Does Indian Stock Market Provide Diversification Benefits Against Oil Price Shocks? A Sectoral Analysis

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Abstract

This paper investigates the time-varying relationship between the oil price and disaggregated stock market of India using DCC-MGARCH and Continuous Wavelet Transformation methodologies. Our findings reveal the evolving relationship between the oil price and disaggregated stock market. The correlations are generally volatile before the 2007-08 crisis but since then the correlations are positive implying no diversification benefits for the investors during rising oil prices. 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), therefore for the stock market to grow, especially the oil-intensive industries, we recommend the government should increase its reliance on alternative energy resources such as coal and renewables. 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: DCC-GARCH, CWT, Disaggregated stock market, India, Oil price shocks, Diversification.

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1. Introduction

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 Perez de Gracia (2003), Gisser and Goodwin (1986), and Jimenez-Rodriguez and Sanchez (2005), extended the work of Hamilton (1983) with different estimation method and data set and found similar result to that of Hamilton (1983).

Two strands of literature have emerged to explain the impact of oil price increase on the stock market. One strand advocates negative impact while the findings of other strand points to the positive impact. As Kilian and Park (2009) pointed out that the stock market reaction to the hike in oil price largely depends on whether the increase is driven by supply or demand shocks in the oil market. Further, response of the stock market to the hike in oil price 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)[1] whereas for oil-exporting countries stock market is expected to react positively to the increase in oil prices (Al-Fayoumi, 2009).

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 explanations 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; Sardosky, 1999). If these firms are unable to pass through this cost to the

[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).

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 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[2]. 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. We contribute to the existing literature in at least two ways. First, as the responses of the different sectors to oil price shocks are expected to vary across sectors, we add to the

[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.

limited literature by examining the relationship between oil price shocks and disaggregated stock market. Second, to the best our knowledge, we are the first one to use DCC GARCH modeling to assess the relationship between oil price and stock market from the sectoral perspective. Rationale behind using the DCC GARCH modeling is to capture the changing relationship between the two variables.

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

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 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&P 500.

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 [see Arouri and Nguyen (2010), Henriques and Sadorsky (2008), Nandha and Faff (2008), Ramos and Veiga (2011)]. 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 Sardosky (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.

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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[3]. 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. We contribute to the existing literature in at least two ways. First, as the responses of the different sectors to oil price shocks are expected to vary across sectors, we add to the limited literature by examining the relationship between oil price shocks and disaggregated stock market. Second, to the best our knowledge, we are the first one to use DCC GARCH modeling to assess the relationship between oil price and stock market from the sectoral perspective.

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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 add to the literature in two ways. First, by examining the impact of oil price shocks on the Indian disaggregated stock market we attempt to fill in the gapleft by the studies carried out mostly for developed economies. Second, we capture the evolving relationship by using DCC-MGARCH modeling.

3. Data and Methodology

Weekly data covering the period 29th December 2000–17th May 2013 were gathered from Datastream for crude oil and 15 sectors in India, namely Oil & Gas (OG), Mining (MG), Basic Materials (BM), Industrial (IL), Construct & 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 & 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. 2012). We use nominal values of all the variables as the weekly CPI of India is not available.

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

3.1. Multivariate GARCH model and Dynamic Conditional Correlations (DCC)

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 multivariate GARCH (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 multivariate GARCH model can be used to estimate the Dynamic Conditional Correlations (DCC) for a financial time series. The main merit of Dynamic Conditional Correlations 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:

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

Where r_t is the k ×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:

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

Where R_t is the k×k time-varying correlation matrix and D_t is a k ×k diagonal matrix of conditional, i.e., time varying, standardized residuals, ε_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:

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

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 × 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 ε_t) from the first step. This step gives the DCC parameters, α and β,

$$R_t = (1 - \alpha - \beta)\overline{R} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta R_{t-1} \qquad (4)$$

If α =β=0, then R_t is simply $\overline{R}$ 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 Oilprices 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	29th December 2000 – 17th May 2013
Oil & Gas	OG	29th December 2000 – 17th May 2013
Mining	MG	29th December 2000 – 17th May 2013
Basic Materials	BM	29th December 2000 – 17th May 2013
Industrial	IL	29th December 2000 – 17th May 2013

Construct & Manufacturing	CMG	29th December 2000 – 17th May 2013
Defense	DE	29th December 2000 – 17th May 2013
Transport. Services	TSS	29th December 2000 – 17th May 2013
Automobiles	AS	29th December 2000 – 17th May 2013
Health care	HCE	29th December 2000 – 17th May 2013
Media	MA	29th December 2000 – 17th May 2013
Telecom	TM	29th December 2000 – 17th May 2013
Utilities	US	29th December 2000 – 17th May 2013
Financials	FS	29th December 2000 – 17th May 2013
Technology	TY	29th December 2000 – 17th May 2013
Food producers	FPS	29th December 2000 – 17th May 2013
Travel & Leisure	TLE	29th December 2000 – 17th May 2013

3.2. Continuous Wavelet Transformation (CWT)

A number of authors have recently begun to use the continuous wavelet transform (CWT) in economics and finance research (for e.g. see Vacha and Barunik (2012), Madaleno and Pinho (2012), Saiti (2012), etc.). The CWT 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.

One major benefit CWT has over DWT/MODWT is that we need not define the number of wavelets (time-scales) in CWT which generates itself according to the length of data. Other than that, the CWT maps the series correlations in a two-dimensional figure that allows us to easily identify and interpret patterns or hidden information. For both MODWT and CWT, we use the Daubechies (1992) least asymmetric wavelet filter of length L=8 denoted by LA (8) based on eight non-zero coefficients. Previous studies on high-frequency data have shown that a moderate-length filter such as L = 8 is adequate to deal with the characteristic features of timeseries data (see Gencay et al., 2001, 2002, In and Kim 2013, etc.). In literature, it is argued that an LA (8) filter generates more smooth wavelet coefficients than other filters such as Haar wavelet filter.

The continuous wavelet transform ***(CWT) Wx(u,s)*** is obtained by projecting a mother wavelet ψ onto the examined time series ***x(t) ϵ 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 simultaneously on time and frequency. To be able to study the interaction between two time series, how closely X and Y are related by a linear transformation, we need to apply a bivariate framework which is called wavelet coherence. The wavelet coherence of two time series is defined as:

$$R_n^2(s) = \frac{\left|S(s^{-1}W_n^{xy}(s))\right|^2}{S(s^{-1}|W_n^x(s)|^2 . S(s^{-1}\left|W_n^y(s)\right|^2}$$

Where S is a smoothing operator, *s* is a wavelet scale, $\boldsymbol{W_n^x(S)}$ is the continuous wavelet transform of the time series X, $\boldsymbol{W_n^y(S)}$ is the continuous wavelet transform of the time series Y, $\boldsymbol{W_n^{xy}(S)}$ is a cross wavelet transform of the two time series X and Y (Madaleno and Pinho, 2012). For brevity, we omit further detailed mathematical equations and interested readers may refer to Gencay et al (2001; 2002) and In and Kim (2013) for full methodological models.

4. Empirical Results and findings

4.1. Unconditional Volatility and Unconditional Correlation

As a first step towards estimating dynamic conditional correlations and volatilities we first take a look at the summarized results of maximum likelihood estimates of λ1 and λ2 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

Table 2: Estimates of λ1 and λ2 and Delta

		Normal Distribution		T – Distribution	
	Parameter	**Estimate**	**T Ratio**	**Estimate**	**T Ratio**
Lambda 1	**OIL**	.80105	14.1841	.83358	18.1960
	OG	.84872	27.9073	.85360	25.9203
	MG	.89536	49.2748	.92209	58.7835
	BMS	.91671	69.0225	.93377	83.3659
	IL	.90399	65.2844	.89207	44.7147
	CMG	.93630	99.3353	.91944	54.2393
	DE	.94179	58.6012	.92752	31.0488
	TSS	.84572	25.8715	.84658	16.0683
	AS	.89494	30.3235	.92265	33.3286
	HCE	.95361	51.7672	.97612	96.3763
	MA	.93265	44.6690	.92574	40.2170
	TM	.96275	108.0368	.96692	96.4766
	US	.91038	66.3504	.89551	38.6371
	FS	.91373	59.0626	.91830	56.9454
	TY	.92105	40.7233	.92304	49.2785
	FPS	.91734	45.2595	.93166	37.3013
	TLE	.87968	29.3216	.89491	30.5518
Lambda 2	**OIL**	.12921	4.4822	.09757	4.3418
	OG	.10825	5.8346	.10250	4.9852
	MG	.09948	5.9900	.07337	5.2285
	BMS	.07024	7.2231	5.2285	6.9415
	IL	08379	7.6370	.09092	6.0139
	CMG	.05768	7.6162	.06710	5.4582
	DE	.04959	4.2073	.05521	2.8716
	TSS	.10528	5.1446	.08791	3.1870
	AS	.08361	4.1820	.05599	3.2755
	HCE	.04154	3.3330	.02218	3.6778
	MA	.05980	3.5251	.06430	3.5317
	TM	.03239	5.1250	.02724	4.1769
	US	.07007	7.2226	.07564	5.0523
	FS	.06945	6.2714	.06144	5.6693
	TY	.07024	3.7140	.06825	4.3640
	FPS	.06791	4.7046	.05407	3.4544
	TLE	.07977	4.7439	.06456	4.0219
Delta 1		.98585	1061.5	.98658	980.9237
Delta 2		.01222	20.8497	.01158	18.2322
Max. Log Likelihood		21834.2		22184.1	
Degrees of Freedom				8.7526	14.2707

Note: Lambda 1 and Lambda 2 are decay factors for variance and covariance, respectively.

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 less than one, 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 & 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.

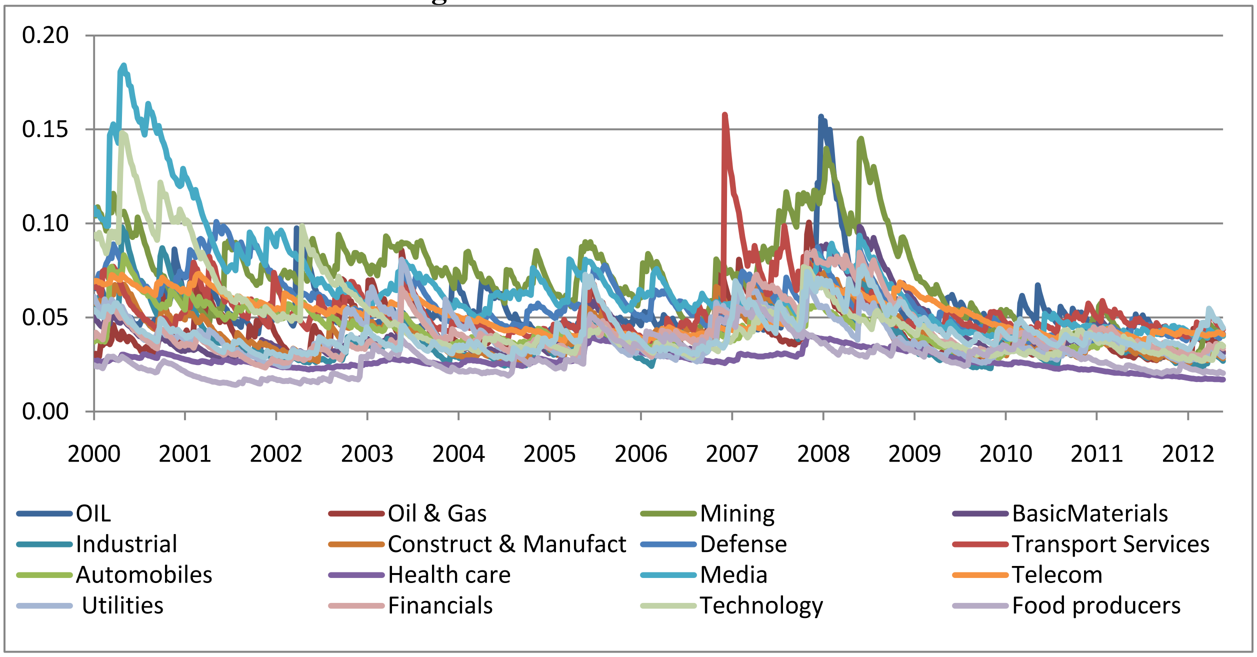
Table 3: Estimated unconditional volatility matrix for Oil price and 15 sector indices.

	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	0.02337	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

From the table 3, we can see the most volatile sector is Mining (.0321) followed by Media (.0315), Defense (.0266), Transport services (.0259), Telecom (.234) and Technology (.02352).

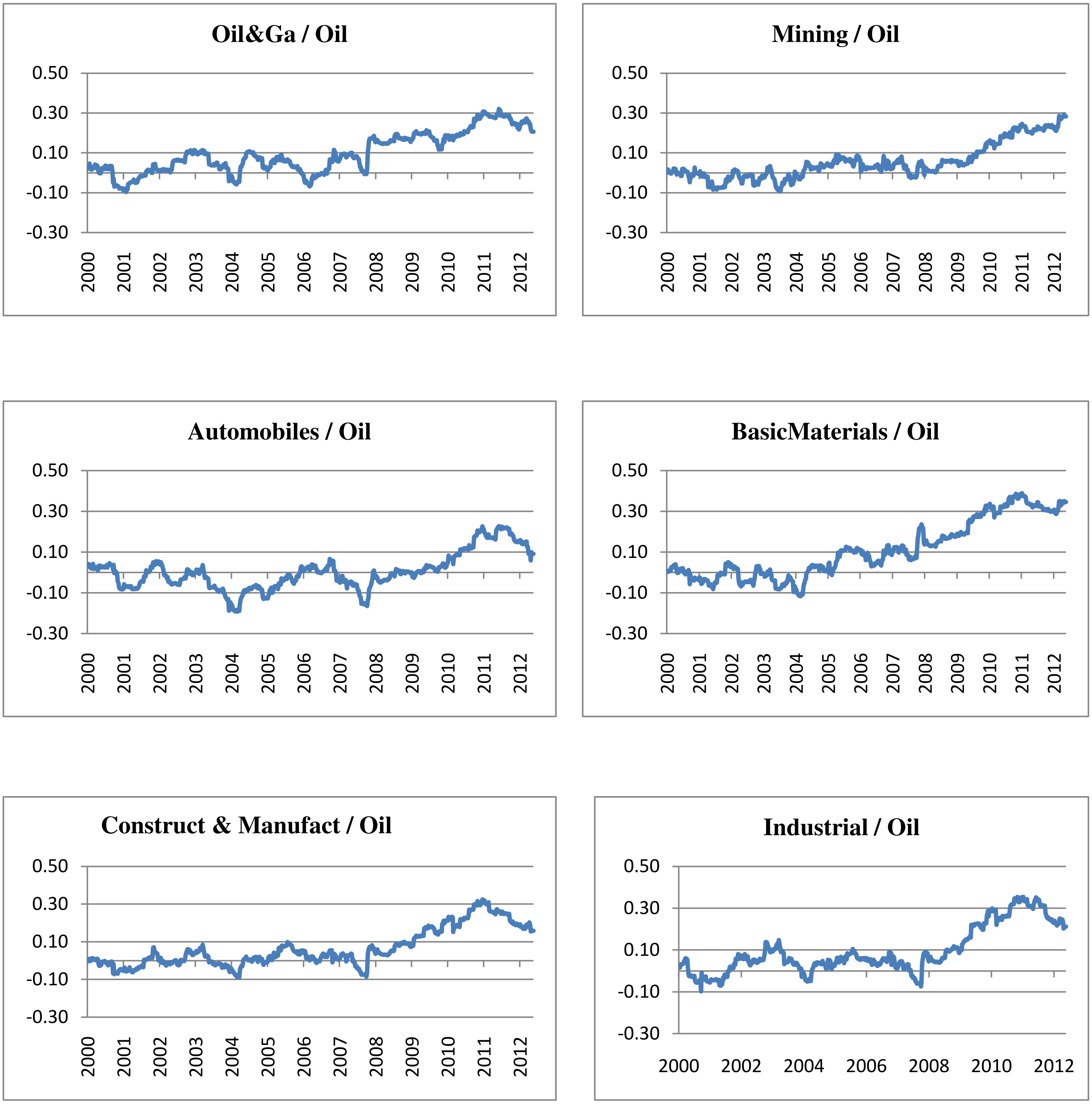
A perfunctory glance at the unconditional volatility numbers shows the highest volatility for the Mining Sector (shown in the figure 1). The sharp increase in prices of minerals specially metals is known to be driven by an upsurge in demand for these commodities from newly industrializing emerging economies, 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 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.

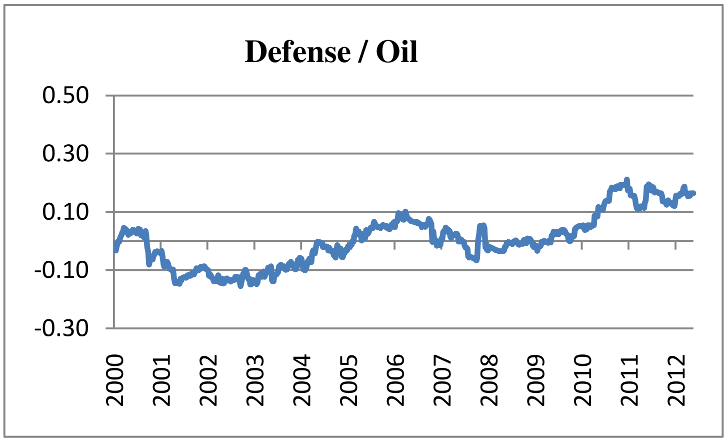
Figure 1: Conditional Volatilities

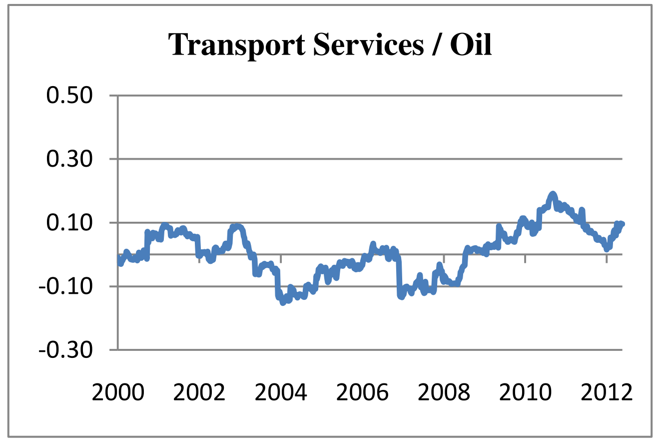


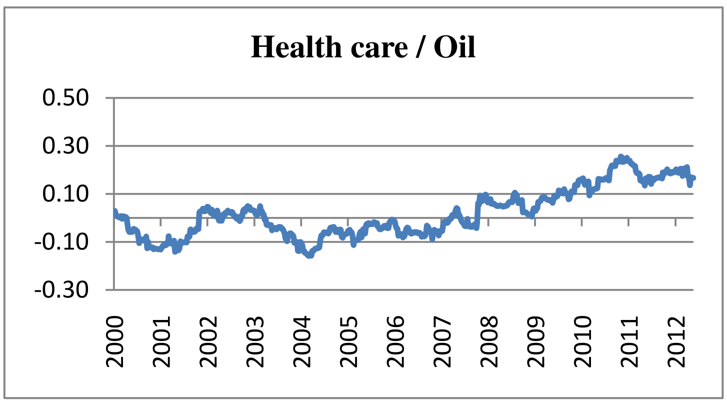
For the assessment of the evolution of the correlations between the oil price and different sectors, we report Dynamic Conditional Correlation (DCC) in Figure 2. The results reveal that the correlations have generally been volatile before the 2007 crisis, but since then have moved with the oil prices. Our results also shed light on the fact that 2007-08 crisis has significantly altered the relationship between oil price and each sector. Moreover, it has also increased the correlation in the volatility.

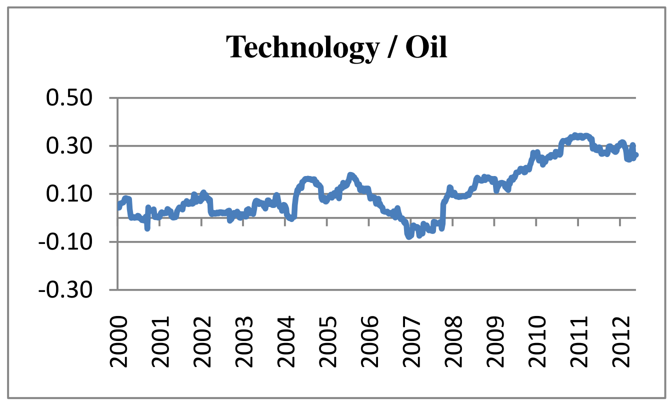
Figure 2: Dynamic Conditional Correlations

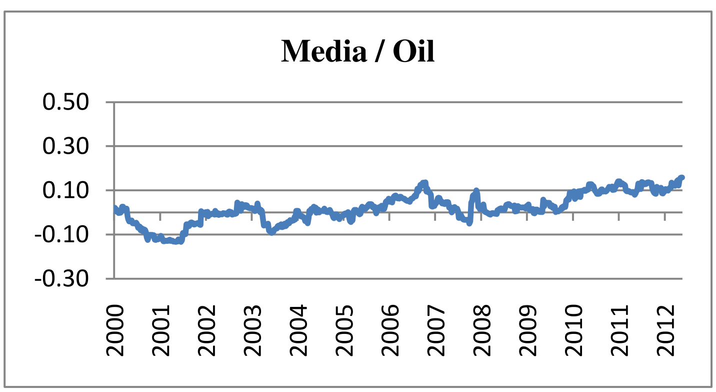


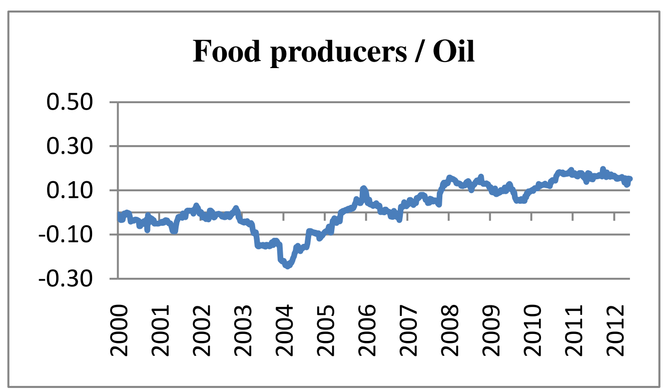

Defense / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012

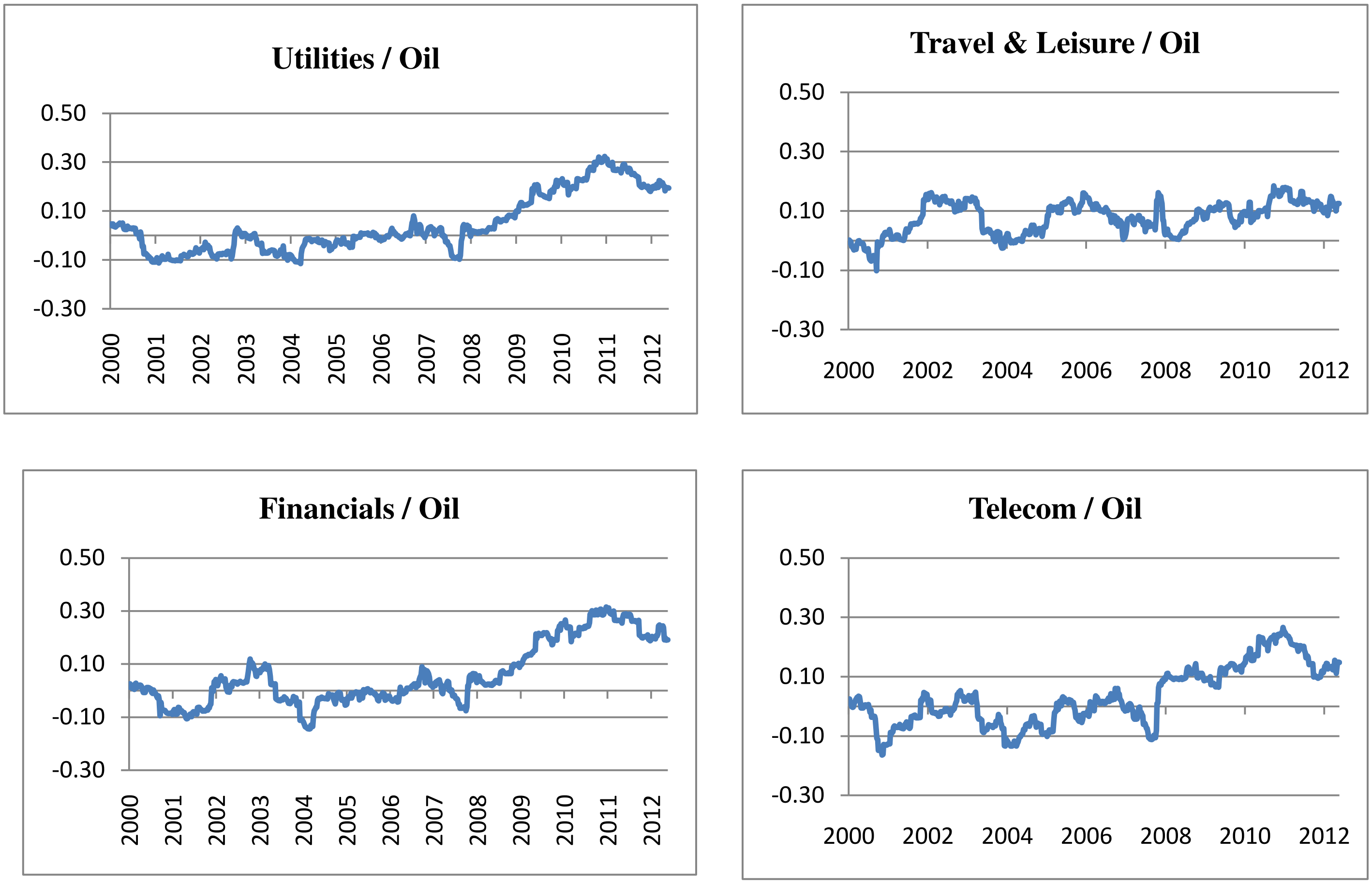

Transport Services / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2002
2004
2006
2008
2010
2012


Health care / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012


Technology / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012


Media / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012


Food producers / Oil
0.50
0.30
0.10
-0.10
-0.30
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012



After the 2007-08 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.

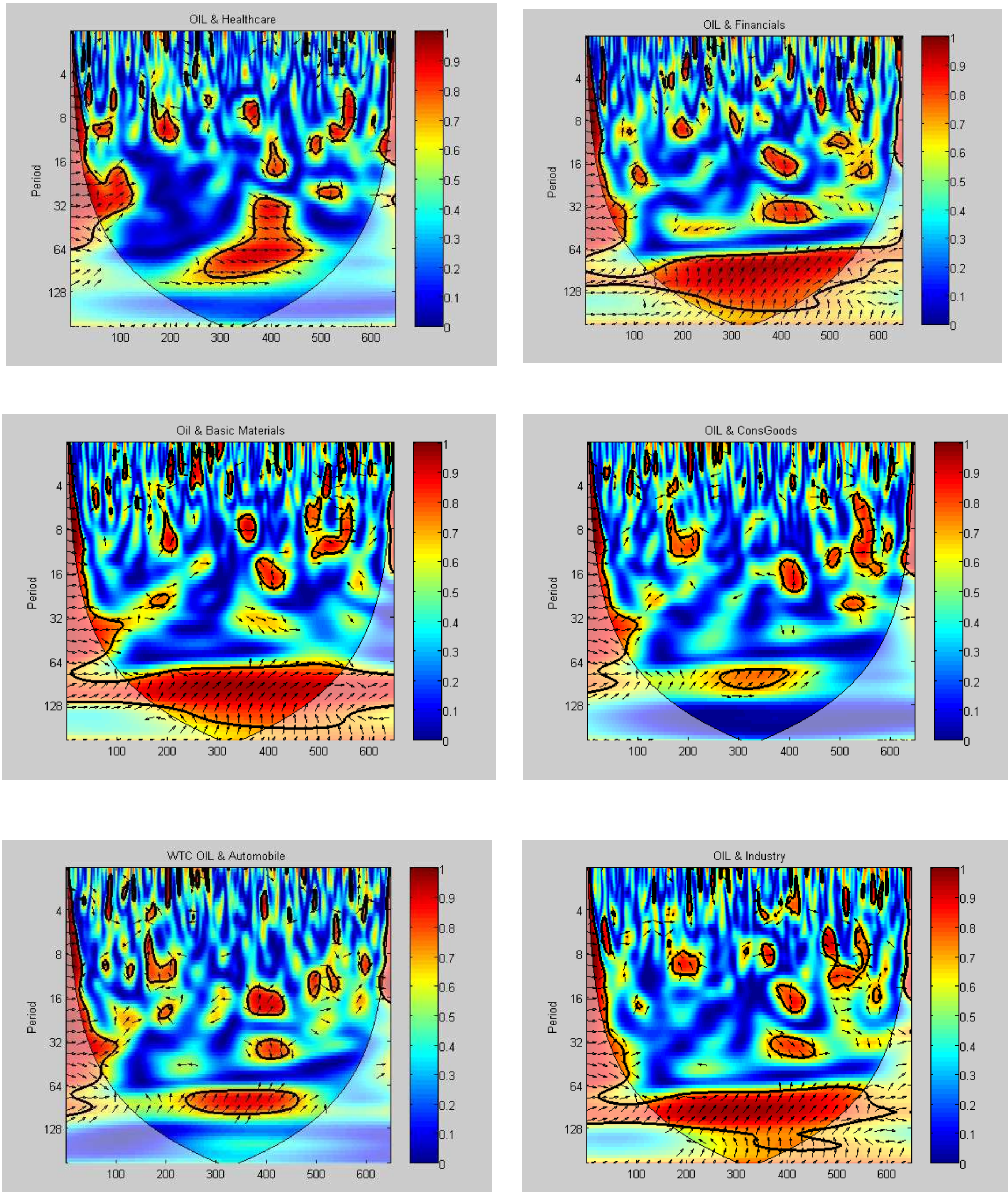
4.2 Oil coherence with sectors

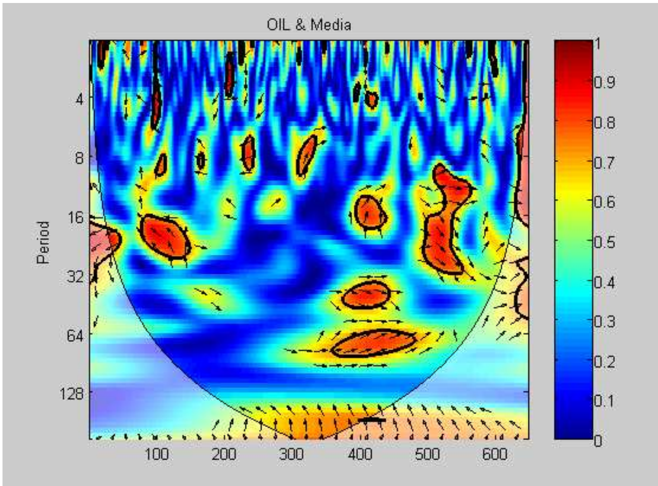
Figure 3 present the estimated continuous wavelet transform and phase difference of Oil WTI prices with indices of different sectors of India from scale 1 (one week) up to scale of 7 (approximately two and a half market years, 128 weeks). Time is shown on the horizontal axis in terms of number of trading 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).

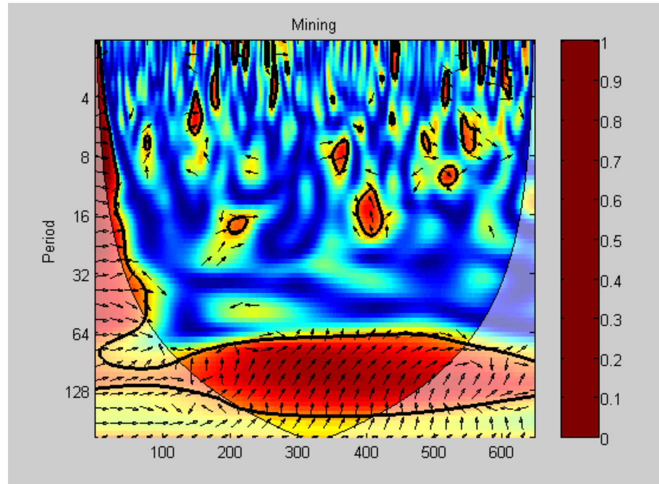
A first layman glance instantly confirms the higher correlations of the Oil prices increase with all the sectors in Bombay stock exchange in the long run as evident by the greater number of red spots on the coherence diagram. More specifically, we find that for very short holding periods consisting of 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 Automobile, healthcare, Oil and gas, Technology, 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 correlation 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 & 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 Travel leisure, Technology and Pharmaceutical sectors.

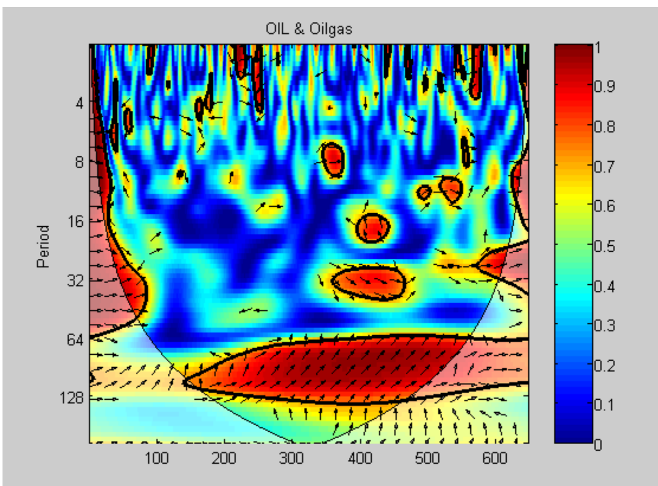
We can clearly see the contributions of the wavelet transformations in helping us understand portfolio diversification opportunities for investors with different investment horizons.

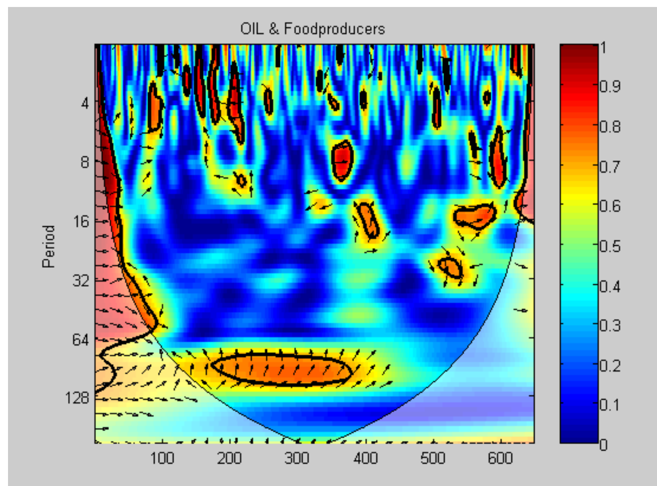
Figure 3: Continuous Wavelet Transformation

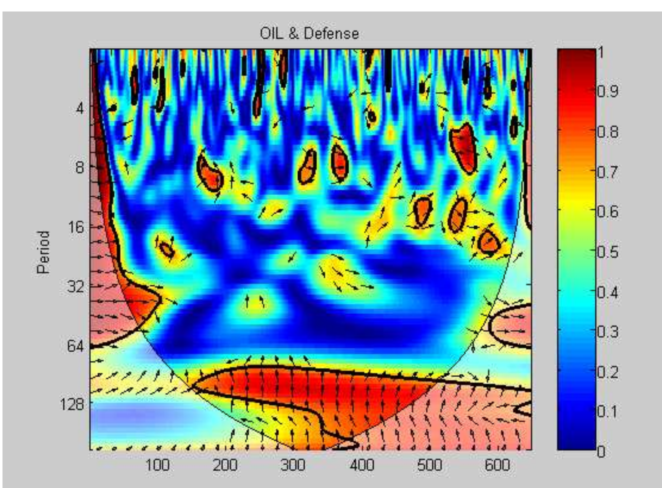


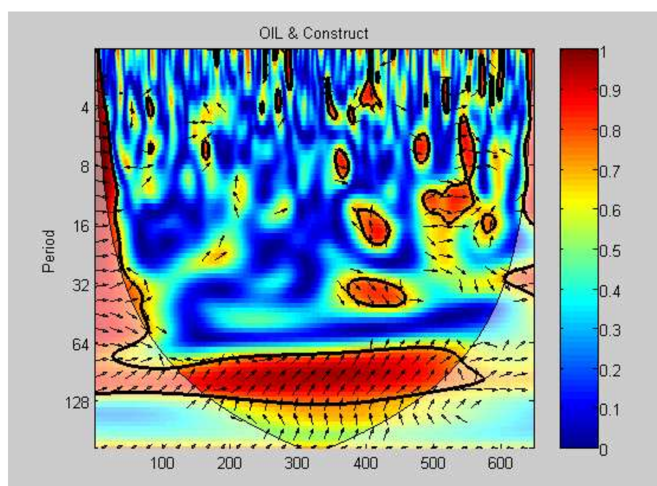

OIL & Media
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

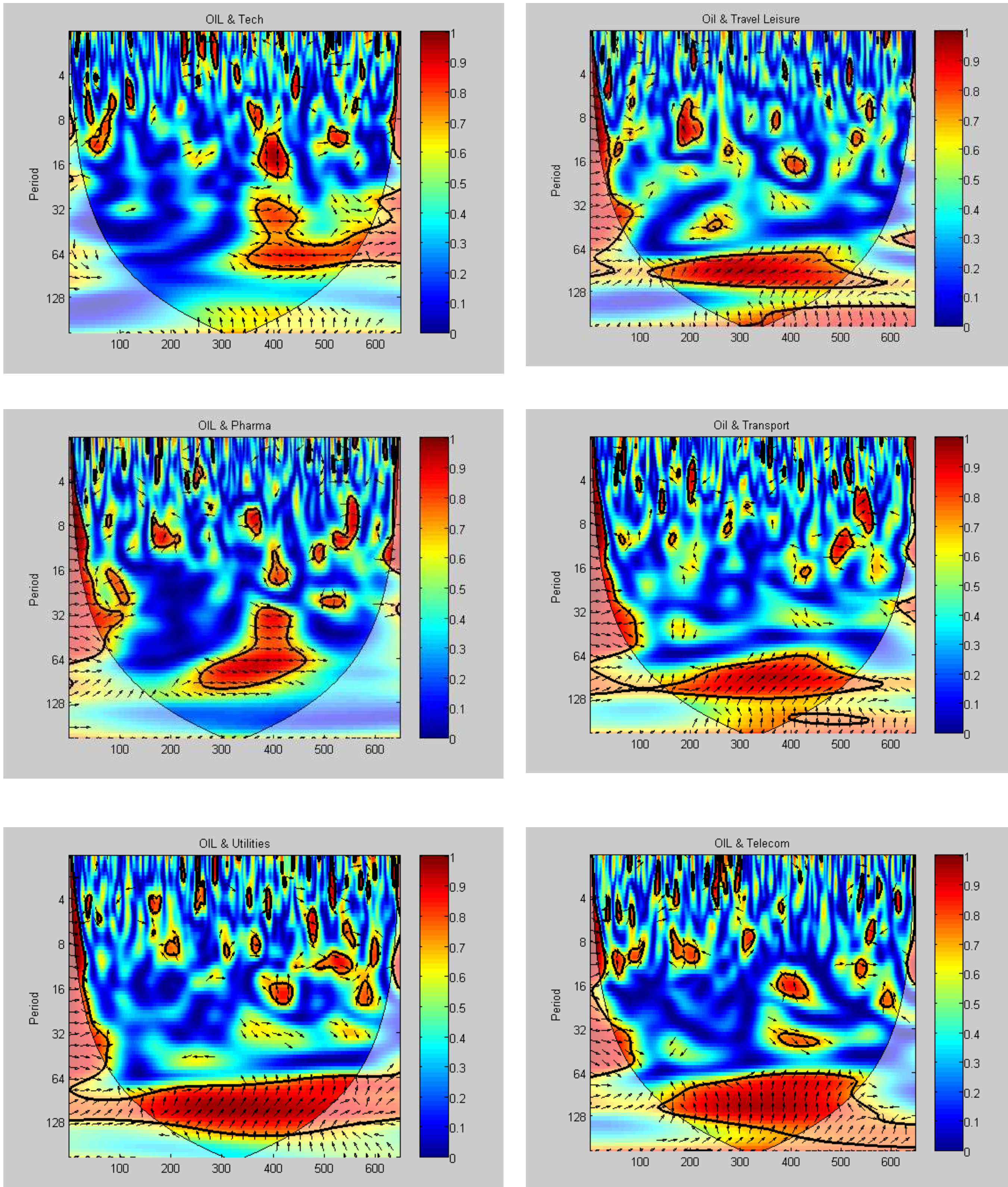

Mining
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0


OIL & Oilgas
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0


OIL & Foodproducers
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0


OIL & Defense
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0


OIL & Construct
Period
4
8
16
32
64
128
100
200
300
400
500
600
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0


OIL & Tech
Oil & Travel Leisure
OIL & Pharma
Oil & Transport
OIL & Utilities
OIL & Telecom
Period
4
8
16
32
64
128
100
200
300
400
500
600
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

5. Findings and Analysis:

Our results from DCC and CWT are validating each others. They have shown some interesting facts about the relationship between oil price and various sectors. From our results, except for those of Oil & Gas, are against the theoretical expectation[4] as we can see that all the sectors have shown positive correlation with the Oil prices, especially after 2007-08 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 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[5]. Fourth, availability of crude oil has increased from 155.79 Million Tonnes in 2007-08 to 209.82 Million Tonnes in 2011-12 (approximately 34%)[6]. 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 Oil and Gas sector and Basic material sectors were volatile before 2007-08 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).

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

[5] World bank Database.

[6] Energy Statistics (2013), Ministry of statistics and programme implementation, Government of India (www.mospi.gov.in).

Similarly, for the Mining sector, the positive correlation can only be seen after 2007-08 crisis and this could be attributed to the speculation (as it is the most volatile sector, see Figure 1)in mining sector due to the increase in oil price volatility (Cong et al. 2008).

Likewise, for the Financial sector, Technology sector and the Utility sectors, the correlation were very volatile before 2007-08 but since then these sectors are positively correlated with the oil price. Our results are in line with Elyasiani et al. (2011). For Technology 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[7]. On the other hand, the electricity production from oil sources has also declined slightly from 1.56% to 1.16%[8]. 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 Automobiles, Defense, Food producers, Industrial, Transport and Travel & Leisure sectors the correlations were very volatile prior to 2007-08 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

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[7] World bank Database.

[8] Ibid.

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 Construction and Manufacturing sector, the positive correlation after 2007-08 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, Media, Telecom and Healthcare have also exhibited the similar volatile behavior prior to 2007-08 as of the other sectors. But after that they have shown positive correlation with the oil prices. Energy consumption in Telecom sector is very high but the positive correlation with oil prices could be attributed to rapid expansion of telecom 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 on alternative energy resources. For the Media 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 hence implying that Media sector is relatively immune to oil price changes.

6. Conclusion

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 2007-08, c) since 2007-08, 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, 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)[9], 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 inflationary pressures arising out of extreme volatility in the oil prices.

[9] 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.

References

Akouma, I., Grahamb, M., Kivihahoc, J., Nikkinenc, J. and M. Omrand, 2012, Co-movement of oil and stock prices in the GCC region: A wavelet analysis. The Quarterly Review of Economics and Finance, 52, 385– 394.

Al-Fayoumi, N.A., 2009, Oil Prices and Stock Market Returns in Oil Importing Countries: The Case of Turkey, Tunisia and Jordan. European Journal of Economics, Finance and Administrative Sciences, 16, 86-101.

Arouri, M.E.H. and Nguyen, D.K., 2010. Oil prices, stock markets and portfolio investment: evidence from sector analysis in Europe over the last decade. Energy Policy, 38, pp. 4528–4539.

Basher, S.A. and P. Sadorsky, 2006, Oil price risk and emerging stock markets. Global Finance Journal, 17, 224–251.

Bjornland, H.C., 2009, Oil Price Shocks and Stock Market Booms in an Oil Exporting Country. Paper provided by Norges Bank in its series Working Paper with number 2008/16. Scottish Journal of Political Economy, 56 (2), 232-254.

Bollerslev, T., Engle, R.F. and D.B. Nelson, 1994, ARCH Models. In Handbook of Econometrics, Vol. 4, Elsevier, North Holland.

Boyer, M.M. and D. Filion, 2007, Common and fundamental factors in stock returns of Canadian oil and gas companies. Energy Economics, 29 (3), 428–453.

Burbridge, J. and A. Harrison, 1984, Testing for the Effects of Oil-Price Rises Using Vector Autoregressions. International Economic Review, 25(1), 459-484.

Campbell, J.Y., 1991, A Variance Decomposition for Stock Returns. Economic Journal, 101(405), 157-79.

Cappiello, L., R.F. Engle and K. Sheppard, 2006, Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics, 4, 537-572.

Cheung, Y.W. and L.K. Ng, 1998, International evidence on the stock market and aggregate economic activity. Journal of Empirical Finance, 5, 281–296.

Cong, R.G, Wei, Y.M, Jiao, J.L and Y. Fan, 2008, Relationships between oil price shocks and stock market: An empirical analysis from China. Energy Policy, 36, 3544– 3553.

Cunado, J. and F. Gracia, 2003, Do Oil Price Shocks Matter? Evidence for some European Countries. Energy Economics, 25, 137-154.

El-Sharif, I. Brown, D. Burton, B., Nixon, B. and A. Russell, 2005, Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. Energy Economics, 27, 819-830.

Elyasiani, E., Mansur, I. and B. Odusami, 2011, Oil price shocks and industry stock returns. Energy Economics, 33, 966-974.

Engle, F.R., 2002, Dynamic conditional correlation: A simple class of multivariate GARCH models. Journal of Business and Economic Statistics, 20, 339-350.

Engle, F.R. and K. Sheppard, 2001, Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH, Working paper No. 2001-15, University of California, San Diego.

Ghosh, S., 2011, Examining crude oil price – Exchange rate nexus for India during the period of extreme oil price volatility. Applied Energy, 88, 1886–1889.

Gisser, M., and Goodwin, T.H., 1986, Crude Oil and the Macroeconomy: Tests of Some Popular Notions. Journal of Money, Credit and Banking, Vol. 18, No.1, 95-103.

Hamilton, J.D., 1983, Oil and the Macroeconomy Since World War II. Journal of Political Economy, 91, 228-248.

Henriques, I., and P. Sadorsky, 2008, Oil prices and the stock prices of alternative energy companies. Energy Economics, 30, 998-1010.

Huang, R.D., Masulis, R.W. and H.R. Stoll, 1996, Energy shocks and financial markets. Journal of Futures Markets, 16(1), 1-27.

Jiménez-Rodríguez, R., and M. Sánchez, 2005, Oil Price Shocks and Real GDP Growth: Empirical Evidence for Some OECD Countries. Applied Economics, 37, 201-228.

Jones, C.M. and G. Kaul, 1996, Oil and the stock markets. Journal of Finance, 51(2), 463-491.

Kearney, C. and V. Poti, 2003, DCC-GARCH modeling of market and firm-level correlation dynamics in the Dow Jones Eurostoxx 50 Index, Working Paper, School of Business Studies, Trinity College, Dublin.

Kilian, L., 2007, Not All Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. American Economic Review, 99, 1053-1069.

Kilian, L. and C. Park, 2009, The impact of Oil Price shocks on the US stock market. International Economic Review, 50(4), 1267-1287.

Le, T.H. and Y. Chang, 2011, The impact of oil price fluctuations on stock markets in developed and emerging economies, Munich Research Papers in Economics, MPRA Paper No. 31936, Munich.

Li, S., Zhu, H. and K. Yu, 2012, Oil prices and stock market in China: A sector analysis using panel cointegration with multiple breaks. Energy Economics, 34, 1951-1958.

Maghyereh, A., 2004, Oil Price Shocks and Emerging Stock Markets: A Generalized VAR Approach. International Journal of Applied Econometrics and Quantitative Studies, 1(2), 27-40.

Nandha, M. and R. Faff, 2008, Does oil move equity prices? A global view. Energy Journal, 30, 986-997.

Narayan, K.P. and S. Narayan, 2010, Modeling the impact of oil prices on Vietnam's stock prices. Applied Energy, 87, 356 – 361.

Park, J. and R. Ratti, 2008, Oil Prices Shocks and Stock Markets in the U.S. and 13 European Countries. Energy Economics, 30(5), 2587-2608.

Pesaran, B. and M.H Pesaran, 2009, Time Series Econometrics using Microfit 5.0. Oxford: Oxford University Press.

Ramos, Sofia B. and H. Veiga, 2013, Oil price asymmetric effects: Answering the puzzle in international stock markets. Energy Economics, 38, 136-145.

Sadorsky, P., 1999, Oil price shocks and stock market activity. Energy Economics, 21, 449–469.