperforms and for FIN, IND and POWER sector DCC EGARCH model outperforms. Fig. 4 presents the dynamic conditional correlation of OIL with various sectors. As evident from the graph, the correlation between OIL and sector returns is time varying in all the cases, therefore constant measure of correlation would be inappropriate and misleading.

From 2006 to 08, when the OIL returns were escalating due to rising demand from emerging economies, it has relatively low correlation with most of the sectors. However in magnitude the correlation is highest for METAL, EN and O & G sector indicating that during that time frame, these sectors provides the least diversification benefit. In 2008, significant drop in correlation is observed for all sectors and it becomes negative for AUTO, FIN, IND, METAL and POWER. This result is explained by the fact that from Jan 2008 to July 2008, the prices of crude oil were rising whereas the returns of different sectors (excluding EN and O & G) were decreasing. In the last quarter of 2008, both OIL returns and stock market crashed owing to global financial crisis, due to which the correlation of all sector with OIL reaches their highest peak. This contagion between OIL and stock market returns can be explained by the fact that due to global crises stock markets becomes bearish, economies decline due to which oil demand and

Table 3
DCC GARCH parameter estimates for OIL and SEN .

Variance Equation	GARCH (SEN)	GARCH (OIL)	GJR/TGARCH (SEN)	GJR/TGARCH (OIL)	EGARCH (SEN)	EGARCH (OIL)
Panel- A Variance equation parameters						
ω	3.48E−05 [0.1380]	3.97E−05 [0.0758]**	3.83E−05 [0.1549]	3.80E−05 [0.0766]**	−0.370831 [0.0257]*	3.83E−05 [0.1549]
α	0.125934 [0.0027]*	0.102740 [0.0107]*	0.081548 [0.1711]	0.040715 [0.4637]*	−0.048643 [0.4107]	0.089120 [0.4167]
β	0.841575 [0.0000]*	0.879031 [0.0000]*	0.836666 [0.0000]*	0.901138 [0.3047]	0.968726 [0.0000]*	0.836666 [0.0000]*
λ	NA	NA	0.089120 [0.4167]	0.075967 [0.0000]*	0.191856 [0.0002]*	0.081548 [0.1711]
Q (20)r	16.706 [0.672]	28.840 [0.091]	16.096 [0.940]	28.862 [0.091]	14.767 [0.790]	29.006 [0.105]
Q (20)r^2	10.950 [0.948]	0.091 [0.114]	11.217 [0.940]	32.831 [0.457]	12.860 [0.883]	34.667 [0.109]
ARCH effect	0.5408 [0.8612]	1.585313 [0.1078]	0.563934 [0.8435]	2.168859 [0.1326]	0.595131 [0.8183]	2.474466 [0.1139]
Panel- B DCC parameters						
θ1	0.165159 [0.0659]*		0.177990 [0.0258]*		0.176094 [0.0310]*	
θ2	0.947241 [0.0000]*		0.940856 [0.0000]*		0.939260 [0.0000]*	
AIC	−7.844204		−7.861070		−7.851732	
Panel- C Asymmetric DCC parameters						
θ1	0.097840 [0.544764]		0.068422 [NA]		0.090825 [0.657789]	
θ2	0.849401 [0.0000]*		0.905594 NA		0.821117 [0.0000]*	
θ3	−0.205802 [1.00E−06]		−0.444817 [NA]		−0.229696 [1.46E−07]	
AIC	−7.852946		−7.852946		−7.852946	

Notes: between parentheses: p-values. ljung–box q statistics correspond to a test of the null of no autocorrelation in residuals and squared residuals with h=20. arch lagrange multiplier statistics correspond to a test of the null of no arch effect.
** Denotes rejection of null hypothesis at 10% significance level.
* Denotes rejection of null hypothesis at 5% significance level.

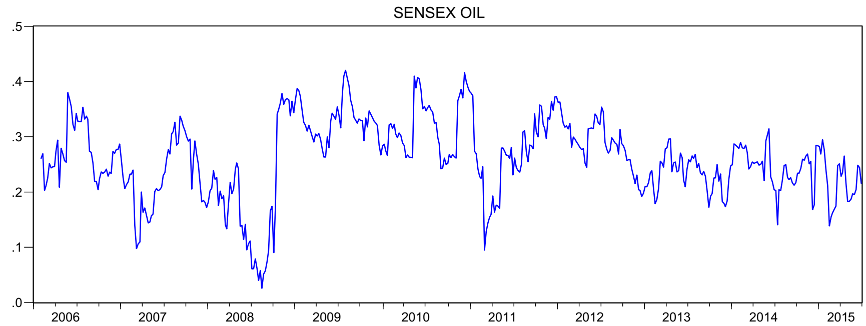

Fig. 3. Time varying correlation between OIL and SEN.

hence their prices also declines. Another possible reason is the herding behavior of the investors which generally increases when stress prevails in the market. These results are line with the results of Chen and Lv (2015) who also confirm the presence of contagion effect in Chinese market during financial crises. These correlations remained at a higher level till late 2010 except for EN and O & G. The important point worth noticing is that POWER in India behaves quite independent to OIL, EN and O & G. This result is explained by the fact that power generation in India is based mainly on coal; therefore power sector is comparatively less affected by the movement in OIL as compared to the EN and O & G sector. After 2010 when the crude oil prices rises again, returns from all the sectors except for AUTO and FIN starts declining, due to which correlation between them falls and reaches to pre crises level again. The result for AUTO and FIN sector can be explained on the basis that after 2010, Indian economy had started recovering due to which demand for automobiles and finance which declined during crises started reviving. Overall the result of the study indicates that correlation of different sector returns with international crude oil returns is dynamic in nature and this distinctive behavior of different sector stock indices provides opportunities for investors to diversify their investment across various sectors so as to reap maximum profits.

6. Conclusion

This study empirically investigates the relationship and volatility spill over from Brent crude returns to stock market returns in India both at the aggregate and at the sector level. Movement of seven sector indices namely- Automotive, Energy, Finance, Industrial, Metal, Power and Oil & Gas; with the international crude prices has been examined from 2006 to 2015 using different versions of VAR-DCC-GARCH framework.

Results of the study indicate that the spillover from international oil market to Indian stock market is not significant. This result is in consensus with Broadstock and Filis (2014), who also refuted the direct impact of crude oil returns on stock market returns in context of China, another developing nation with colossal oil imports like India. Being the first study conducted at sector level, it reports volatility spill over to be significant in case of Automotive, Power and Financial sector. The parameter of dynamic correlation is significant in all cases indicating the importance of time varying co movements. For all the sectors under study, volatility shocks are persistent in nature. The time varying correlation of SENSEX and different sectors with Brent crude oil shows very interesting behavior. From 2006 to mid of 2008, the correlation

Table 4
DCC GARCH parameter estimates for different sectors.

	AUTO	EN	FIN	IND	METAL	O & G	POWER
Panel- A Variance equation parameters							
ω	3.56E–05 [0.3599]	2.38E–05 [0.2066]	4.03E–05 [0.2265]	4.79E–05 [0.1693]	8.03E–05 [0.009]**	2.22E–05 [0.2336]	3.14E–05 [0.2032]
α	0.069257 [0.0289]	0.069806 [0.0043]*	0.091901 [0.0016]*	0.124592 [0.0000]*	0.102043 [0.002]*	0.068180 [0.0059]*	0.125907 [0.0007]*
β	0.903709 [0.0000]*	0.913551 [0.0000]*	0.888204 [0.0000]*	0.855730 [0.0000]*	0.866043 [0.000]*	0.915936 [0.0000]*	0.860970 [0.000]*
Q (20)r	12.862 [0.883]	10.524 [0.958]	12.377 [0.902]	17.128 [0.645]	15.343 [0.756]	10.551 [0.957]	11.023 [0.946]
Q (20)r^2	12.235 [0.908]	7.6932 [0.994]	8.3520 [0.989]	9.1613 [0.981]	23.948 [0.245]	8.5148 [0.988]	7.5639 [0.994]
ARCH effect	0.697567 [0.7270]	0.208807 [0.9955]	0.395501 [0.9486]	0.459168 [0.9158]	1.087855 [0.3697]	0.270310 [0.9873]	0.244416 [0.9915]
Panel- B DCC parameters							
θ1	0.148382 [0.0559]*	0.136082 [0.1979]	0.119761 [0.0214]*	0.148846 [0.0180]*	0.171422 [0.000]*	0.123271 [0.1657]	0.140822 [0.0279]*
θ2	0.965874 [0.0000]*	0.933582 [0.0000]*	0.983533 [0.0000]*	0.974020 [0.0000]*	0.973175 [0.000]*	0.956310 [0.0000]*	0.970313 [0.0000]*
AIC	−7.454637	−7.425423	−7.107175	−7.165577	−6.910023	−7.440236	−7.340320
Panel- C Asymmetric DCC parameters							
θ1	0.118417 [0.1058]	0.037194 [0.8326]	0.114182 [0.0277]*	0.125574 [0.0301]*	0.142880 [0.0063]*	0.043918 [0.7718]	0.132412 [0.0583]*
θ2	0.979087 [0.0000]*	0.981246 [0.0000]*	0.984256 [0.0000]*	0.979488 [0.0000]*	0.979284 [0.0000]*	0.980272 [0.0000]*	0.973590 [0.0000]*
θ3	0.085926 [0.1518]	0.104686 [0.0582] **	0.062006 [0.379633]	0.097803 [0.0604]**	0.089996 [0.0063]*	0.108015 [0.0410]*	0.061491 [0.57323]
AIC	−7.484702	−7.429804	−7.131212	−7.169511	−6.902579	−7.448952	−7.345804

Notes: between parentheses: p-values. ljung–box q statistics correspond to a test of the null of no autocorrelation in residuals and squared residuals with h=20. arch lagrange multiplier statistics correspond to a test of the null of no arch effect.
** Denotes rejection of null hypothesis at 10% significance level.
* Denotes rejection of null hypothesis at 5% significance level.

Table 5
DCC GJR/TGARCH parameter estimates for different sectors.

	AUTO	EN	FIN	IND	METAL	O & G	POWER
Panel- A Variance equation parameters							
ω	5.87E−06 [0.1332]	2.16E−05 [0.2343]	4.97E−05 [0.2577]	4.91E−05 [0.2144]	8.36E−05 [0.0950]**	1.91E−05 [0.2763]	3.17E−05 [0.2228]
α	−0.044073 [0.0158]*	0.092890 [0.0509]*	0.014847 [0.6205]	0.092562 [0.0404]*	0.093093 [0.0914]**	0.096188 [0.0494]*	0.106837 [0.0448]*
β	1.007100 [0.0000]*	0.917594 [0.0000]*	0.896170 [0.0000]*	0.857939 [0.0000]*	0.863482 [0.0000]*	0.920987 [0.0000]*	0.860700 [0.0000]*
λ	0.063010 [0.0036]*	−0.049303 [0.4209]	0.123391 [0.0027]*	0.055428 [0.4956]	0.020080 [0.7963]	−0.058952 [0.3508]	0.038349 [0.5344]
Q (20)r	16.131 [0.708]	11.261 [0.939]	11.792 [0.923]	17.311 [0.633]	15.310 [0.758]	11.358 [0.936]	10.701 [0.954]
Q (20)r²	20.407 [0.433]	7.7234 [0.994]	9.2014 [0.980]	8.7865 [0.985]	24.604 [0.217]	8.6338 [0.987]	7.4179 [0.995]
ARCH effect	1.265456 [0.2473]	0.176537 [0.9978]	0.549954 [0.8543]	0.419599 [0.9372]	1.133087 [0.3353]	0.223201 [0.9941]	0.244546 [0.9914]
Panel- B DCC parameters							
θ1	0.117395 [0.0523]*	0.144228 [0.1236]	0.124428 [0.0141]*	0.153700 [0.0106]*	0.179436 [0.0003]*	0.130345 [0.1694]	0.147664 [0.0158]*
θ2	0.979843 [0.0000]*	0.922465 [0.0000]*	0.983188 [0.0000]*	0.973278 [0.0000]*	0.969994 [0.0000]*	0.946606 [0.0000]*	0.969041 [0.0000]*
AIC	−7.519347	−7.442328	7.137846	−7.180538	−6.922120	−7.459722	−7.354613
Panel- C Asymmetric DCC parameters							
θ1	0.107347 [0.0689]**	0.037010 [0.82300]	0.115750 [0.02056]*	0.128226 [0.020535]*	0.145906 [0.0049]*	0.005100 [NA]	0.135835 [0.038257]*
θ2	0.979780 [0.0000]*	0.982475 [0.0000]*	0.983989 [0.0000]*	0.978340 [0.0000]*	0.977426 [0.0000]*	1.002744 [NA]	0.973198 [0.0000]*
θ3	0.089878 [0.20205]	0.106439 [0.03376]*	0.082010 [0.18503]	0.115489 [0.023682]*	0.104367 [0.01917]*	0.129146 [NA]	0.079648 [0.373827]
AIC	−7.484702	−7.429804	−7.131212	−7.169511	−6.902579	7.448952	−7.345804

Notes: between parentheses: p-values. ljung–box q statistics correspond to a test of the null of no autocorrelation in residuals and squared residuals with h=20. arch lagrange multiplier statistics correspond to a test of the null of no arch effect.
** Denotes rejection of null hypothesis at 10% significance level.
* Denotes rejection of null hypothesis at 5% significance level.

Table 6
DCC EGARCH parameter estimates for different sectors.

	AUTO	EN	FIN	IND	METAL	O & G	POWER
Panel- A Variance equation parameters							
ω	−0.035278 [0.4128]	−0.210037 [0.0374]*	−0.305751 [0.1131]	−0.334935 [0.0896]**	−0.360373 [0.0243]*	−0.204296 [0.0423]*	−0.366551 [0.0433]*
λ	−0.010829 [0.5471]	0.151982 [0.0002]*	0.156816 [0.0110]*	0.210198 [0.0000]*	0.198032 [0.0046]*	0.152694 [0.0001]*	0.252793 [0.0003]*
α	−0.069041 [0.0003]*	0.026022 [0.5423]	−0.077001 [0.0409]*	−0.051237 [0.2997]	−0.006669 [0.9068]	0.033109 [0.4577]	−0.022626 [0.6186]
β	0.993148 [0.0000]*	0.986446 [0.0000]*	0.971467 [0.0000]*	0.973451 [0.0000]*	0.966205 [0.0000]*	0.987482 [0.0000]*	0.974404 [0.0000]*
Q (20)r	14.979 [0.778]	11.497 [0.932]	12.360 [0.903]	19.246 [0.506]	15.670 [0.737]	11.573 [0.930]	11.890 [0.920]
Q (20)r²	21.073 [0.393]	8.3642 [0.989]	8.0725 [0.991]	10.517 [0.958]	24.986 [0.3338]	9.4520 [0.977]	8.3615 [0.989]
ARCH effect	1.47231 [0.1465]	0.169080 [0.9982]	0.484955 [0.9000]	0.549161 [0.8549]	1.135111 [0.202]	0.230643 [0.9932]	0.328286 [0.9735]
Panel- B DCC parameters							
θ1	0.116942 [0.0680]**	0.149680 [0.1003]	0.126622 [0.0175]*	0.146602 [0.0151]*	0.172171 [0.0003]*	0.14026 [0.1381]	0.152564 [0.0100]*
θ2	0.979979 [0.0000]*	0.913798 [0.0000]*	0.982072 [0.0000]*	0.974319 [0.0000]*	0.972167 [0.0000]*	0.93678 [0.0000]*	0.966356 [0.0000]*
AIC	−7.505676	−7.440291	−7.140202	−7.190341	−6.912704	−7.457165	−7.368840
Panel- C Asymmetric DCC parameters							
θ1	0.095572 [0.10842]	0.062579 [0.0000]*	0.114456 [0.0262]*	0.114171 [0.04287]*	0.135306 [0.00909]*	0.044769 [0.75124]	0.137452 [0.0374]*
θ2	0.982751 [0.0000]*	1.003795 [0.0000]*	0.983786 [0.0000]*	0.980437 [0.0000]*	0.979185 [0.0000]*	0.980755 [0.0000]*	0.971776 [0.0000]*
θ3	0.105289 [0.0803]**	0.092225 [0.0000]*	−0.087203 [0.1427]	−0.117495 [0.0143]*	0.106367 [0.0084]*	0.113955 [0.0154]*	0.085920 [0.3087]
AIC	−7.484702	−7.429804	7.131212	−7.169511	−6.902579	−7.448952	−7.345804

Notes: between parentheses: p-values. ljung–box q statistics correspond to a test of the null of no autocorrelation in residuals and squared residuals with h=20. arch lagrange multiplier statistics correspond to a test of the null of no arch effect.
** Denotes rejection of null hypothesis at 10% significance level.
* Denotes rejection of null hypothesis at 5% significance level.

was low for all the sectors, however with the onset of financial crisis; the correlation rose significantly thereby reducing the benefits of diversification. During 2009, contagion of crude oil with Energy and Oil & Gas sector decreased while it increased for Automotive, Financial, Industrial, Metal and Power. However after 2011, correlation took a downward trend for all the sectors and reaches even below pre-2008 levels for Metal and Power sector. Overall the result of the study indicates the time varying differential dependence of Indian stock sector indices on oil price fluctuations. These results of the study are in alignment with (Jain and Biswal, 2016; Sardosky, 1999; Bouri, 2015; Lin et al., 2014) in context of Indian, US, Lebanon and Ghana stock markets.

This paper has practical implications for policy makers and investment professionals. As discussed earlier, increase in crude oil price

Fig. 4. Time varying correlation of Brent crude with various sectors.

doesn't directly affect stock markets instead this effect imbibes indirectly through the channel of monetary policy. Recently when the crude oil prices declines, the market hopes the RBI to ease its monetary policy on the expectation that inflation will decline. As expected, monetary policy was revised and there was a drop of 50 basis points in the interest rates. Fund managers also continuously take combined cues from oil prices and monetary policy so as to adjust their fixed income portfolios.

Additionally, as established in this study change in crude prices doesn't have uniform effect on the sectors. For sectors like cement, electricity, iron and steel, chemicals, textiles and transportation, where fuel constitute around 5% of their input cost, there is an inverse relationship between their profitability and international crude oil prices. This can also be seen during 2015 when there was a drop in crude prices; stock price of some sectors like oil marketing companies, paints, plastics, aviation, FMCG and automobiles escalates while it declines for upstream oil companies.

As investors tend to diversify their investment across different sectors, results of this study would be crucial input for investors in portfolio diversification and hedging. The contagion effect of Automotive, Financial, Industrial, and Metal and Power post crises provides an indication to investors that the benefits of diversification declines by holding a portfolio of these sector stocks and oil. Additionally, using the estimates of our bivariate models, an investor can hedge his stock position against unfavorable effects from oil price movements by calculating the optimal holding weight of oil in a portfolio of oil/ stock market indices at a given point of time in accordance to a formula given by Kroner and Ng (1998). This will help the investor to minimize risk while keeping unchanged the expected return.

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