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Correlations and volatility spillovers between oil, natural gas, and stock prices in India

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ABSTRACT

This study investigates the extent of time-varying volatility and correlations between crude oil, natural gas, and stock prices in India using various multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models with and without asymmetry. Our empirical results reveal that there is no long-run cointegration between crude oil, natural gas, and stock prices in India. We find that the VARMA-DCC-GARCH model is more efficient compared to the CCC model with asymmetry in estimating time-varying correlations. We also analyze optimal portfolio weights and hedging ratios through pair trading between stocks and energy commodity futures. Our results have several implications for portfolio investors dealing with the Indian stock market and energy commodity futures for forecasting potential market risk exposure and determining the existence of portfolio diversification benefits.

1. Introduction

The growing demand for oil and natural gas is concomitant with the economic growth worldwide. The increased demand for oil in emerging countries has caused a manifold rise in prices, which has augmented the interest among policymakers to understand the relationship between oil prices, stock markets, and the overall economy (Herrera and Pesavento, 2009; Basher et al., 2012; Sadorsky, 2014; Bal and Rath, 2015). Higher oil and natural gas prices lead to cost-push inflation in oil importing countries and, consequently, have a negative impact on the financial markets, particularly the stock markets (Cong et al., 2008).

Many studies have found evidence of a long-run cointegration relationship between oil and natural gas prices (Brown and Yucel, 2002; Villar and Joutz, 2006; Panagiotidis and Rutledge, 2007; Hartley et al., 2008; Asche et al., 2012; Nick and Thoenes, 2014; Batten et al., 2017; Brown, 2017). However, Ramberg and Parsons (2012) argued the stability of the cointegration relationship due to the decoupling of oil and gas prices. Similarly, other studies have examined the relationship between oil prices and stock markets (Hammoudeh et al., 2004; Basher and Sadorsky, 2006; Boyer and Filion, 2007; Henriques and Sadorsky, 2008; Park and Ratti, 2008; Hayat and Narayan, 2011; Narayan and Sharma, 2011, 2014; Sadorsky, 2014). However, to the best of our knowledge, no study has investigated the relationship between natural gas prices and stock prices in India.

Although many empirical studies have explored the relationship between oil prices and stock prices, very little is known about the volatility of crude oil, natural gas, and stock prices, and possible correlations among them. We intend to fill this important gap. The inclusion of natural gas makes our paper unique due to the following reasons. First, natural gas is one of the leading energy commodities as it supplies 22% of the energy used worldwide, contributes to a quarter of electricity generation, and plays a significant role as feedstock for industry (International Energy Agency (IEA)). Second, natural gas releases lower levels of CO_2 than oil and coal and is the most commonly used alternative fuel in vehicles. The growth of natural gas is linked with environmental benefits, which makes it a crucial source of energy to be used in transportation.

Unlike previous studies, which mostly focused on the United States or the European countries, we analyze this relationship in the context of India. The case of India is useful for several reasons. First, India has

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emerged as an important player in the world oil market. It recently replaced Japan to become the world's third-largest oil importer, after the United States and China.[1] According to the IEA, by 2040, India's crude oil imports would amount to 7.2 million barrels per day to become the world's second-largest importer, just behind China.[2] Second, India's natural gas production is expected to increase from 35 billion cubic meters (bcm) in 2013 to 90 bcm in 2040, though with imports still meeting a sizeable 80 bcm requirement.[3] Nearly 85% of the total imports are estimated to be met through liquefied natural gas (LNG) and the remaining through pipeline supplies. Third, India's real GDP growth rate is currently about 7.2 percent, and it is expected to be among the fastest growing economies in the world by 2040, growing at an average of 6.5% per year to reach five times its current size.[4] This projected high GDP growth rate indicates that India would have a greater influence on the global financial markets.

In this study, we investigate the empirical properties of crude oil, natural gas, and stock price volatilities using multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models in the context of India. This study aims to estimate the MGARCH models with constant conditional correlation (CCC) and dynamic conditional correlation (DCC) to examine the spillovers and interactions between oil, natural gas, and stock prices. For the CCC-and DCC-GARCH models, the conditional variance is derived using both AR-GARCH (1,1) and VARMA-GARCH (1,1) specifications. In all the models, the variances are computed using the VARMA-MGARCH model of Koutmos (1996).

Moreover, all the models assume both symmetric and asymmetric effects. An asymmetric reaction to positive and negative shocks is important for the energy and stock markets as they also exhibit asymmetric behavior in response to positive and negative shocks during both bull and bear markets and this leads to portfolio rebalancing due to changing correlations (Sadorsky, 2014; Zhang et al., 2013). Therefore, we compare the performance of various CCC− and DCC-GARCH models to quantify volatility correlations and to measure spillovers between the Indian stock and commodity futures markets. Finally, this study examines the optimal portfolio design and hedge ratios using the estimated conditional covariances between the stock and energy commodity markets. From a portfolio management perspective, an accurate estimation of the time-varying covariance matrix is required to develop financial and strategic decisions for accurate asset pricing, risk management, and portfolio allocation.

The remainder of this paper is organized as follows. Section 2 presents a review of related literature. Section 3 provides the methodology used in the study. Section 4 describes the data and conducts some preliminary analyses. Section 5 discusses the empirical results. Section 6 provides the concluding remarks.

2. Literature review

Many studies have investigated the link between oil prices and stock market indices. Most of them found a negative impact of oil price shocks on international stock market returns (Chiou and Lee, 2009; Jones and Kaul, 1996; Lee and Chiou, 2011; Narayan and Narayan, 2010; Park and Ratti, 2008; Sadorsky, 1999). These studies suggested that oil price shocks cause input prices to increase, driving profits and returns in different countries or industries (or even firms). However, Huang et al. (1996) used a vector autoregressive (VAR) model and found weak evidence of a relationship between oil prices and the S&P 500 index. Surprisingly, there is a positive relationship between oil prices and stock prices of oil companies (Boyer and Filion, 2007; El-Sharif et al., 2005; Sadorsky, 2001). This indicates that a hike in oil prices leads to higher stock returns for oil-related firms.

Given the recent uncertainty in oil prices, the dynamic volatility spillover between oil and stock markets are of increasing interest to the construction of optimal risky portfolios and hedge ratios in financial risk management. In this context, many studies have focused on using various MGARCH models to examine the dynamic correlation, portfolio design, and hedging effectiveness of commodity-equity portfolios. Choi and Hammoudeh (2010) applied the DCC approach to investigate the relationship between the S&P 500 index and commodity prices including oil, copper, gold, and silver. They demonstrated evidence of increasing correlations between all the commodities but a decreasing correlation with the S&P 500 index. Arouri et al. (2011, 2012, 2015) examined the extent of volatility transmission, portfolio design, and hedging effectiveness in oil, gold, and stock returns using the following MGARCH models: CCC-GARCH, DCC-GARCH, diagonal BEKK-GARCH, scalar-BEKK-GARCH, and full-BEKK-GARCH.

In their analysis, Filis et al. (2011) employed the DCC-GARCH model with asymmetry to segregate oil importing and exporting countries and found that oil prices had a negative effect on all stock markets except during the 2008 global financial crisis (GFC). The dynamic correlations exhibited similar patterns based on normal and t-distributions over time. The values of the dynamic conditional correlations that are negative indicate the possibility of portfolio diversification. Sadorsky (2012, 2014) analyzed volatility spillover between commodities (oil, copper, and wheat) and stock prices using BEKK-, diagonal-, CCC−, and DCC-MGARCH models. Mensi et al. (2013) used the VAR−CCC−GARCH model to investigate the return links and volatility transmission between the S&P 500 and commodity price indices (energy, food, gold, and beverages). Hammoudeh et al. (2014) examined the dependence structure between commodities and Chinese stock markets using multivariate copula functions. They provided strong evidence of low and positive correlations between these markets, implying that commodity futures play an important role in portfolio diversification benefits and risk reduction in the Chinese stock market. Chkili (2016) explored the dynamic correlation and hedging effectiveness between gold and stock markets of the BRICS countries using the asymmetric DCC-MGARCH model.

More recently, Zhang et al. (2017) employed the volatility threshold dynamic conditional correlations (VT-DCC) approach to investigate the spillover effect of stock market volatility index for crude oil and natural gas markets during 1999–2015 and found evidence of similarities in the correlation dynamics between crude oil and stock volatility series. Boubaker and Raza (2017) examined the spillover effects and shocks between oil prices and BRICS stock markets using VARMA-DCC-GARCH model and wavelet multiresolution. They found strong evidence of time-varying volatility in all markets. Shrestha et al. (2018) estimated the minimum variance (MV) and quantile hedge ratios for three energy-related commodities: crude oil, heating oil, and natural gas. They demonstrated that for longer hedging horizons, the quantile hedge ratios converge on the MV hedge ratio and hedging effectiveness increases with the hedging horizon.

Overall, it is apparent that the previous empirical studies provide strong evidence of low and positive correlations between commodity and developed equity markets, implying that commodity futures offer diversification benefits and play an important role in reducing equity risk in an investment portfolio.

3. Empirical methodology

3.1. Multivariate GARCH modeling

Since the advent of the multivariate approach, the MGARCH model has become the most popular tool to specify time-varying variances and

[1] The International Energy Agency (IAE) predicts that India will burn through 4.1 mb/d in the second quarter of this year, edging out Japan's 3.8 mb/d (http://oilprice.com/Energy/Crude-Oil/India-Becomes-3rd-Largest-Oil-Importer.html).

[2] International Energy Agency (2015, p 118).

[3] International Energy Agency (2015, p 119).

[4] International Energy Agency (2015, p 51).

covariances among different stock market indices (Booth et al., 1997; Cha and Jithendranathan, 2009; Karolyi, 1995; Karolyi and Stulz, 1996; Lin et al., 1994), oil prices (Chang et al., 2010a; Cifarelli and Paladino, 2010; Malik and Hammoudeh, 2007; Sadorsky, 2006) and natural gas prices (Ewing et al., 2002). There are several MGARCH models discussed in econometric literature including the VECH models, the diagonal VECH models, and the BEKK, diagonal, and CCC models. For the diagonal, CCC, and DCC models, conditional variance is assumed to be VARMA-GARCH (1,1) (Chang et al., 2010a, 2010b; Hammoudeh et al., 2009; Ling and McAleer, 2003). McAleer et al. (2009) extended the VARMA-GARCH model to include the asymmetric GARCH effects and this is referred to as the VARMA-AGARCH model.[5]

In this study, we employ the VARMA-AGARCH model to estimate the mean and conditional variance of the daily returns of natural gas (NTG), crude oil (OIL), and the Nifty 50 index (N50), by avoiding the generated explanatory variable problem associated with the two-step estimation (Pagan, 1984).

$$r_{it} = m_{i0} + \sum\nolimits_{j=1}^{3} m_{ij} r_{jt-1} + \varepsilon_{it},\ \varepsilon_{it}|\Omega_{it-1} \sim N(0,\ h_{it}),\quad i = 1,2,3, \tag{1}$$

$$\varepsilon_{it} = v_{it} h_{it}^{1/2},\ \ v_{it} \sim N(0,1) \tag{2}$$

$$h_{it} = c_{it} + \sum\nolimits_{j=1}^{3} \alpha_{ij}\varepsilon_{jt-1}^{2} + \sum\nolimits_{j=1}^{3} \beta_{ij} h_{jt-1} + d_i \varepsilon_{it-1}^{2} I(\varepsilon_{it-1}), \tag{3}$$

where is the return for the series i(NTG, OIL, and N50) and ε_{it} is the random error term with conditional variance h_{it} in Eq. (1). $\mathrm{h_{it}}$ Market information available at time $t-1$ is denoted as Ω_{it-1}. Eq. (2) represents the relation between the error term and conditional variance. Eq. (3) specifies an AGARCH (1,1) process with the VARMA terms (McAleer et al., 2009). In Eq. (3), the dummy variable I is equal to one if $\varepsilon_{it-1} < 0$ and 0, otherwise. For this specification, a positive value of d implies that negative shocks tend to increase the variance more than the positive ones, referred to as the leverage effect (Sadorsky, 2014). The modeling of conditional variances allows large shocks to one variable to affect the variances of the other variables too. This specification allows volatility spillovers between the concerned variables (Sadorsky, 2012).

3.2. Dynamic conditional correlation

We employ the DCC model of Engle (2002) that deals with time-varying correlations and is estimated in two steps. In the first step, we test the GARCH parameters. In the second step, the correlations are estimated as follows:

$$H_t = D_t R_t D_t, \tag{4}$$

In Eq. (4), H_t is a 3×3 conditional covariance matrix, R_t is a conditional correlation matrix, and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag(h_{11t}^{1/2}, ..., h_{33t}^{1/2}), \tag{5}$$

$$R_t = diag(p_{11t}^{-1/2}, ..., p_{33t}^{-1/2}) A_t\, diag(p_{11t}^{-1/2}, ..., p_{33t}^{-1/2}), \tag{6}$$

A_t is the symmetric positive definite matrix.

$$A_t = (1 - \theta_1 - \theta_2)\bar{A} + \theta_1(\xi_{t-1}\xi_{t-1}') + \theta_2 A_{t-1}, \tag{7}$$

where $\bar{A}$ is the 3×3 unconditional correlation matrix of the standardized residuals ξ_{it}. The parameters θ_1 and θ_2 are non-negative with a sum of less than unity. The correlation estimator is:

$$\rho_{i,j,t} = \frac{p_{i,j,t}}{\sqrt{p_{i,i,t}\,p_{j,j,t}}}, \tag{8}$$

In the CCC model, $R_t = R$ and $R_{ij} = \rho_{ij}$. In the diagonal MGARCH model, $\rho_{ij} = 0$ for all i and j. The diagonal case is very restrictive because it assumes that the dynamic conditional correlations between the variables are all zero ($h_{ij} = 0$ for all i not equal to j). The standardized residuals from the MGARCH diagonal model can be used to compute an unconditional covariance matrix.

4. Data and preliminary analysis

4.1. Data

In this study, we consider the daily data for crude oil futures (OIL) and natural gas futures (NTG) sourced from the Multi Commodity Exchange of India Limited. OIL prices are measured in Indian rupees per barrel while NTG prices are denoted in Indian rupees per million British thermal units. The proxy for the Indian stock market is the S&P CNX Nifty 50 index (N50) obtained from National Stock Exchange of India. We use the daily data for all variables from July 10, 2006 to November 30, 2015, which is an advantage over previous studies. For instance, while Acaravci et al. (2012) used the quarterly data from the period 1990 through 2008 to investigate the long-run relationship between natural gas prices and stock prices, they did not examine the effect of the GFC. Further, though Tiwari et al. (2019) had recently examined the relationship between natural gas and crude oil prices for the U.S. economy between January 1997 and July 2017, they, however, have considered the monthly data. The choice of daily data gives us a detailed picture of the energy and financial markets.

Fig. 1 plots the daily evolution of NTG, Oil, and N50 indexes during the sample period. A closer examination of this figure reveals that all markets decreased after 2008–2009, corresponding to the GFC period. During the crisis, the N50 index declined almost 43 percent between September 2, 2008 and March 9, 2009. The energy markets further exhibited a second important decline between mid-2014 and 2015.

4.2. Preliminary analysis

We calculate the continuously compounded daily returns by considering the difference in the logarithmic values of two consecutive prices: $r_{i,t} = \ln(P_{i,t}/P_{i,t-1}) \times 100$, where $r_{i,t}$ denotes the continuously compounded percentage daily returns for index i at time t, while $P_{i,t}$ denotes the price level of index i at time t.

Table 1 shows the descriptive statistics for the daily returns of OIL, NTG, and N50. For each series, the mean values are insignificantly different from zero while the standard deviations are larger than the mean values. The skewness value is small but positive for all the variables, indicating a thicker upper tail of the distribution. The kurtosis values for all return series exceed three, indicating the presence of peaked distributions and fat tails. The Jarque and Bera (1987) test results reject the null hypothesis of non-normality in the returns. That is, all return series display a leptokurtic distribution with a higher peak and a fatter tail than that of a normal distribution.

Further, we examine the existence of the ARCH effect using the Lagrange multiplier test proposed by Engle (1982). All return series exhibit an ARCH behavior and, therefore, estimation of a GARCH model is appropriate for modeling stylized facts, such as fat tails, clustering volatility, and persistence of commodity price and bank index returns. According to the Ljung-Box test $Q(20)$ and $Q^2(20)$ results, we provide evidence for serial correlations for both the residuals and squared residuals at 1% significance level. We use unit root tests, such as the augmented Dickey and Fuller (ADF) (1979) test, Phillips and Perron (PP) (1988) test, and the Kwiatkowski et al. (KPSS) (1992) test to check the stationarity of the time series variables. The results indicate that all index return series are stationary at the conventional 1% level of significance.

In Fig. 2, we apply the Markov-switching dynamic regression (MS-DR) model to detect the tranquil and volatile periods in the return series and allow one to specify the length of the volatile regime, which is of

[5] A comprehensive overview of these models is provided in Hakin and McAleer (2010).

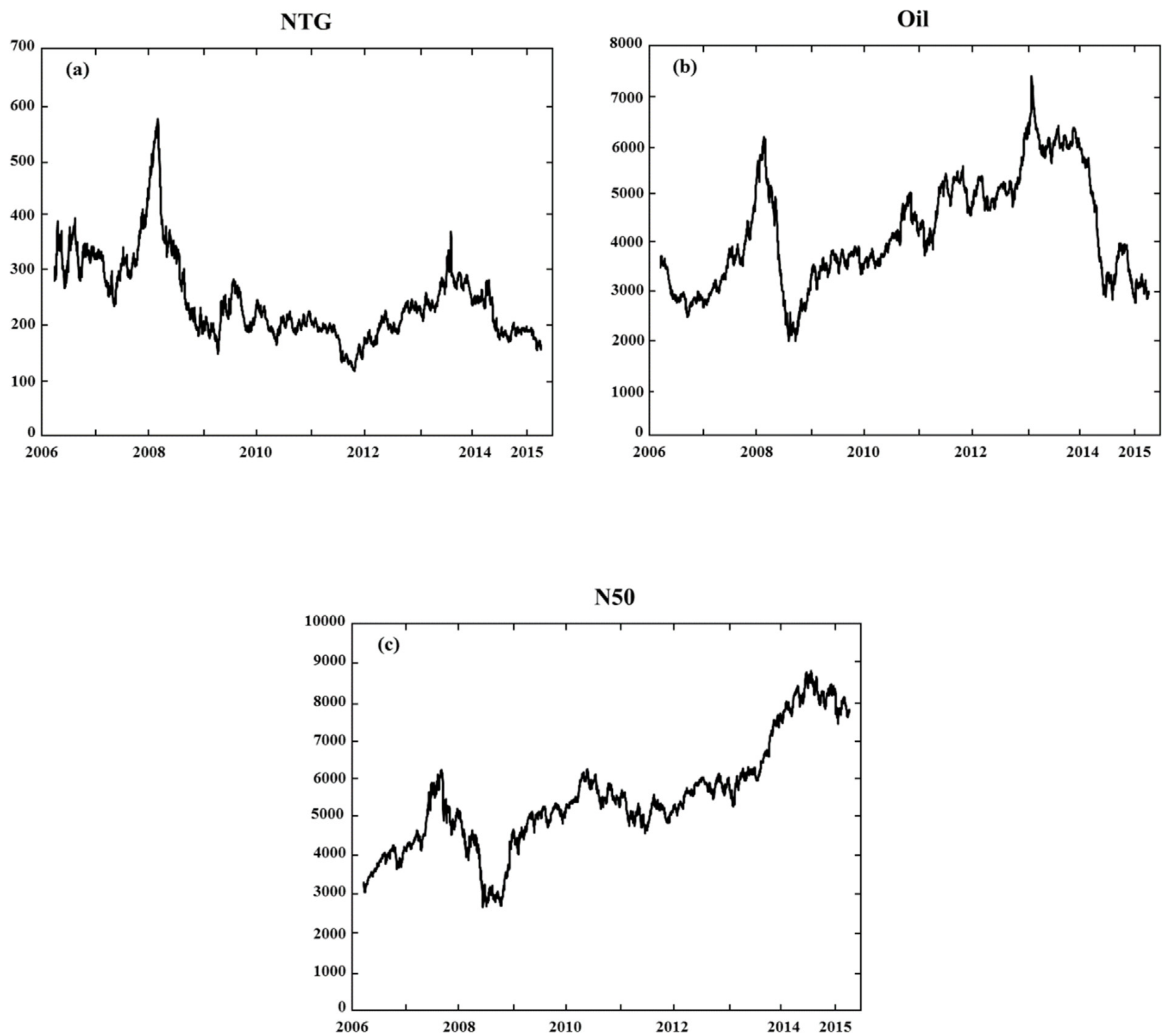

Fig. 1. Time-variations in daily NTG, OIL, and N50.

Table 1
Descriptive statistics of daily returns.

	NTG	OIL	N50
Mean	−0.026	−0.008	0.040
Maximum	11.736	12.863	16.334
Minimum	−16.536	−14.049	−13.014
Standard Deviation	2.399	1.738	1.544
Skewness	0.039	0.101	0.029
Kurtosis (Excess)	2.224	5.519	9.979
Jarque-Bera	479.35***	2952.14***	9638.46***
$Q(20)$	110.09***	134.39***	55.745***
$Q^2(20)$	459.37***	1567.67***	710.02***
ARCH-LM(10)	18.831***	50.293***	25.433***
ADF	−31.851***	−8.892***	−10.167***
PP	−38.555***	−39.635***	−45.317***
KPSS	0.0464	0.1905	0.05039

Note: The table shows the descriptive statistics of the daily returns for natural gas (NTG), crude oil (OIL), and the Nifty 50 (N50) index. The Jarque-Bera tests for normality of return series. The Ljung-Box test of $Q(20)$ and $Q^2(20)$ check for autocorrelation of returns and squared returns respectively. The ADF, PP, and KPSS tests are the empirical statistics of the Augmented Dickey and Fuller (1979) test, the Phillips and Perron (1988) unit root tests, and the Kwiatkowski et al. (1992) stationarity test respectively. Engle's (1982) ARCH-LM(10) test checks for the presence of ARCH effects.***denotes rejection of the null hypotheses at 1% significance level.

great importance when dealing with cross-market spillovers. The shaded regions highlight periods of excessive volatilities according to the MS-DR model and show the effects of the GFC on these return series. In fact, both OIL and N50 show significant volatility clustering during the GFC; however, NTG does not exhibit pronounced volatility around that time.[6]

Table 2 presents four cointegration tests to examine the long-run relationships among all the returns. Panel A of Table 2 presents the results for the Engle and Granger (1987) cointegration tests. Since none of the parameters is significant, we rule out the presence of cointegration between OIL, NTG, and N50. These findings are further confirmed by the Phillips and Ouliaris (1988) cointegration test shown in Panel B. Similarly, the results for the Johansen (1988) cointegration tests also indicate that there is no cointegration among the variables since the trace statistic and Eigen-value are both insignificant at 5% level of significance. Finally, the Gregory-Hansen cointegration test also corroborates the results of the first three tests of cointegration.

Our results are in congruence with the results of previous studies carried out between natural gas prices and stock prices and between oil futures and stock prices. For instance, Kandir et al. (2013) found no long-run relationship between natural gas prices, real GDP, real

[6] For further details on the MS-DR model, see Hamilton (1989) and Hamilton and Susmel (1994).

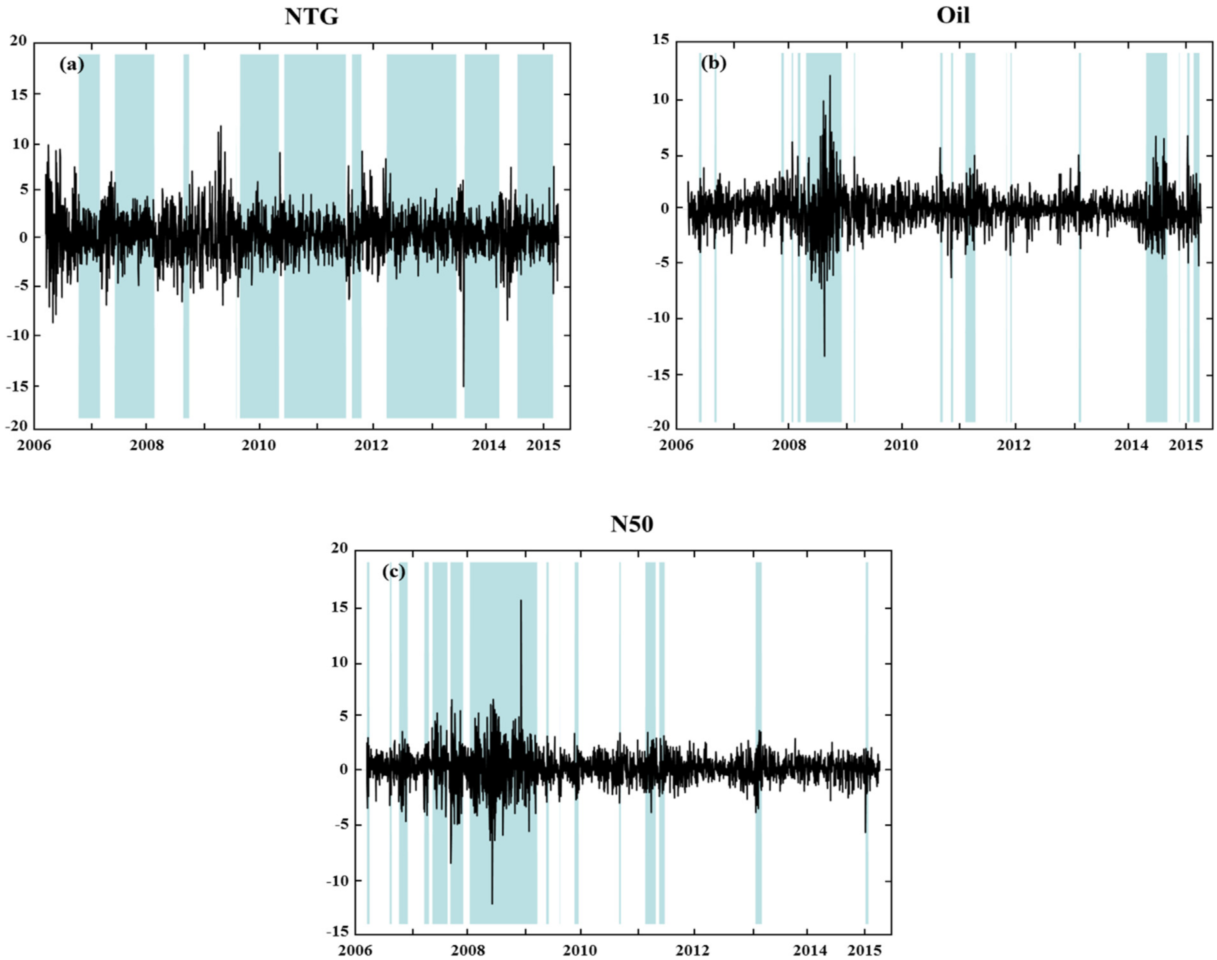

Fig. 2. Time-series plot of daily returns of OIL, NTG, and N50.
Note: The shaded areas highlight periods of excessive volatility according to the Markov-switching dynamic regression (MS-DR).

Table 2
Cointegration tests for OIL, NTG, and N50.

Panel A: Engle-Granger cointegration tests				
ADF (no trend)	CV at 5%	ADF (with trend)	CV at 5%	
−2.2943	−3.7465	−2.6427	−4.1245	
Panel B: Phillips-Ouliaris cointegration test				
Z-stat (no trend)	CV at 5%	Z-stat (with trend)	CV at 5%	
−2.2714	−3.7465	−2.7354	−4.1245	
Panel C: Johansen cointegration tests				
Cointegration order	Eigenvalue	Trace Statistic	CV at 5% (Trace)	CV at 5% (Eigenvalue)
None	0.0032	11.5507	29.7971	21.1316
At most 1	0.0012	4.0780	15.4947	14.2646
At most 2	0.0005	1.2314	3.8415	3.8415
Panel D: Gregory-Hansen cointegration test				
t-stat (no trend)	CV at 5%	*t*-stat (with trend)	CV at 5%	
−3.2510	−4.9200	−3.2470	−5.2900	

Note: The table shows the results for the cointegration tests between crude oil, natural gas, and the Nifty 50 index. CV stands for critical value.

exchange rates, and stock prices in Turkey. Similarly, other empirical studies failed to detect any relationship between oil futures and stock prices (see Maghyereh, 2004; Al-Fayoumi, 2009). In another work, Nandha and Hammoudeh (2007) found no significant oil price effect on stock prices for a sample of fifteen Asia-Pacific countries. Nevertheless, studies pertaining to the developed countries have shown significant relationship between energy and stock prices (see Sadorsky, 1999; Park and Ratti, 2008; Kilian and Park, 2009).

The absence of cointegration between natural gas prices, oil prices and stock prices might be due to three reasons. First, the nonexistence of cointegration could be due to market inefficiency. A semi-strong form of market efficiency necessitates all relevant information to be reflected in the stock prices. Our findings do not seem to support this proposition as any information arising from natural gas or oil returns does not seem to be fully transmitted to stock returns. Second, the absence of cointegration might be due to a company's pricing strategy, which is related to its costs incurred. Since, oil and natural gas contribute significantly to the overall costs in the manufacturing and transportation sectors, hence, any increase in costs would increase the prices. In such a situation, prices of oil and natural gas would not have a direct impact on stock prices. Third, we find little evidence of cointegration among the three variables due to an integration of diverse markets. If markets dealing with oil and natural gas and stock markets are integrated, then stock prices would reflect the changes in the oil and natural gas prices. Therefore, the absence of cointegration from our analysis indicates an information gap among the markets dealing with Indian commodity futures (oil and natural gas) and stock markets.

5. Empirical results and portfolio analysis

5.1. Empirical results

We estimate the MGARCH modeling and report the results of AR

Table 3
AR (1)-multivariate GARCH(1,1) models.

	Without Asymmetry		With Asymmetry	
	DCC	CCC	DCC	CCC
Panel A: AR (1) mean equation				
Constant	−0.004 (0.041)	−0.020 (0.048)	−0.021 (0.040)	−0.015 (0.040)
NTG{1}	0.223 (0.023)***	0.223 (0.019)***	0.223 (0.015)***	0.224 (0.015)***
Constant	0.035 (0.026)	0.037 (0.024)	0.020 (0.027)	0.016 (0.026)
OIL{1}	0.237 (0.021)***	0.242 (0.019)***	0.236 (0.014) ***	0.241 (0.024)***
Constant	0.071 (0.023)***	0.073 (0.020)***	0.040 (0.018)**	0.041 (0.001)***
N50{1}	0.068 (0.022)***	0.063 (0.022)***	0.072 (0.014)***	0.078 (0.001)***
Panel B: GARCH variance equation				
C (1)	0.097 (0.030)***	0.105 (0.029)***	0.102 (0.022)***	−0.082 (0.023)***
C (2)	0.024 (0.011)***	0.029 (0.009)***	0.024 (0.004)***	−0.168 (0.025)***
C (3)	0.026 (0.009)***	0.025 (0.007)***	0.035 (0.010)***	−0.169 (0.021)***
A (1,1)	0.068 (0.009)***	0.155 (0.022)***	0.073 (0.012)***	0.155 (0.022)***
A (1,2)	0.005 (0.019)	0.018 (0.020)	0.007 (0.028)	0.018 (0.020)
A (1,3)	−0.018 (0.012)	−0.020 (0.016)	−0.019 (0.015)	−0.020 (0.016)
A (2,1)	0.021 (0.004)***	0.034 (0.013)**	0.019 (0.009)**	0.034 (0.013)**
A (2,2)	0.070 (0.013)***	0.153 (0.029)***	0.046 (0.015)***	0.153 (0.029)***
A (2,3)	0.027 (0.013)**	0.046 (0.014)***	0.018 (0.021)	0.046 (0.014)***
A (3,1)	0.011 (0.008)	0.023 (0.023)	0.012 (0.019)	0.023 (0.023)
A (3,2)	0.002 (0.012)	0.030 (0.020)	0.003 (0.005)	0.030 (0.020)
A (3,3)	0.083 (0.012)***	0.178 (0.022)***	0.023 (0.012)*	0.178 (0.022)***
B (1)	0.915 (0.011)***	0.977 (0.008)***	0.914 (0.008)***	0.977 (0.008)***
B (2)	0.914 (0.013)***	0.982 (0.004)***	0.913 (0.004)***	0.982 (0.004)***
B (3)	0.903 (0.015)***	0.974 (0.006)***	0.893 (0.006)***	0.974 (0.006)***
D (1)	–	–	−0.011 (0.096)	0.025 (0.085)
D (2)	–	–	0.053 (0.010)***	0.363 (0.080)***
D (3)	–	–	0.133 (0.028)***	0.627 (0.077)***
R (2,1)	–	0.217 (0.217)***	–	0.217 (0.217)***
R (3,1)	–	−0.033 (0.026)	–	−0.033 (0.026)
R (3,2)	–	0.101 (0.024) ***	–	0.101 (0.024) ***
DCC (A)	0.018 (0.003)***	–	0.017 (0.003)***	–
DCC (B)	0.976 (0.005)***	–	0.976 (0.004)***	–
Shape	10.28 (1.023)***	9.948 (1.247)***	10.31 (1.023)***	10.05 (1.134)***
AIC	11.163	11.193	11.163	11.194
SBC	11.238	11.262	11.237	11.271
MQ (10)	84.590 [0.641]	82.897 [0.689]	84.833 [0.634]	83.414 [0.674]
MQ (20)	187.51 [0.335]	187.28 [0.339]	189.01 [0.307]	187.61 [0.333]
Log L	−12965.75	−12966.72	−12930.05	−12966.72

Note: The GARCH models are estimated using the quasi-maximum likelihood estimate (QMLE) with robust (heteroskedasticity/misspecification) standard errors in brackets. A(*i,j*) represents the ARCH impact of volatility *j* on volatility *i*, B(*i,j*) represents the GARCH impact of volatility *j* on volatility *i*. The variables are based on chronological order NTG(1), OIL(2), N50(3). *, **, and ***denote significance at the 1%, 5%, and 10% levels respectively.

(1)-GARCH (1,1) model in Table 3 and the VARMA (1,1)-GARCH (1,1) models in Table 4. The mean model equations of NTG{1}, OIL{1}, and N50{1} indicate persistence in the returns. The coefficients of the NTG equation are positive and significant for with asymmetry and without asymmetry for all the models. The coefficients of the OIL equation are positive and significant in the case of with and without asymmetry except the DCC estimates of the asymmetry model. For the N50 equation, the estimated coefficients are statistically positive and significant for all the models and specifications. The elements of the A matrix represent the estimated coefficients for GARCH volatility that measure short-term persistence. All variables show evidence of short-term persistence. Moreover, the VARMA (1,1)-GARCH (1,1) model measures the short-term volatility spillovers between the variables. We find evidence of short-term spillovers between OIL, NTG, and N50 at 1% significance level.

The elements of matrix B presented in AR (1)-GARCH(1,1) model (in Table 3) and VARMA (1,1)-GARCH(1,1) models (in Table 4) explain the coefficients of GARCH volatility, which measure long-term persistence. We find evidence of own long-term persistence, which is greater than the estimated coefficient of own short-term persistence. For instance, the coefficient of B (1) is greater than that of A (1,1) presented in the AR (1)-GARCH (1,1) models. Similarly, the coefficient of B (1) is also greater than that of A (1,1) presented in the VARMA (1,1)-GARCH (1,1) models. Hence, we find evidence of long-term volatility spillovers from OIL to NTG, NTG to N50, and OIL to N50. The reasons for the persistence of volatility spillovers could be the determinants of the equity markets or herd behavior in the financial markets.

The elements of matrix D represent the asymmetric effects of the variables. First, considering the coefficient results of D (2) and D (3) presented in the AR (1)-GARCH(1,1) model, we find a positive and statistically significant asymmetric effect between OIL and N50 for both DCC and CCC models with asymmetry.

For the VARMA (1,1)-GARCH (1,1) models, the results of D (2) and D (3) show positive and statistically significant asymmetric effects for the DCC and CCC models between OIL and N50, except for the insignificant values of D (3) for CCC cases. Hence, we are unable to find a positive and a statistically significant leverage effect for NTG, as evident from the coefficient for D (1) presented in both the AR (1)-GARCH(1,1) and the VARMA (1,1)-GARCH(1,1) models. This leverage effect is attributable to arbitrage and heterogenous and asymmetric information in the market. The constant conditional correlations from the AR-GARCH model with and without asymmetry are very similar to the VARMA-GARCH model with and without asymmetry.

The DCC model shows that DCC(A) and DCC(B) are positive and statistically significant at the 1% level. As the sum of the values of DCC(A) and DCC(B) is less than one, it indicates that dynamic

Table 4
VARMA (1,1)–multivariate GARCH(1,1) models.

	Without Asymmetry		With Asymmetry	
	DCC	CCC	DCC	CCC
Panel A: Mean equation				
Mean Model NTG				
NTG{1}	0.229 (0.021)***	0.231 (0.019)***	0.229 (0.021)***	0.230 (0.019)***
OIL{1}	0.003 (0.023)	−0.001 (0.024)	0.002 (0.021)	−0.001 (0.025)
N50{1}	0.033 (0.034)	0.042 (0.025)	0.034 (0.025)	0.040 (0.032)
Constant	−0.003 (0.046)	−0.018 (0.047)	0.012 (0.046)	−0.017 (0.043)
U (1){1}	−0.040 (0.000)***	−0.026 (0.000)***	0.011 (0.000)***	0.003 (0.000)***
U (2){1}	−0.054 (0.000)***	−0.038 (0.000)***	−0.016 (0.000)***	0.057 (0.000)***
U (3){1}	−0.015 (0.000)***	−0.029 (0.000)***	−0.013 (0.000)***	−0.028 (0.000)***
Mean Model OIL				
NTG{1}	0.015 (0.011)	0.014 (0.011)	0.014 (0.012)	−0.028 (0.008)
OIL{1}	0.229 (0.017)***	0.232 (0.021)***	0.228 (0.022)***	0.229 (0.022)***
N50{1}	0.050 (0.021)***	0.048 (0.022)**	0.050 (0.023)***	0.050 (0.016)***
Constant	0.029 (0.029)	0.032 (0.024)	0.019 (0.027)	0.014 (0.026)
U (1){1}	0.029 (0.000)***	−0.028 (0.000)***	−0.014 (0.000)***	−0.010 (0.000)***
U (2){1}	−0.112 (0.000)***	−0.034 (0.000)***	−0.008 (0.000)***	0.001 (0.000)***
U (3){1}	−0.004 (0.000)***	−0.160 (0.000)***	0.002 (0.000)***	−0.020 (0.000)***
Mean Model N50				
NTG{1}	−0.016 (0.010)*	−0.015 (0.007)**	−0.015 (0.009)*	−0.013 (0.010)
OIL{1}	−0.007 (0.019)	−0.007 (0.018)	0.003 (0.018)	−0.002 (0.016)
N50{1}	0.071 (0.023)***	0.064 (0.018)***	0.075 (0.023)***	0.067 (0.022)***
Constant	0.071 (0.022)***	0.072 (0.022)***	0.039 (0.0239)*	0.041 (0.021)*
U (1){1}	0.041 (0.000)***	−0.020 (0.000)***	0.004 (0.000)***	−0.004 (0.000)***
U (2){1}	0.045 (0.000)***	0.026 (0.000)***	0.008 (0.000)***	−0.013 (0.000)***
U (3){1}	−0.117 (0.000)***	0.013 (0.000)***	−0.033 (0.000)***	−0.008 (0.000)***
Panel B: Variance equation				
C (1)	0.098 (0.031)***	−0.086 (0.031)***	0.102 (0.032)***	0.089 (0.034)***
C (2)	0.024 (0.008)***	0.023 (0.011)**	0.024 (0.012)**	0.019 (0.014)
C (3)	0.026 (0.009)***	0.024 (0.012)**	0.035 (0.013)***	0.030 (0.010)***
A (1,1)	0.068 (0.011)***	0.069 (0.011)***	0.074 (0.020)***	0.075 (0.016)***
A (1,2)	0.002 (0.013)	−0.012 (0.013)	0.003 (0.011)	−0.015 (0.013)
A (1,3)	−0.019 (0.015)	−0.012 (0.009)	−0.020 (0.014)	−0.007 (0.009)
A (2,1)	0.021 (0.002)***	0.004 (0.002)**	0.019 (0.009)**	0.004 (0.002)**
A (2,2)	0.070 (0.012)***	0.082 (0.015)***	0.047 (0.013)***	0.046 (0.013)***
A (2,3)	0.028 (0.012)**	0.005 (0.008)	0.019 (0.016)	−0.000 (0.006)
A (3,1)	0.011 (0.013)	−0.001 (0.002)	0.012 (0.011)	−0.000 (0.001)
A (3,2)	0.002 (0.005)	0.006 (0.007)	0.003 (0.008)	0.005 (0.007)
A (3,3)	0.084 (0.012)***	0.081 (0.013)***	0.023 (0.0011)**	0.020 (0.008)**
B (1)	0.915 (0.013)***	0.900 (0.013)***	0.915 (0.014)***	0.911 (0.013)***
B (2)	0.914 (0.014)***	0.903 (0.017)***	0.913 (0.021)***	0.904 (0.019)***
B (3)	0.903 (0.014)***	0.903 (0.015)***	0.892 (0.020)***	0.892 (0.020)***
D (1)	–	–	−0.012 (0.024)	−0.013 (0.021)
D (2)	–	–	0.052 (0.013)**	0.067 (0.020)***
D (3)	–	–	0.133 (0.032)***	0.134 (0.032)***
R (2,1)	–	0.213 (0.020)***	–	0.214 (0.019)***
R (3,1)	–	−0.034 (0.022)	–	−0.032 (0.023)
R (3,2)	–	0.109 (0.021)***	–	0.106 (0.021)***
DCC (A)	0.018 (0.004)***	–	0.017 (0.005)***	–
DCC (B)	0.976 (0.006)***	–	0.976 (0.008)***	–
Shape	10.09 (0.952)***	9.881 (0.947)***	10.11 (0.867)***	9.864 (0.956)***
AIC	11.203	11.234	11.179	11.210
SBC	11.337	11.370	11.320	11.354
MQ (10)	79.120 [0.786]	78.814 [0.794]	79.496 [0.777]	79.161 [0.785]
MQ (20)	181.01 [0.464]	181.45 [0.455]	182.43 [0.435]	181.90 [0.446]
Log L	−12952.63	−12987.91	−12921.88	−12957.28

Note: The GARCH models are estimated using the quasi-maximum likelihood estimate (QMLE) with robust (heteroskedasticity/misspecification) standard errors in brackets. A(*i,j*) represents the ARCH impact of volatility *j* on volatility *i*, B(i,j) represents the GARCH impact of volatility j on volatility *i*. The variables are based on chronological order NTG, OIL, N50. *, **, and *** denote significance at the 1%, 5%, and 10% levels respectively.

conditional correlations are mean reverting. The AIC and SBC criterion show that the DCC model is better than the CCC model for both with asymmetry and without asymmetry. The multivariate Q (MQ) test for serial correlation with 10 and 20 degrees of freedom results shows no evidence of autocorrelation at the 1% level in either of the DCC-VARMA (1,1) and GARCH (1,1) models with and without asymmetry.

Fig. 3 presents the conditional correlation obtained from the VARMA-DCC-GARCH model from July 2006 to November 2015. The correlation coefficients are not constant but vary tremendously with time in pair-wise comparisons. Note that the correlations indicate the benefit of diversifying and investing in the Indian stock and energy futures markets. To be precise, the pair of OIL-N50 shows more

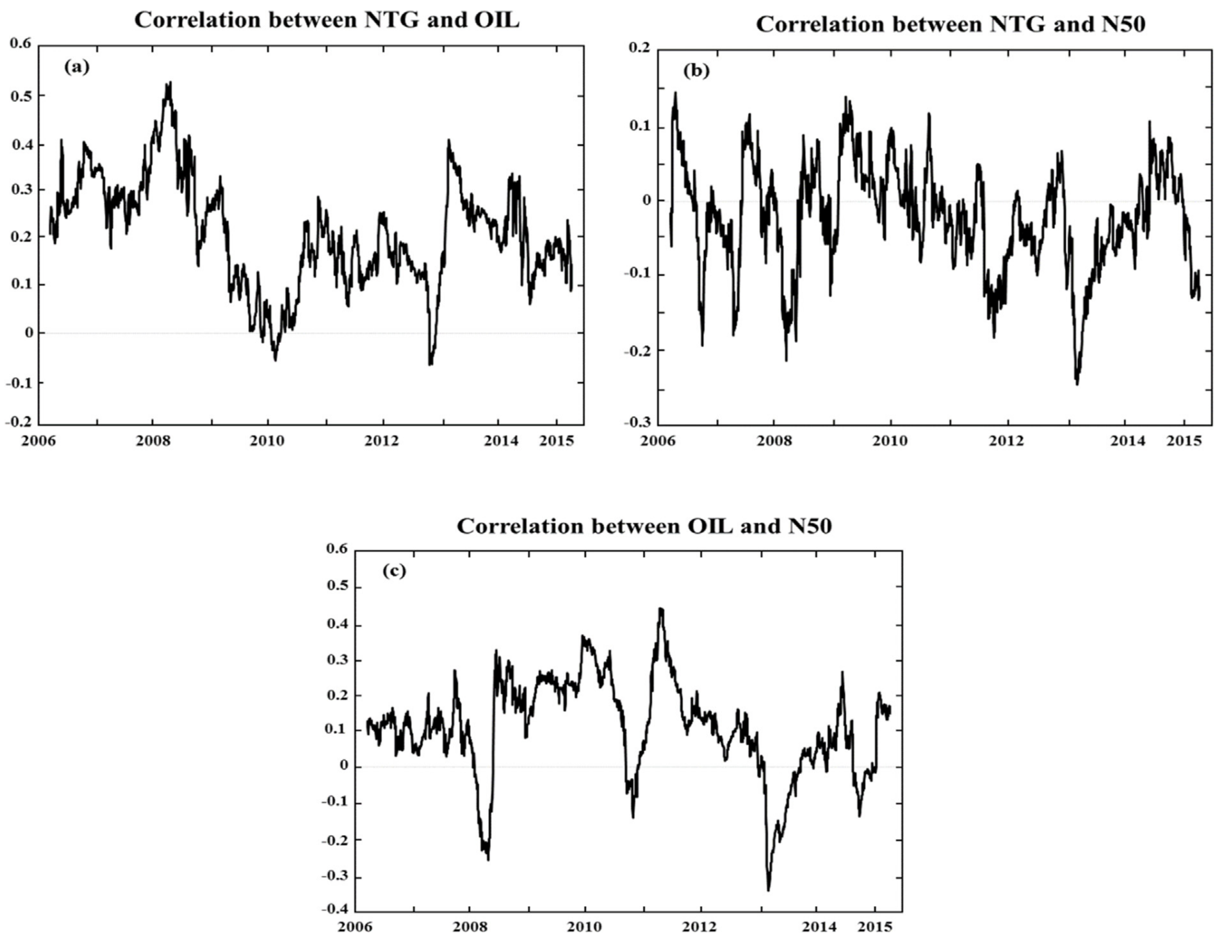

Fig. 3. Conditional correlations from the VARMA-DCC-GARCH model.

volatility and higher correlation coefficients than the NTG-N50 pair, indicating that there is little benefit of portfolio diversification between the Indian stock and oil futures markets. Indeed, the DCCs revealed that investors adjust their portfolio structure accordingly. It is also important to compute the optimal portfolio weights and the time-varying hedge ratios, which are of concern to investors and portfolio managers.

5.2. Optimal portfolio designs and dynamic hedging ratios

Our findings suggest that the volatility link across the Indian stock and energy markets are an important element for more efficient diversification of portfolios and risk management. In practical terms, building an optimal portfolio by making risk management and portfolio allocation decisions requires a preliminary and accurate estimation of the temporal covariance matrix. To manage the risks in both the Indian stock and energy markets more efficiently, we compute optimal portfolio weights and hedge ratios for designing optimal hedging strategies.

For minimizing the risks without reducing expected returns, we construct a portfolio of Indian stocks and two energy indices. We show that a portfolio investor seeks to hedge the exposure to the stock price movements by investing in India's energy market. Following Kroner and Ng (1998), the portfolio weight of the commodity futures holdings is given by:

$$w_t^C = \frac{h_t^S - h_t^{CS}}{h_t^C - 2h_t^{CS} + h_t^S}, \text{ with } w_t^C = \begin{cases} 0 & w_t^C < 0 \\ w_t^C & 0 \le w_t^C \le 1, \\ 1 & w_t^C > 1 \end{cases} \tag{9}$$

where h_t^C, h_t^S, and h_t^{CS} are the conditional volatility of each energy commodity returns, the conditional volatility of N50 returns, and the conditional covariance between energy commodity and N50 returns at time t respectively. From the budget constraint, the optimal weight of the stock is equal to $(1 - w_t^C)$. For each energy-stock pair, all information needed to compute w_t^C is obtained from the VARMA (1,1)-GARCH(1,1)-DCC model.

Next, we consider the hedge ratios of Kroner and Sultan (1993) to minimize the risk of this portfolio (Indian stock index and energy index). We measure by how much should a long position (buy) of one dollar in the stock market be hedged by a short position (sell) of β dollar in the energy markets, where β at time t is given by:

Table 5
Optimal portfolio weights and hedge ratios.

	Optimal portfolio weights				Hedging ratios			
	Mean	Std. dev.	Max	Min	Mean	Std. dev.	Max	Min
N50/NTG	0.2735	0.1591	0.8951	0.0144	0.0133	0.0529	0.2570	−0.2862
N50/OIL	0.4233	0.1713	0.9440	0.0834	0.1000	0.1387	0.6681	−0.3322

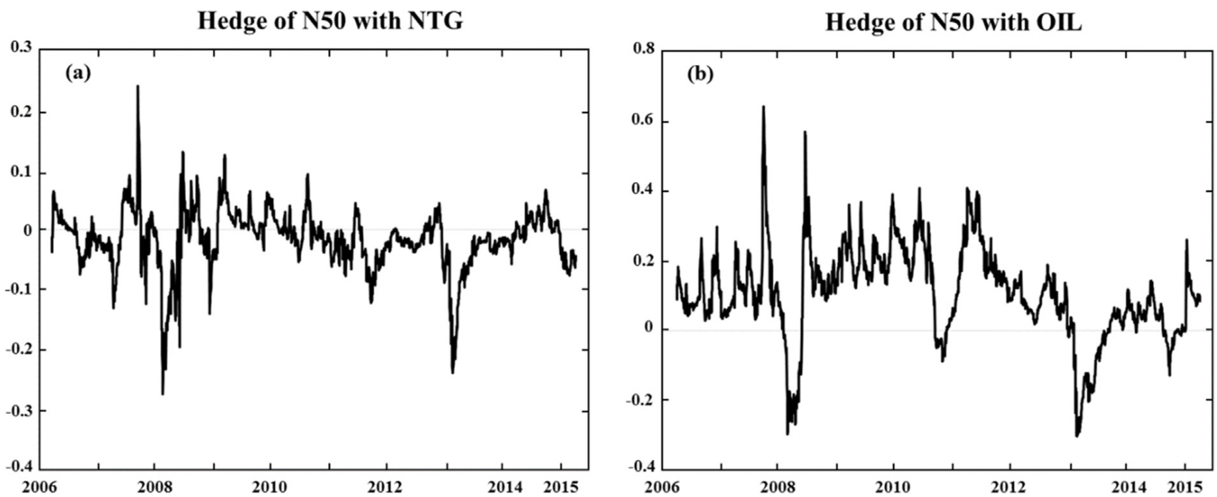

Fig. 4. Time-varying hedging ratios between the Indian stock and energy futures markets.

$$\beta_t = \frac{h_t^{CS}}{h_t^{C}} \tag{10}$$

Table 5 summarizes the values of the optimal weight and hedge ratios of the energy markets based on the VARMA (1,1)-GARCH (1,1)-DCC model with asymmetry. As shown in Table 5, the N50/OIL pair shows a higher average weight value than the N50/NTG pair, indicating that investors hold more Indian stock proportions in the stock-oil portfolio than its counterpart. The average optimal hedge ratio of natural gas is lower than that of oil. More precisely, the hedge ratio value of the N50/OIL pair is 0.1000, meaning that a dollar long position in the stock market should be hedged by shorting (selling) a ten-cent investment in the oil market. However, the hedge ratio value of the N50/NTG pair is 0.0133, suggesting that a one-cent investment in the natural gas market can minimize risk for investors with stock holdings. Thus, we find that Indian stock investors prefer natural gas over oil to hedge their positions against unfavorable and extreme stock price movements, indicating that energy commodities are the perfect assets for reducing portfolio risk.

Fig. 4 displays the dynamic hedge ratios across the Indian stock and energy markets. The paths suggest that variability is in the order of the estimated hedge ratio. In fact, we observe significant time-varying hedge ratios over the sample data, suggesting dissimilarity between the stock and energy pairs and investors' risk-switching behavior. Therefore, investors frequently adjust their portfolio structure and hedging positions according to the Indian stock and energy futures market conditions (bear, normal, and bull markets).

6. Conclusions and implications

The dynamics of energy commodity prices are an important element for investors in diversifying their stock portfolios, as they have low or negative correlations with equity assets. This paper investigates the time-varying volatilities and dynamic conditional correlations between crude oil, natural gas, and stock prices in India using various MGARCH models (with and without asymmetry). Furthermore, with respect to portfolio management, we analyze the optimal weights and hedge ratios for portfolios to minimize exposure to portfolio risk.

Our empirical results suggest that there is no long-run cointegration between energy futures and the stock market in India. Of the various multivariate GARCH models analyzed, we find that the DCC model performs better than the CCC model with asymmetry in estimating time-varying correlations. Furthermore, the comparison of optimal portfolio weights and hedging ratios between stock-energy futures pairs suggests that in optimal portfolios, stocks outweigh commodity futures, and that the stock market risks can be hedged with relatively lower costs.

These results have two important implications for portfolio investors dealing with the Indian stock market and energy commodity futures while forecasting portfolio risk exposures and determining the existence of diversification benefits. First, the superiority of DCC models over the CCC models demonstrates mean reverting tendencies and persistence of asymmetric effects in OIL and N50 stock markets but no asymmetric effects in the NTG market. In other words, the presence of asymmetric effect or "leverage effect" explains that an unexpected drop in asset prices (bad news) increases volatility more than an unexpected increase in asset prices (good news) with an equal force. From a market contagion perspective, the findings of asymmetric volatility spillovers help us to understand the source of negative market shock transmission between Indian stock and energy markets. These findings are important for portfolio investors in designing decoupling strategies to protect against market contagion risks.

Second, in the context of portfolio risk management, we construct synthetic portfolios of Indian stock and energy markets to quantify optimal portfolio weights and find the hedging ratios of these constructed portfolios. To foreshadow the key findings, this study focuses on optimal hedge ratios and shows that the average hedge ratio for oil is relatively higher than that of natural gas. In sum, a long position (buy) of one dollar in the stock market should be hedged with a short selling of 10-cent in the oil futures or investing 1-cent in the natural gas futures, which is cheaper than oil futures. Therefore, investors investing in Indian stock market choose to invest in natural gas over oil to hedge their positions against critical and abrupt movement in stock prices, indicating that energy commodities are the perfect assets for reducing portfolio risk.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2019.04.004.

References

Acaravci, A., Ozturk, I., Kandir, S.Y., 2012. Natural gas prices and stock prices: evidence from EU-15 countries. Econ. Modell. 29, 1646–1654.

Al-Fayoumi, N.A., 2009. Oil prices and stock market returns in oil importing countries:

the case of Turkey, Tunisia and Jordan. Eur. J. Econ. Financ. Adm. Sci. 16, 86–101.
Arouri, M.E.H., Jouini, J., Nguyen, D.K., 2012. On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. Energy Econ. 34 (2), 611–617.
Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2011. Return and volatility transmission between world oil prices and stock markets of the GCC countries. Econ. Modell. 28 (4), 1815–1825.
Arouri, M.E.H., Lahiani, A., Nguyen, D.K., 2015. World gold Prices and stock returns in China: insights for hedging and diversification strategies. Econ. Modell. 44, 273–282.
Asche, F., Oglend, A., Osmundsen, P., 2012. Gas versus oil prices the impact of shale gas. Energy Policy 47, 117–124.
Bal, D.P., Rath, B.N., 2015. Nonlinear causality between crude oil price and exchange rate: a comparative study of China and India. Energy Econ. 51, 149–156.
Basher, S.A., Sadorsky, P., 2006. Oil price risk and emerging stock markets. Glob Financ. J. 17, 224–251.
Basher, S.A., Haug, A.A., Sadorsky, P., 2012. Oil prices, exchange rates and emerging stock markets. Energy Econ. 34, 227–240.
Batten, J.A., Ciner, C., Lucey, B.M., 2017. The dynamic linkages between crude oil and natural gas markets. Energy Econ. 62, 155–170.
Booth, G.G., Martikainen, T., Tse, Y., 1997. Price and volatility spillovers in Scandinavian stock markets. J. Bank. Financ. 21, 811–823.
Boubaker, H., Raza, S.A., 2017. A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. Energy Econ. 64, 105–117.
Boyer, M.M., Filion, D., 2007. Common and fundamental factors in stock returns of Canadian oil and gas companies. Energy Econ. 29, 428–453.
Brown, S.P.A., 2017. Natural gas vs. oil in U.S. transportation: will prices confer an advantage to natural gas? Energy Policy 110, 210–221.
Brown, S.P.A., Yucel, M.K., 2002. Energy prices and aggregate economic activity: an interpretative survey. Q. Rev. Econ. Finance 42, 193–208.
Cha, H.-J., Jithendranathan, T., 2009. Time-varying correlations and optimal allocation in emerging market equities for the US investor. Int. J. Financ. Econ. 14, 172–187.
Chang, C.-L., McAleer, M., Tansuchat, R., 2010a. Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil markets. Energy Econ. 32, 1445–1455.
Chang, C.-Y., Lai, J.-L., Chuang, I.-Y., 2010b. Futures hedging effectiveness under the segmentation of bear/bull energy markets. Energy Econ. 32, 442–449.
Chiou, J.-S., Lee, Y.-H., 2009. Jump dynamics and volatility: oil and the stock markets. Energy 34 (6), 788–796.
Chkili, W., 2016. Dynamic correlations and hedging effectiveness between gold and stock markets: evidence for BRICS countries. Res. Int. Bus. Finance 38, 22–34.
Choi, K., Hammoudeh, S., 2010. Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. Energy Policy 38, 4388–4399.
Cifarelli, G., Paladino, G., 2010. Oil price dynamics and speculation: a multivariate financial approach. Energy Econ. 32, 363–372.
Cong, R.G., Wei, Y.M., Jiao, J.L., Fan, Y., 2008. Relationships between oil price shocks and stock market: an empirical analysis from China. Energy Policy 36, 3544–3553.
Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74, 427–431.
El-Sharif, I., Brown, D., Burton, B., Nixon, B., Russell, A., 2005. Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Econ. 27 (6), 819–830.
Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50 (4), 987–1007.
Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 55, 251–276.
Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. 20, 339–350.
Ewing, B.T., Malik, F., Ozfidan, O., 2002. Volatility transmission in the oil and natural gas markets. Energy Econ. 24, 525–538.
Filis, G., Degiannakis, S., Floros, C., 2011. Dynamic correlation between stock market and oil prices: the case of oil-importing and oil-exporting countries. Int. Rev. Financ. Anal. 20, 152–164.
Hakin, A., McAleer, M., 2010. Modelling the interactions across international stock, bond and foreign exchange markets. Appl. Econ. 42, 825–850.
Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica 57 (2), 357–384.
Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroscedasticity and changes in regime. J. Econom. 64, 307–333.
Hammoudeh, S., Dibooglu, S., Aleisa, E., 2004. Relationships among US oil prices and oil industry equity indices. Int. Rev. Econ. Financ. 13, 427–453.
Hammoudeh, S., Yuan, Y., McAleer, M., 2009. Shock and volatility spillovers among equity sectors of the Gulf Arab stock markets. Q. Rev. Econ. Finance 49, 829–842.
Hammoudeh, S., Nguyen, D.K., Reboredo, J.C., Wen, X., 2014. Dependence of stock and commodity futures markets in China: implications for portfolio investment. Emerg. Mark. Rev. 21, 183–200.
Hartley, P.R., Medlock III, K.B., Rosthal, J.E., 2008. The relationship of natural gas to oil prices. Energy J. 29 (3), 47–65.
Hayat, A., Narayan, P.K., 2011. Do demand and supply shocks explain USA's oil stock fluctuations? Appl. Energy 88, 2908–2915.
Henriques, I., Sadorsky, P., 2008. Oil prices and the stock prices of alternative energy companies. Energy Econ. 30, 998–1010.
Herrera, A.M., Pesavento, E., 2009. Oil price shocks, systematic monetary policy, and the "Great Moderation". Macroecon. Dyn. 13, 107–137.
Huang, R.D., Masulis, R.W., Stoll, H.R., 1996. Energy shocks and financial markets. J. Futures Mark. 16 (1), 1–27.
International Energy Agency, 2015. Energy and Climate Change. World Energy Outlook Special Report. . https://www.iea.org/publications/freepublications/publication/WEO2015SpecialReportonEnergyandClimateChange.pdf.
Jarque, C.M., Bera, A.K., 1987. A test for normality of observations and regression residuals. Int. Stat. Rev. 2, 163–172.
Johansen, S., 1988. Statistical analysis of cointegration vectors. J. Econ. Dyn. Control 12, 231–254.
Jones, C.M., Kaul, G., 1996. Oil and the stock markets. J. Financ. 51 (2), 463–491.
Kandir, S.Y., Ozturk, I., Acaravci, A., 2013. Causality between natural gas prices and stock market returns in Turkey. Econ. Pol. 30 (2), 203–220.
Karolyi, G.A., 1995. A multivariate GARCH model of international transmissions of stock returns and volatility: the case of the United States and Canada. J. Bus. Econ. Stat. 13, 11–25.
Karolyi, G.A., Stulz, R.M., 1996. Why do markets move together? An investigation of US-Japan stock return comovements. J. Financ. 51, 951–986.
Kilian, L., Park, C., 2009. The impact of oil price shocks on the US Stock Market. Int. Econ. Rev. 50 (4), 1267–1287.
Koutmos, G., 1996. Modeling the dynamic interdependence of major European stock markets. J. Bus. Financ. Account. 23, 975–988.
Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Rev. Financ. Stud. (4), 817–844.
Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. J. Financ. Quant. Anal. 28 (4), 535–551.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? J. Econom. 54 (1–3), 159–178.
Lee, Y.-H., Chiou, J.-S., 2011. Oil sensitivity and its asymmetric impact on the stock market. Energy 36 (1), 168–174.
Lin, W.L., Engle, R.F., Ito, T., 1994. Do bulls and bears move across borders? International transmission of stock returns and volatility. Rev. Financ. Stud. 7, 507–538.
Ling, S., McAleer, M., 2003. Asymptotic theory for a vector ARMA-GARCH model. Econom. Theor. 19, 278–308.
Maghyereh, A., 2004. Oil prices shocks and emerging stock markets: a generalized VAR approach. Int. J. Appl. Econom. Quant. Stud. 2, 28–40.
Malik, S., Hammoudeh, S., 2007. Shock and volatility transmission in the oil, US and Gulf equity markets. Int. Rev. Econ. Financ. 17, 357–368.
McAleer, M., Hoti, S., Chan, F., 2009. Structure and asymptotic theory for multivariate Asymmetric conditional volatility. Econom. Rev. 28 (5), 422–440.
Mensi, W., Beljid, M., Boubaker, A., Managi, S., 2013. Correlations and volatility spillovers across commodity and stock markets: linking energies, food, and gold. Econ. Modell. 32, 15–22.
Nandha, M., Hammoudeh, S., 2007. Systematic risk, and oil price and exchange rate sensitivities in Asia-Pacific stock markets. Res. Int. Bus. Finance 21, 326–341.
Narayan, P.K., Narayan, S., 2010. Modelling the impact of oil prices on Vietnam's stock prices. Appl. Energy 87 (1), 356–361.
Narayan, P.K., Sharma, S.S., 2011. New evidence on oil price and firm returns. J. Bank. Financ. 35, 3253–3262.
Narayan, P.K., Sharma, S.S., 2014. Firm return volatility and economic gains: the role of oil prices. Econ. Modell. 38, 142–151.
Nick, S., Thoenes, S., 2014. What drives natural gas prices? A structural VAR approach. Energy Econ. 45, 517–527.
Pagan, A., 1984. Econometric issues in the analysis of regressions with generated regressors. Int. Econ. Rev. 25 (1), 221–247.
Panagiotidis, T., Rutledge, E., 2007. Oil and gas markets in the UK: evidence from a cointegrating approach. Energy Econ. 29, 329–347.
Park, J., Ratti, R.A., 2008. Oil price shocks and stock markets in the US and 13 European countries. Energy Econ. 30, 2587–2608.
Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.
Phillips, P.C.B., Ouliaris, S., 1988. Testing for cointegration using principal component methods. J. Econ. Dyn. Control 12, 205–230.
Ramberg, D.J., Parsons, J.E., 2012. The weak tie between natural gas and oil prices. Energy J. 33, 13–35.
Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Econ. 21, 449–469.
Sadorsky, P., 2001. Risk factors in stock returns of Canadian oil and gas companies. Energy Econ. 23 (1), 17–28.
Sadorsky, P., 2006. Modeling and forecasting petroleum futures volatility. Energy Econ. 28, 467–488.
Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34 (1), 248–255.
Sadorsky, P., 2014. Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil and wheat. Energy Econ. 43, 72–81.
Shrestha, K., Subramaniam, R., Peranginangin, Y., Philip, S.S.S., 2018. Quantile hedge ratio for energy markets. Energy Econ. 71, 253–272.
Tiwari, A.K., Mukherjee, Z., Gupta, R., Balcilar, M., 2019. A wavelet analysis of the relationship between oil and natural gas prices. Resour. Pol. 60, 118–124.
Villar, J.A., Joutz, F.L., 2006. The relationship between crude oil and natural gas prices. Energy Inform. Adm. Off. Oil Gas 1–43.
Zhang, B., Li, X., Yu, H., 2013. Has recent financial crisis changed permanently the correlations between BRICS and developed stock markets? N. Am. J. Econ. Finance 26, 725–738.
Zhang, Y.J., Chevallier, J., Guesmi, K., 2017. "De-financialization" of commodities? Evidence from stock, crude oil and natural gas markets. Energy Econ. 68, 228–239.