

## Portfolio Diversification and Oil Price Shocks: A Sector Wide Analysis

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### ABSTRACT

This paper investigates the time-varying relationship between the oil price and disaggregated stock market of India using dynamic conditional correlation multivariate GARCH and continuous wavelet transformation modelling approaches. Our findings reveal the evolving relationship between the oil price and disaggregated stock market. The correlations are generally volatile before the 2007-2008 crisis but since then the correlations are positive implying no diversification benefits for the investors during rising oil prices. As emerging markets in general, and India in particular, is expected to increase its share of oil consumption in the world's energy market, therefore for the stock market to grow, especially the oil-intensive industries, we recommend the government should increase its reliance on alternative energy resources. Furthermore, as rising oil prices can also have its adverse effect through exchange rate channel, we suggest the monetary policies should be time varying to manage the oil inflationary pressures arising out of extreme volatility in the oil prices.

**Keywords:** Dynamic Conditional Correlation Multivariate GARCH, Continuous Wavelet Transformation, Disaggregated Stock Market, India, Oil Price Shocks, Diversification

**JEL Classifications:** C50, G10, O53, Q43

## 1. INTRODUCTION

There are two main strands of literature on the relationship between increase in oil price and stock market. One strand advocates negative impact while the findings of other strand points to the positive impact. Kilian and Park (2009) pointed out that the stock market reaction to the hike in oil price depends on whether the increase is driven by supply or demand shocks in the oil market. Likewise, response of the stock market to the hike in oil prices would depend on whether the country is oil-importing or oil-exporting. For instance, hike in oil prices is expected to have negative impact on the stock market in case of the oil-importing countries (Cheung and Ng, 1998; Park and Ratti, 2008; Sadorsky, 1999)<sup>1</sup> whereas for oil-exporting countries stock market is expected to react positively to the increase in oil prices (Al-Fayoumi, 2009; Minor, 2015; Aimer, 2016).

As opposed to the number of literature on the link between oil price changes and stock market, few studies have looked into the oil price and stock market dynamics at the sector level. Moreover, with the notable exception of Cong et al. (2008) and Li et al. (2012), the literature on the relationship between oil price and disaggregated stock market is not only few but they are also limited to developed economies.<sup>2</sup> Second, most of these studies have investigated the relationship at most 2 time scales (long and short run). The relationship between oil prices and stock market is more complex as the changes in oil prices not only effect (negative/positive contingent on the firm's oil reliance) the future cash flows of a firm but also its discount factors through its effect on the macroeconomic stability (interest rates, inflation and exchange rate). These two impacts on firm values may not be captured in 1 or 2 time scales, so we hypothesize that effect of changes in oil prices

1 On the contrary, Al-Fayoumi (2009) found know no association between oil price increase and stock market in Turkey, Tunisia and Jordan (all of them are oil-importing countries). Similarly, Narayan and Narayan (2010) suggest positive impact of oil price increase on stock market in Vietnam (oil-importing country).

2 With the notable exception of Cong et al. (2008) and Li et al. (2012), both of them examined the relationship between the oil price and Chinese stock market at sector level, most of the studies that examined the relationship between oil price and disaggregated stock market focus on the developed economy.

on stock values should be modelled at multiple time horizons. Moreover, from the investors' perspective, it is important to capture the relationship between oil prices and stock market at different time scales owing to the heterogeneity of oil/stock investor in terms of their investment horizon. This is also argued by Reboredo and Rivera-Castro (2014), "*investors in oil and stock markets are heterogeneous with respect to their investment horizons, so the transmission of an oil shock through market transactions may vary according to time scale.*" (p. 145-146). In other words, taking investment horizons into account is relevant as both the markets consist of traders/investors with heterogeneous time horizons with regard to their entry/exit strategy. Therefore the true dynamics of association between stock market and oil market is expected to fluctuate across multiple time scales (Dewandaru et al., 2015).

We make two important and notable contribution to the oil price - stock market literature. First, as the responses of the different sectors to oil price shocks are expected to vary across sectors (depending on the oil dependence), we add to the limited literature by examining the relationship between oil price shocks and disaggregated stock market. This is important as capturing the relationship at the aggregate level would conceal the true relationship between the two through imposition of assumption that all the sectors respond similarly to oil price changes. Second, we present a methodologically improved investigation of oil price - stock market relationship by capturing the time-varying relationship between the two. If the relationship between two do exists at multiple scales then the modelling approaches that restrict the relationship to one or two scales are misspecified and hence inferences drawn from results would be wrong. To model the relationship at multiple scales, we make use of dynamic conditional correlation multivariate GARCH (DCC-MGARCH) and continuous wavelet transformation (CWT) modeling.

Therefore, the main objective of this paper is to fill the gap by analyzing the relationship between oil price and disaggregated stock market for India. More specifically, we examine the evolving relationship between oil price and disaggregated stock market.

Taking India as a case has several interesting aspects. First, India is the fourth largest oil consumer in the world and also ranked fourth among the largest oil importer in the world, therefore India's role has become important in the world oil market. Second, India has seen a rapid expansion in the past few years and is expected to grow in near future as well. Such rapid expansion is also expected to expedite the development of financial markets and hence would attract global investors to the Indian stock market. Therefore, examining the association between oil and stock market is important from both theoretical and the practical perspectives. Third, although it has been generally accepted that rising oil prices have adverse impact on oil-importing countries, there has been little research to assess the relation between the two in India. Our findings would allow international and domestic investors for better portfolio diversification. Further, our findings would also be helpful for policymakers to design policies that are conducive to the growth of stock market in an atmosphere of rising oil prices.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review followed by data and methodology in Section 3 and the results and discussion in Section 4. Finally we conclude with Section 5.

## 2. LITERATURE REVIEW

In a pioneer work, Hamilton (1983) argued that after 1973, oil price shocks have much larger impact on world economy (as oil prices were fairly stable before 1973). Further he blamed high oil prices for almost all the recessions after the World War II. Later on, others such as Burbridge and Harrison (1984), Cunado and Gracia (2003), Gisser and Goodwin (1986), and Jiménez-Rodríguez and Sánchez (2005), extended the work of Hamilton (1983) with different estimation method and data set and reinforced the findings of Hamilton (1983).

Two of the pioneer works on the relationship between oil prices and stock market is Jones and Kaul (1996) and Huang et al. (1996). Jones and Kaul (1996) used standard cash flow dividend model from Campbell (1991) to explain the relationship between oil prices and stock market. Their results suggest that oil price shocks have a significant effect on the stock market for Canada, U.K, U.S and Japan. However, in case of U.K and Japan, stock market over reacts to oil price shocks. On the other hand, Huang et al. (1996) using vector autoregressive (VAR) approach found unidirectional causality running from oil future returns to stock returns in U.S. Further, their findings suggest unidirectional causality running from oil price volatility to petroleum stock index volatility. Moreover, they suggest that oil future returns do not have much impact on the broad market indices like S and P 500.

On theoretical grounds, there are several mechanisms through which oil price shocks affect the stock market. The literature on the negative association between oil prices and stock market suggest unidirectional causality running from oil prices to stock market. There are two possible channels for the negative association. First, at micro-level, any increase in oil price will increase the cost of production of the firms that has oil as one of the factors of production, (Maghyereh, 2004; Sadorsky, 1999). If these firms are unable to pass through this cost to the consumers, their earnings will go down and hence stock price (Al-Fayoumi, 2009). But the reaction of the stock market to such shocks will depend on the relative efficiency of the stock market (Le and Chang, 2011). Second, at macro-level, increase in oil prices is expected to bring inflationary pressures that force central banks to control it by raising interest rates. Increased interest rates make bonds investment more attractive as compare to stocks and that will result into lower stock prices.

As far as positive association between oil price increase and stock market is concerned, income and wealth effects are identified as channels through which increase in oil price is expected to have positive effect on stock market in oil-exporting countries. Positive association between oil price increase and stock market is expected due to increase government revenues and infrastructure development for the oil-exporting countries (Al-Fayoumi, 2009). If these increased revenues are channeled back to the economy

this will result in increase in economic activity and improve stock market performance (Bjornland, 2009).

As far as the literature directly comparable to our work is concerned, with the notable exception of Cong et al. (2008) and Li et al. (2012), most of the studies focused on the developed economies (Arouri and Nguyen, 2010; Henriques and Sadosky, 2008; Nandha and Faff, 2008; Ramos and Veiga, 2011; Reboredo and Rivera-Castro, 2014). Using multivariate VAR, Cong et al. (2008) examined the impact of oil price shock on the disaggregated Chinese stock market. Their findings point to the insignificant impact of oil price shocks on most of the Chinese stock market indices, except for the manufacturing industry and some oil companies. On the contrary, using four variable VAR model, the finding of Henriques and Sadosky (2008) suggest unidirectional causality running from oil prices to alternative energy firms.

The findings of Arouri and Nguyen (2010) suggest that the response of the stock returns to oil price shocks vary significantly across industries. More recently, using panel cointegration and Granger causality, Li et al. (2012) examined the relationship between oil price shocks and the Chinese stock market at the sector level. Their estimates suggest that real oil price has a positive significant impact on sectoral returns in the long run.

Therefore, the empirical findings from the existing literature on the relationship between oil price shock and stock market is inconclusive. This finding may be due to the evolving relationship between these two variables and that strongly calls for the methodologies that can capture the evolving relationship (Akouma et al., 2012).

Thus this paper seeks to investigate following two hypotheses:

- $H_1$ : Do the effect of oil price shocks vary across different sectors?
- $H_2$ : Is oil shocks-sectoral returns vary across different time scales depending on the time horizons of investors?

### 3. DATA AND METHODOLOGY

Weekly data covering the period 29<sup>th</sup> December 2000-17<sup>th</sup> May 2013 were gathered from data stream for crude oil and 15 sectors in India, namely oil and gas (OG), mining (MG), basic materials, industrial (IL), construct and manufacturing (CMG), defense (DE), transport services (TSS), automobiles (AS), health care (HCE), media (MA), telecom (TM), utilities (US), financials (FS), technology (TY), food producers (FPS), travel and leisure (TLE). Crude oil prices are the spot prices: West texas intermediate (WTI) - Cushing Oklahoma. We use this benchmark as it is widely considered as benchmark for world oil markets (Basher et al., 2016). We use nominal values of all the variables as the weekly CPI of India is not available. We deliberately chose this time period as the oil prices became very volatile after this period.

Prior to estimation, we transformed all the series into log form and calculated returns (in log first differenced form).

#### 3.1. MGARCH Model and DCCs

To address our research objective, we utilize MGARCH DCC. The DCC model allows us to observe and analyze the precise timings of shifts in conditional correlation. Estimation of DCC is a two-step process to simplify estimation of time varying correlations between different variables. In a MGARCH (p, q) model, conditional variance and covariance of each asset depend upon not only on its own past conditional variance and past squared innovations but also on the past squared innovations and past conditional variances of the other assets (Bollerslev et al., 1994). The MGARCH model can be used to estimate the DCCs for a financial time series. The main merit of DCCs in relation to other time-varying estimating methods is that it accounts for changes in both the mean and variances of the time. In other words, DCC allows for changes both in the first moment (mean) and the second moment (variance). Understanding how correlations and volatility change over time and when they would be strong or weak is a persuasive motivation for the use of DCC models particularly in the financial markets. The DCC modeling allows us to pinpoint changes (both when they occur and how) in the interdependence between time series variables.

DCC estimation involves 2 steps, which simplifies the estimation of a time-varying correlation matrix. In the first stage, univariate volatility parameters are estimated using GARCH models for each of the variables. In the second stage, the standardized residuals from the first stage are used as inputs to estimate a time-varying correlation matrix. Two-step estimation of the likelihood function is consistent, albeit inefficient (Engle and Sheppard 2001). The DCC allows asymmetries, meaning that the weights are different for positive and negative changes to a series, which is an insightful advantage of this model Engle (2002) and Kearney and Poti (2003) provide guidance on how the model is implemented. We begin with:

$$r_t | I_{t-1} \sim N(0, H_t) \quad (1)$$

Where  $r_t$  is the  $k \times 1$  vector of demeaned variable values conditional on information available at  $t-1$ , which is denoted as  $I_{t-1}$ ;  $r_t$  is assumed to be conditionally multivariate normal;  $H_t$  is the conditional covariance matrix and is:

$$H_t = D_t R_t D_t \quad (2)$$

Where  $R_t$  is the  $k \times k$  time-varying correlation matrix and  $D_t$  is a  $k \times k$  diagonal matrix of conditional, i.e., time varying, standardized residuals,  $\varepsilon_t$ , that are obtained from the univariate GARCH models. The key point to note is that  $R_t$  is a correlation matrix that varies over time, distinguishing the model from the constant conditional correlation model, which uses  $D_t R_t D_t$ .

Engle (2002) shows that the likelihood of the DCC estimator may be written as:

$$L = -0.5 \sum_{t=1}^T (k \log(2\pi) + 2 \log(|D_t|) + \log(|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t)) \quad (3)$$

Importantly, there are two components in the likelihood function that can vary. The first is the volatility component and contains

only terms in  $D_t$ . The second is the correlation component and contains only terms in  $R_t$ . This is why the estimation can occur in two steps.

In the first step, only the volatility component,  $D_t$ , is maximized. This is done by replacing  $R_t$  with a  $k \times k$  identity matrix, giving the first-stage likelihood. Doing this means that the log likelihood is reduced to the sum of the log likelihoods of univariate GARCH equations.

In the first step, only the volatility component  $D_t$  is maximized; i.e., the log likelihood is reduced to the sum of the log likelihood of univariate GARCH equations.

The second step maximizes the correlation component,  $R_t$ , conditional on the estimated  $D_t$  (with elements  $\varepsilon_t$ ) from the first step. This step gives the DCC parameters,  $\alpha$  and  $\beta$ ,

$$R_t = (1 - \alpha - \beta) \bar{R} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta R_{t-1} \quad (4)$$

If  $\alpha = \beta = 0$ , then  $R_t$  is simply  $\bar{R}$  and constant conditional correlation model is sufficient. Engle and Sheppard's (2001) original article provides extensive discussion of the estimation procedure and the theoretical and empirical properties of the estimator.

The models have GARCH-type dynamics for both the conditional correlations and the conditional variances. The time-varying conditional variances can be interpreted as a measure of uncertainty and thus give us insight into what causes movement in the variance. The DCC allows asymmetries, meaning the weights are different for positive and negative changes to a series. The asymmetries are in the variances (not in the correlations) (Cappiello et al., 2006). In short, we gain modeling flexibility and lose assumptions about constant relationships.

In this empirical investigation, we modeled the volatility of daily WTI oil prices and daily returns of selected sector-based Indian equity market indices. Further details, including sample periods, are shown in Table 1.

**Table 1: Details of variables and sample period**

Sector index name	Symbol	Sample period and duration
WTI oil price	OIL	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Oil and gas	OG	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Mining	MG	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Basic materials	BM	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Industrial	IL	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Construct and manufacturing	CMG	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Defense	DE	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Transport services	TSS	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Automobiles	AS	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Health care	HCE	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Media	MA	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Telecom	TM	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Utilities	US	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Financials	FS	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Technology	TY	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Food producers	FPS	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013
Travel and leisure	TLE	29 <sup>th</sup> December 2000-17 <sup>th</sup> May 2013

WTI: West texas intermediate

### 3.2. CWT

CWT is a new technique being used in economics and finance research (for e.g. Vacha and Barunik, 2012; Madaleno and Pinho, 2012; Saiti, 2012, etc.). It maps the original time series, which is a function of just one variable time-separate into function of two different variables such as time and frequency.

In wavelet transformations there are quite a few variant models available. But CWT has a major plus over these variants (like DWT/MODWT) is that in CWT we do not required to define the number of time-scales (wavelets), which is being generated itself on the basis of data length. Besides, CWT also maps correlations of series correlations in a two-dimensional figure that permits us to identify and interpret patterns or hidden information very easily. For CWT, we can use the Daubechies (1992) least asymmetric wavelet filter of length  $L = 8$  denoted by LA (8) based on eight non-zero coefficients. Previous research on high-frequency data have revealed that a moderate-length filter such as  $L = 8$  is sufficient to deal with the characteristic features of time series data (Gencay et al., 2001; 2002; In and Kim 2013, etc.). In literature, it is argued that an LA (8) filter provides more smooth wavelet coefficients as compared to other filters such as Haar wavelet filter.

The CWT  $Wx(u, s)$  is obtained by extrapolating a mother wavelet  $\psi$  onto the examined time series  $x(t) \in L2(R)$  that is:

$$W_x(u, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) dt$$

The position of the wavelet in the time domain is given by  $u$ , while its position in the frequency domain is given by  $s$ . Therefore, the wavelet transform, by mapping the original series into a function of  $u$  and  $s$ , gives us information concurrently on time and frequency. To be able to study the interaction between 2 time series, how closely  $X$  and  $Y$  are related by a linear transformation, we need to apply a bi-variate model which is called wavelet coherence. The wavelet coherence of 2 time series can defined as:

$$R_n^2(s) = \frac{|S(s^{-j}W_n^{xy}(s))|^2}{S(s^{-j})|W_n^x(s)|^2 \cdot S(s^{-j})|W_n^y(s)|^2}$$

Where  $S$  is a smoothing operator,  $s$  is a wavelet scale,  $W_n^x(S)$  is the CWT of the time series  $X$ ,  $W_n^y(S)$  is the CWT of the time series  $Y$ ,  $W_n^{xy}(S)$  is a cross wavelet transform of the 2 time series  $X$  and  $Y$  (Madaleno and Pinho, 2012). To be brief, further detailed mathematical equations have been omitted and interested readers may refer to Gencay et al. (2001; 2002) and In and Kim (2013) for full methodological modeling.

## 4. EMPIRICAL RESULTS AND FINDINGS

### 4.1. Unconditional Volatility and Unconditional Correlation

As a first step towards estimating DCCs and volatilities we first take a look at the summarized results of maximum likelihood estimates of  $\lambda 1$  and  $\lambda 2$  in the Table 2. The table also summarizes the delta 1 and delta 2 estimates while comparing multivariate normal distribution with multivariate student t-distribution. From results it is evident that all estimates are highly significant implying gradual volatility decay for all variables. Also, if we analyze the sum of Lambda 1 and Lambda 2 values for different indices, we observe that their summation is  $<1$ , pointing that the indices are not following IGARCH; which means that shocks to the volatility is not permanent.

It is observed from the results that the maximized log-likelihood value for t-distribution 22184.1 is larger than the maximized log likelihood under normal distribution 21834.2. This implies that the student t-distribution is a more appropriate representation of the fat tailed nature of indices' returns. These findings are in agreement with findings of Pesaran and Pesaran (2009). To further substantiate this we observe the degrees of freedom which is 14.27, well below the critical level of 30. Henceforth our analysis of the study works with the t-distribution estimates.

Table 3 presents the unconditional correlation and volatility matrix for the 15 different Indian sector indices and WTI oil price index, within our study helps us to further delve into the correlations between the indices and their unconditional volatiles. The estimated unconditional volatilities are the diagonal elements highlight and in bold while off diagonal elements represent unconditional correlations.

From the Table 3, we can see the most volatile sector is MG (0.0321) followed by MA (0.0315), DE (0.0266), TSS (0.0259), TM (0.234) and TY (0.02352).

A perfunctory glance at the unconditional volatility numbers shows the highest volatility for the MG Sector (Figure 1). The sharp increase in prices of minerals specially metals is known to be driven by an upsurge in demand for these commodities from newly industrializing emerging economies, in particular, from the rapidly growing economy of India - due to intensive use of these raw materials for their industrialization drive, physical infrastructure building and urbanization trends. However, a dramatic fall was

**Table 2: Estimates of  $\lambda 1$  and  $\lambda 2$  and delta**

Parameter	Normal distribution		T-Distribution	
	Estimate	T ratio	Estimate	T ratio
<b>Lambda 1</b>				
OIL	0.80105	14.1841	0.83358	18.1960
OG	0.84872	27.9073	0.85360	25.9203
MG	0.89536	49.2748	0.92209	58.7835
BMS	0.91671	69.0225	0.93377	83.3659
IL	0.90399	65.2844	0.89207	44.7147
CMG	0.93630	99.3353	0.91944	54.2393
DE	0.94179	58.6012	0.92752	31.0488
TSS	0.84572	25.8715	0.84658	16.0683
AS	0.89494	30.3235	0.92265	33.3286
HCE	0.95361	51.7672	0.97612	96.3763
MA	0.93265	44.6690	0.92574	40.2170
TM	0.96275	108.0368	0.96692	96.4766
US	0.91038	66.3504	0.89551	38.6371
FS	0.91373	59.0626	0.91830	56.9454
TY	0.92105	40.7233	0.92304	49.2785
FPS	0.91734	45.2595	0.93166	37.3013
TLE	0.87968	29.3216	0.89491	30.5518
<b>Lambda 2</b>				
OIL	0.12921	4.4822	0.09757	4.3418
OG	0.10825	5.8346	0.10250	4.9852
MG	0.09948	5.9900	0.07337	5.2285
BMS	0.07024	7.2231	5.2285	6.9415
IL	0.08379	7.6370	0.09092	6.0139
CMG	0.05768	7.6162	0.06710	5.4582
DE	0.04959	4.2073	0.05521	2.8716
TSS	0.10528	5.1446	0.08791	3.1870
AS	0.08361	4.1820	0.05599	3.2755
HCE	0.04154	3.3330	0.02218	3.6778
MA	0.05980	3.5251	0.06430	3.5317
TM	0.03239	5.1250	0.02724	4.1769
US	0.07007	7.2226	0.07564	5.0523
FS	0.06945	6.2714	0.06144	5.6693
TY	0.07024	3.7140	0.06825	4.3640
FPS	0.06791	4.7046	0.05407	3.4544
TLE	0.07977	4.7439	0.06456	4.0219
Delta 1	0.98585	1061.5	0.98658	980.9237
Delta 2	0.01222	20.8497	0.01158	18.2322
Max. log likelihood	21834.2		22184.1	
Degrees of freedom			8.7526	14.2707

Lambda 1 and Lambda 2 are decay factors for variance and covariance, respectively, OG: Oil and gas, MG: Mining, BM: Basic materials, IL: Industrial, CMG: Construct and manufacturing, DE: Defense, TSS: Transport services, AS: Automobiles, HCE: Health care, MA: Media, TM: Telecom, US: Utilities, FS: Financials, TY: Technology, FPS: Food producers, TLE: Travel and leisure

reported for a number of mined metal prices such as nickel, zinc and copper due to immediate and impending reduction in world demand, notably, a drastic deterioration in global prospects for construction and automobile industries especially after the crisis.

For the assessment of the evolution of the correlations between the oil price and different sectors, we report DCC in Figure 2. The results reveal that the correlations have generally been volatile before the 2007 crisis, but since then have moved with the oil prices. Our results also shed light on the fact that 2007-2008 crisis has significantly altered the relationship between oil price and each sector. Moreover, it has also increased the correlation in the volatility.

After the 2007-2008 crisis, we can see that each sector is positively correlated to the movement in Oil prices, with the dip in correlation after 2011 up until the end of the study period.

Table 3: Estimated unconditional volatility matrix for oil price and 15 sector indices

	OIL	OG	MG	BMS	IL	CMG	DE	TSS	AS	HCE	MA	TM	US	FS	TY	FPS
OIL	0.02435	0.09741	0.01668	0.08801	0.05575	0.07331	0.00956	0.01574	0.03634	0.05265	0.00685	0.05726	0.06212	0.08285	0.05583	0.04226
OG	0.09741	0.01862	0.37755	0.66705	0.64866	0.61153	0.41407	0.33118	0.43423	0.53564	0.33322	0.52568	0.6661	0.6795	0.44034	0.28872
MG	0.01668	0.37755	0.0321	0.56416	0.43025	0.40171	0.30406	0.20853	0.26008	0.35707	0.23696	0.30736	0.38389	0.40949	0.30199	0.21693
BMS	0.08801	0.66705	0.56416	0.01885	0.72039	0.71392	0.45293	0.34392	0.46854	0.58903	0.37528	0.52408	0.68152	0.7254	0.48429	0.34221
IL	0.05575	0.64866	0.43025	0.72039	0.01843	0.75365	0.51402	0.36884	0.50941	0.63528	0.48502	0.58608	0.67931	0.7499	0.64521	0.35535
CMG	0.07331	0.61153	0.40171	0.71392	0.75365	0.0199	0.42115	0.29598	0.46099	0.555	0.35655	0.51155	0.6214	0.70078	0.46641	0.31662
DE	0.00956	0.41407	0.30406	0.45293	0.51402	0.42115	0.02658	0.27695	0.32165	0.39343	0.30146	0.37216	0.42091	0.43133	0.35694	0.23458
TSS	0.01574	0.33118	0.20853	0.34392	0.36884	0.29598	0.27695	0.02595	0.2291	0.28709	0.19609	0.24568	0.31512	0.34836	0.2278	0.20854
AS	0.03634	0.43423	0.26008	0.46854	0.50941	0.46099	0.32165	0.2291	0.01915	0.44603	0.24946	0.37051	0.45478	0.50377	0.34711	0.25619
HCE	0.05265	0.53564	0.35707	0.58903	0.63528	0.555	0.39343	0.28709	0.44603	0.01258	0.36162	0.4864	0.56121	0.58705	0.48444	0.3795
MA	0.00685	0.33322	0.23696	0.37528	0.48502	0.35655	0.30146	0.19609	0.24946	0.36162	0.03148	0.34159	0.36101	0.38318	0.43397	0.1973
TM	0.05726	0.52568	0.30736	0.52408	0.58608	0.51155	0.37216	0.24568	0.37051	0.4864	0.34159	0.52337	0.52063	0.58282	0.46023	0.24808
US	0.06212	0.6661	0.38389	0.68152	0.67931	0.6214	0.42091	0.31512	0.45478	0.56121	0.36101	0.52063	0.01998	0.68893	0.46972	0.32005
FS	0.08285	0.6795	0.40949	0.7254	0.7499	0.70078	0.43133	0.34836	0.50377	0.58705	0.38318	0.58282	0.68893	0.01947	0.49604	0.32817
TY	0.05583	0.44034	0.30199	0.48429	0.64521	0.46641	0.35694	0.2278	0.34711	0.48444	0.43397	0.4602	0.46972	0.49604	0.02352	0.2327
FPS	0.04226	0.28872	0.21693	0.34221	0.35535	0.31662	0.23458	0.20854	0.25619	0.3795	0.1973	0.24808	0.32005	0.32817	0.2327	0.01437

OG: Oil and gas, MG: Mining, BM: Basic materials, IL: Industrial, CMG: Construct and manufacturing, DE: Defense, TSS: Transport services, AS: Automobiles, HCE: Health care, MA: Media, TM: Telecom, US: Utilities, FS: Financials, TY: Technology, FPS: Food producers, TLE: Travel and leisure

## 4.2. Oil Coherence with Sectors

Figure 3 present the estimated CWT and phase difference of Oil WTI prices with indices of different sectors of India from scale 1 (1 week) up to scale of 7 (approximately two and a half market years, 128 weeks). Time is shown on the horizontal axis in terms of number of trading weeks, while the vertical axis refers to the investment horizon. The vertical axis from point 400 to 450 covers the crisis period. The curved line below shows the 5% significance level which is estimated using Monte Carlo simulations. The figure follows a colour code as illustrated on the right with power ranges from blue (low correlations) to red (high correlations).

A first glance instantly confirms the higher correlations of the Oil prices increase with all the sectors in Bombay stock exchange in the long run as evident by the greater number of red spots on the coherence diagram. More specifically, we find that for very short holding periods consisting of 2-4 weeks and 4-8 weeks, almost all the sectors of the country are consistently weakly correlated to oil prices over the past 7 years thus offering effective portfolio diversification opportunities. For the short investment horizon consisting of 8-16 and 16-32 weeks periods, once again we find almost all the sectors to be lower correlated as compared to the longer period. Thus, investors have portfolio diversification opportunities in the shorter run. However, moving towards medium investment horizons consisting of 32-64 weeks, interestingly we observe post financial-crisis a bit higher correlations for majority of the sectors namely AS, HCE, OG, TY, Pharmaceutical etc. suggesting that investors with such holding periods are unable to exploit diversification opportunities against the oil price shocks. The interesting part in these positive correlations is that most of the arrows are angling downwards which means that the oil prices are acting as a leader in the correlation relationship. For long-term investors as well we have most of the arrows right and upwards and consisting of 64-128 weeks periods, there are very strong positive correlations among the oil prices and most of the sectors that eliminate potential diversification opportunities against the oil price shocks. There are some cases where it is very difficult to tell that which variable is leading specially in the case of TLE, TY and pharmaceutical sectors.

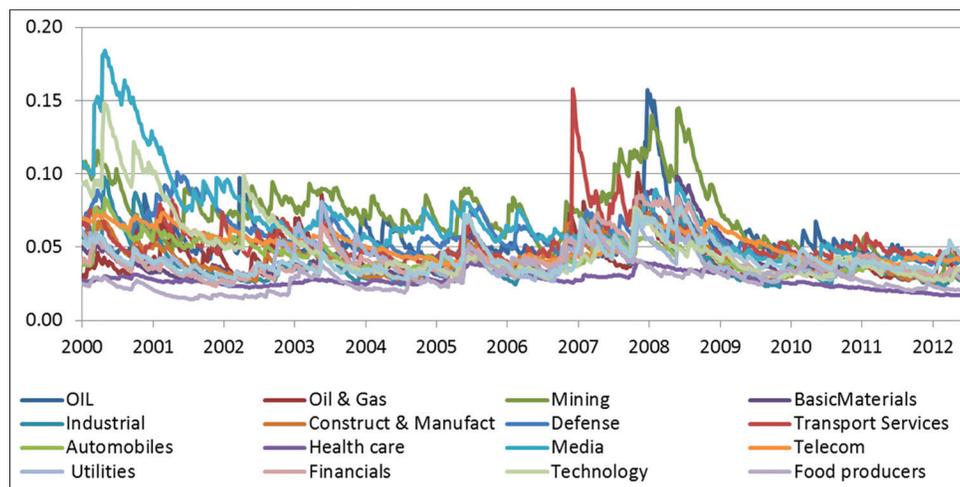
We can clearly see the contributions of the wavelet transformations in helping us understand portfolio diversification opportunities for investors with different investment horizons.

## 5. FINDINGS AND ANALYSIS

Our results from DCC and CWT are validating each other. They have shown some interesting facts about the relationship between oil price and various sectors. From our results, except for those of oil and gas, are against the theoretical expectation<sup>3</sup> as we can see that all the sectors have shown positive correlation with the Oil prices, especially after 2007-2008 crisis. There can be several explanations for such relationship. First, it could be attributed to the portfolio switch from the foreign assets to domestic assets (Ghosh, 2011). As a net oil-importing country any increase in oil

3 As a net oil importing country, stock market is expected to respond negatively to the increase in oil prices (Sardosky, 1999).

Figure 1: Conditional volatilities



price will lead to the depreciation of Indian rupee against the US dollar and hence for a domestic investor, foreign assets would become expensive and thus would result in the substitution from the foreign assets to the domestic assets and as a consequence stock market would go up due to increased demand (Ghosh, 2011). Second, weak Indian currency against the US dollar has attracted FDI inflows due to the lower investment cost as the FDI inflows have increased from in 2007 to 2011. Third, India's reliance on alternative and nuclear energy resources has increased from 2.6% in 2007 to 3% in 2011 (World Bank Database). Fourth, availability of crude oil has increased from 155.79 Million Tonnes in 2007-2008 to 209.82 Million Tonnes in 2011-12 (approximately 34%).<sup>4</sup> Fifth, it may also imply leveraged investment in stock (Li et al., 2012).

If we analyze each sector separately, the results are similar to DCC-MGARCH we can see OG sector and Basic material sectors were volatile before 2007-2008 crisis but since then is positively correlated with the oil prices. This relationship is consistent and theoretically expected as oil is the primary output for these sectors (Boyer and Filion, 2007; El-Sharif et al., 2005; Nandha and Faff, 2008).

Similarly, for the MG sector, the positive correlation can only be seen after 2007-2008 crisis and this could be attributed to the speculation (as it is the most volatile sector, Figure 1) in MG sector due to the increase in oil price volatility (Cong et al., 2008).

Likewise, for the Financial sector, TY sector and the Utility sectors, the correlation were very volatile before 2007-2008 but since then these sectors are positively correlated with the oil price. Our results are in line with Elyasiani et al. (2011). For TY and Utility sectors, the positive correlation may be due to the increased use of alternative energy sources in total electricity production as the electricity production from renewable sources, nuclear sources and coal sources has increased from 3.2% in

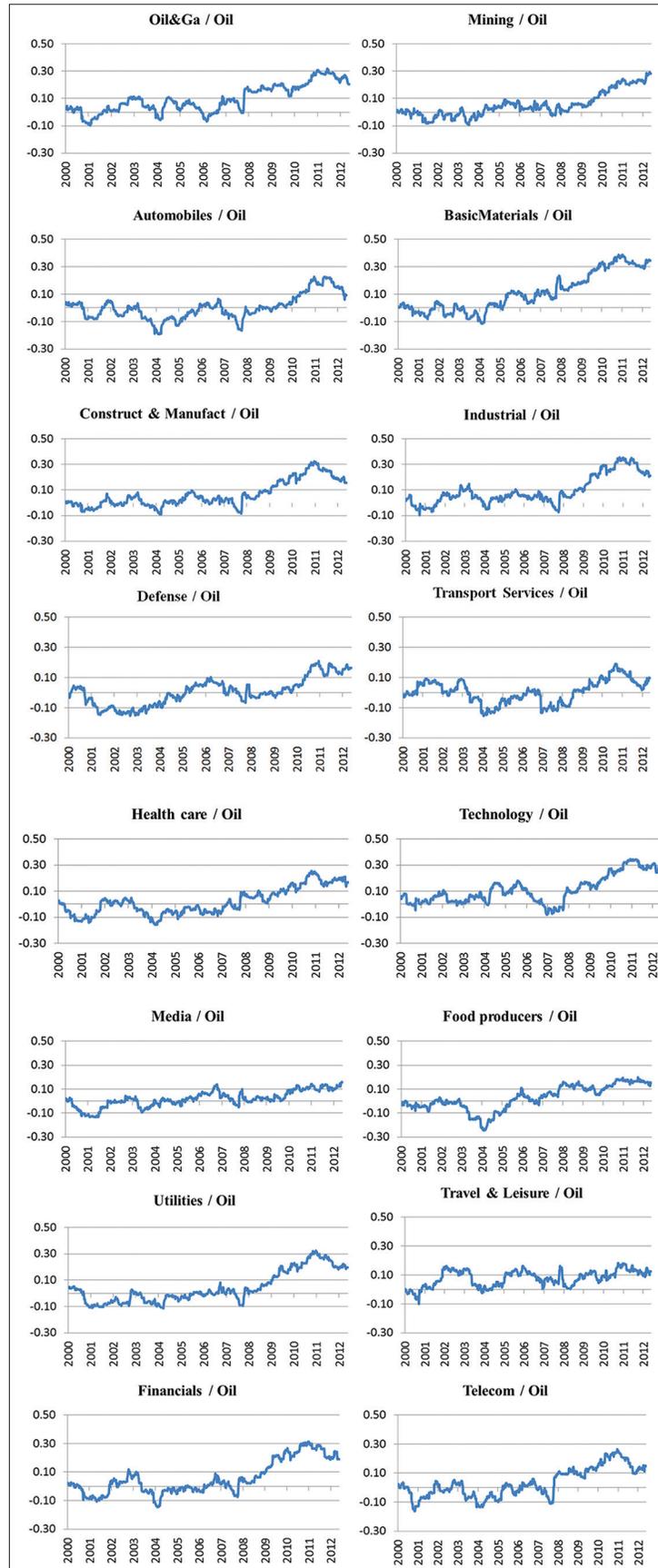
2007 to 5% in 2011, 2% in 2007 to 3.17% in 2011 and 66.6% in 2007 to 68% in 2011 respectively. On the other hand, the electricity production from oil sources has also declined slightly from 1.56% to 1.16% (World Bank Database.<) For Financial sector, Elyasiani et al. (2011) sights two reason for the positive correlation, (a) financial institutions are the most active investors in the oil-related derivatives and hence can benefit from taking such positions during the upswing in the oil prices, and (b) during the period of volatile oil prices, investors would like to switch to safer assets and if this asset substitution increases the demand for the financial sector stocks then it may perhaps result in increased return in these stocks.

Again for the AS, DE, FPS, IL, Transport and TLE sectors the correlations were very volatile prior to 2007-2008 crisis but after that these sectors have moved positively with the oil prices. Our results are contrary to the intuition as these sectors are oil intensive and oil is the most important input in these sectors. However, our findings are in line with those of Elyasiani et al. (2011). The reason for positive correlation could be due to the ability of these sectors to successfully pass on the increased costs to their customers and thus neutralizing the negative impact of higher oil prices (Elyasiani et al., 2011; Nandha and Faff, 2008). The second explanation for positive correlation could also be due to some internal and domestic factors that are more dominant than the increase in oil prices. For instance, price of the petroleum products are still regulated and is under government control (Ghosh, 2011).

For CMG sector, the positive correlation after 2007-2008 could be attributed to the increased demand of new homes as they are more energy efficient (Elyasiani et al., 2011). As far as the remaining three sectors are concerned, MA, TM and HCE have also exhibited the similar volatile behavior prior to 2007-2008 as of the other sectors. But after that they have shown positive correlation with the oil prices. Energy consumption in TM sector is very high but the positive correlation with oil prices could be attributed to rapid expansion of TM sector over the last few years coupled with the subsidies provided by the Government of India to this sector. Furthermore, India has also increased its reliance

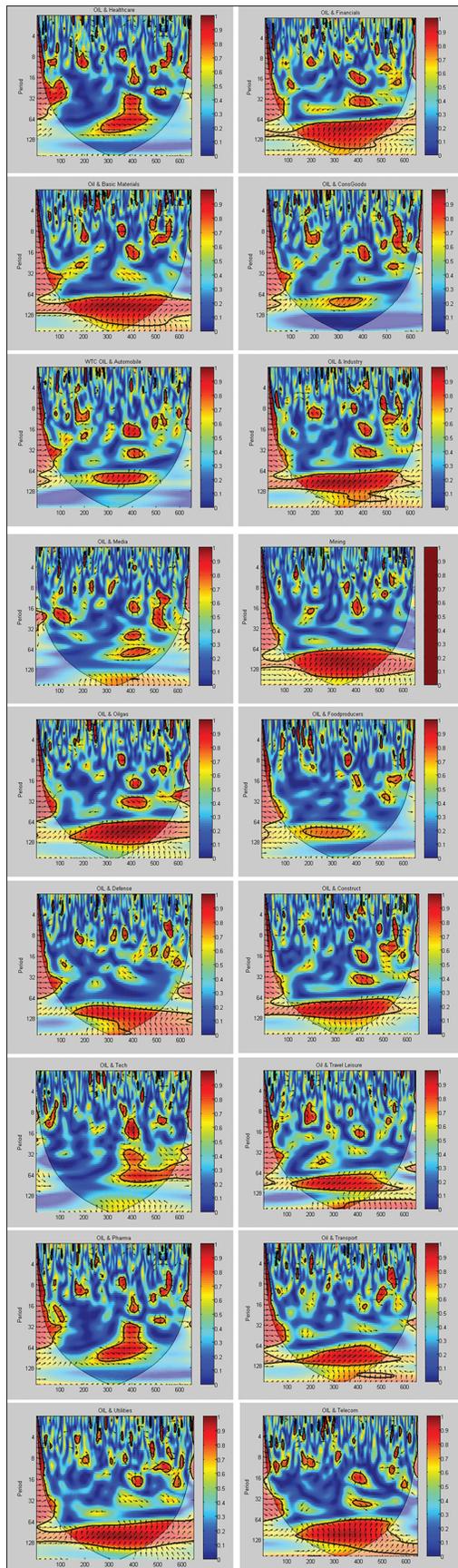
<sup>4</sup> Energy Statistics (2013), Ministry of statistics and programme implementation, Government of India ([www.mospi.gov.in](http://www.mospi.gov.in)).

**Figure 2:** Dynamic conditional correlations



on alternative energy resources. For the MA sector, except for the period of 2001-02 where it is negatively correlated with the

oil prices and after 2009 where it has weak positive correlation with that of oil prices, the correlation is more or less zero and

**Figure 3:** Continuous wavelet transformation

hence implying that MA sector is relatively immune to oil price changes.

As a robustness, we also investigated the relationship at monthly and quarterly frequency. The findings are similar to the main results.<sup>5</sup>

## 6. CONCLUSION AND POLICY IMPLICATIONS

According to U.S. Energy Information Administration India is the fourth largest oil consumer in the world with the total consumption of 3622 thousands barrel per day and it is also the fourth largest oil importer with the total import of 2632 thousands barrel per day. Given the lack of research and importance of India in world oil market, the main objective of the paper is to assess the relationship between the rising oil price and disaggregated Indian stock. The previous literature suggests the presence of time varying volatility between the stock market and oil prices and hence to address the evolving relationship between the two we employ DCC-MGARCH and CWT methodologies.

Our findings can be summarized as follows, (a) our result confirms the presence of time varying relationship between the oil prices and each sector, (b) our findings suggest that the correlations of all the sectors with the oil price were highly volatile prior to 2007-2008, (c) since 2007-2008, the correlations of each sector with the oil price has become positive and hence it does not provide any diversification benefits to the investors against the rising oil prices in the long run, and (d) since, emerging markets in general, and India in particular, is expected to increase its share of oil consumption in the world's energy market (due to rapid expansion)<sup>6</sup>, for the stock market to grow, especially the oil-intensive industries, the government should make policies that do not pose any hindrance to the growth of such sectors. For instance, emphasis on relying on alternative energy resources such as coal and renewables would further provide growth opportunities to these sectors and would provide some solutions to the ever increasing energy demand in India. Similarly, India should also substitute imported fuels with domestic fuels like bio-deisel and ethanol (Ghosh, 2011). Furthermore, as rising oil prices can also have its adverse effect through exchange rate channel, we suggest the monetary policies should be time varying to manage the oil

5 The results are available upon request.

6 According to International Energy Outlook 2011 (IEO2011), China and India together is expected to consume 31% of the world's energy in 2035, up from 21% in 2008.

inflationary pressures arising out of extreme volatility in the oil prices.

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