
WORKING PAPER 95/2014

**VOLATILITY SPILLOVER BETWEEN OIL AND
STOCK MARKET RETURNS**

**B. Anand
Sunil Paul
M. Ramachandran**



**MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India**

November 2014

Volatility Spillover between Oil and Stock Market Returns

B. Anand

Department of Economics, Pondicherry University, Puducherry 605014

Sunil Paul

Assistant Professor, Madras School of Economics

sunilpaul@mse.ac.in

and

M. Ramachandran

Department of Economics, Pondicherry University, Puducherry 605014

WORKING PAPER 95/2014

**MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India**

November 2014

Phone: 2230 0304/2230 0307/2235 2157

Fax : 2235 4847/2235 2155

Email : info@mse.ac.in

Price : Rs. 35

Website: www.mse.ac.in

Volatility Spillover between Oil and Stock Market Returns

B. Anand, Sunil Paul and M. Ramachandran

Abstract

In the recent past, international crude oil markets have witnessed significant fluctuations and such fluctuations tend to have ramifications on the economy as a whole. In this regard, this paper makes an attempt to model such volatility spillover from oil price returns to the returns of the Indian stock market. The study also makes a comparative analysis of the volatility transmission mechanism between the periods prior to and after the eruption of global financial crisis. The empirical analysis employs BEKK parameterization of bivariate GARCH model and various tools of continuous wavelet transform to understand the dynamics of volatility spillover between these two markets. The empirical evidence suggests that the fluctuations in the crude oil price returns exert significant impact on the volatility of stock market returns. More importantly, such volatility spillovers are found to be much stronger during the post financial crisis period and the results obtained from the wavelet analysis indicate the dominance of high frequency components in the oil-stock market relationship.

Keywords: *Crude oil, Volatility Spillover, BEKK, Continuous Wavelet Transform*

JEL Codes: *C32, C1, E0*

ACKNOWLEDGMENT

We are grateful to participants at the 50th Annual Conference of the Indian Econometric Society (TIES) held at IGIDR on Dec 22-23, 2013, for insightful comments and suggestions. We would also like to thank Dr. Raja Sethu Durai for his valuable suggestions.

INTRODUCTION

Oil has been playing a pivotal role in shaping up the geo-political and economic horoscope of the entire world for several decades. Late 1980s and 1990s had witnessed the surge of oil as a crucial factor of production and one of the fundamental drivers of the world economic growth. Thus, the fluctuations in oil price assumed to have ramifications on many macroeconomic variables. For instance, the episode of high inflation across the globe during 70's are often attributed to the increase in oil prices during that time. Moreover, the supply constraints of oil will reduce basic inputs to production which may further lead to a slowdown in growth (Hamilton, 2003, 2009). Oil price shocks can reduce the productivity and cause fluctuations in the business cycle (Olson, 1988). The theoretical literature suggests that oil price may affect various sectors of an economy through different channels (Brown and Yucel, 2002). Many studies have empirically examined various aspects of oil price and macroeconomic relationship for different countries for different time periods¹.

If oil price changes can affect the economic activity then there is hardly any reason to think that financial markets alone would be left unscathed. Oil price or oil price volatility can directly affect financial markets and indirectly through its impact on other macroeconomic variables. For instance, oil price shocks can impact stock prices through

¹Hamilton (1983) is considered to be a pioneering work in this area and he examined the relationship between macroeconomic activity and oil price using US data. Later, many researchers have tested Hamilton's empirical findings by employing different data sets and methodologies, see for example, Burbridge and Harrison (1984) and Gisser and Goodwin (1986). Similarly, some studies have examined the asymmetry in the oil price and economic activity (Mork, 1989). Further, some studies argued that the oil price volatility need to be taken into account while analyzing oil and macroeconomic dynamics, see for e.g. Federer (1996). Also, Cunado and Perez de Garcia (2003, 2005) found that the relationship between oil price and economic activity is limited to the short run and is missing in the long-run. Also refer Davis and Haltiwanger (2001) for employment effects of oil price shocks; Hamilton and Herrera (2004), Bernanke *et. al.* (1997) on the role of monetary policy responses to oil price shocks; and DeLong (1997) on the inflationary effects of oil price shocks.

its effect on consumer and business spending as oil is considered to be an input in production. [Mussa \(2000\)](#) observes that an oil price increase that hits the aggregate economic activity by affecting inflation, monetary policy and corporate earnings would have spillover effects on the financial markets. In this context [Jones and Kaul \(1996\)](#) argued that oil price shocks may affect stock prices through its effects on expected earnings of stock prices. However, the literature in this area is still growing and the dynamics between oil and financial sector is yet to be completely explored both theoretically and empirically.

In this context, the emerging economies are considered to more adversely affected by oil price shocks than developed countries as they are apparently more energy intensive ([Basher and Sadorsky, 2006](#)). However, unlike many of the other developed and emerging economies, India's retail petroleum sector has been regulated and the price fluctuations in the international crude oil markets are being curbed through petroleum subsidies, but it does not ensure that the Indian economy is fully insulated from the oil price volatility. In fact, the financial markets around the world are highly integrated especially after 90's and Indian stock markets alone cannot be considered to be completely protected from such shocks. An examination of oil price and stock market dynamics are very relevant particularly in the background of recent global financial crisis.

In this context this study i) identifies the structural break in the oil price data ii) examines the volatility spill over from oil price returns to Indian stock market returns during pre as well as post break periods iii) explores the dynamics of relationship between oil price volatility and stock returns in frequency domain. To capture the volatility spillover from oil sector to the financial sector a bivariate GARCH parameterization called BEKK has been employed in the time domain. The Continuous Wavelet Tools (CWT) like wavelet coherency, partial coherency and

phase difference has been utilized to examine the dynamics of oil shocks and stock return in the frequency domain.

OIL PRICE SHOCKS AND FINANCIAL MARKETS: A BRIEF REVIEW OF LITERATURE

From a theoretical background we can link the oil price shocks and the financial sector, particularly the stock market via equity pricing model. According to this model the price of equity at any point of time can be equated to the present discounted value of the future net earnings of a company. Hence oil price shocks can be expected to be reflected in stock prices immediately. In this context an increase in oil prices may reduce the expected future earnings and hence the stock prices are expected to be negatively correlated with oil price shocks (Huang *et. al.*, 1996). Adjustments to oil price shocks can have lags if the equity markets are not efficient. Similarly there can be a negative relation between equity prices and oil price changes through the interest rate channel. For instance, policy makers may respond to an increase in oil price by raising interest rate to ease inflationary pressure. The increased interest rate can affect stock prices in two ways. First it increases the discount rate used in the stock pricing formula, second it makes alternative investment options such as bonds more attractive. Both these effects tend to decrease the stock prices (Huang *et. al.*, 1996).

In this context, most of the empirical literature documented a negative relationship between oil price and stock market activities (Jones and Kaul, 1996; Sadorsky, 1999; Papapetrou, 2001; Li and Majerowska, 2008; Malik and Hammoudeh, 2007; Malik and Ewing, 2009; Chen, 2010; Masih *et. al.*, 2011; Basher *et. al.*, 2012). However, oil price changes can have a positive correlation with stock prices if the prices are driven by global aggregate demand. (Huang *et. al.*, 1996; Apergis and Miller, 2009; Miller and Ratti, 2009; Kilian and Park, 2009).

Similarly, transmission of volatility in different markets is an important issue to be addressed in this respect. Specifically, there are many studies which analyzed the spillover of volatility among oil and equity markets. For example, [Malik and Hammoudeh \(2007\)](#) examined the spillover of volatility among U.S equity, Gulf equity and global crude oil markets using multivariate GARCH models. They found significant volatility spillovers from oil to Gulf equity markets and in the case of Saudi Arabia there was evidence for significant volatility spillover from the equity market to oil market. Similarly, [Malik and Ewing \(2009\)](#) analyzed the volatility transmission between oil prices and returns of five different U.S sector indices employing the BEKK parameterization of bivariate GARCH model and found evidence for the transmission of volatility between some of the examined markets.

Most of the conventional literature on volatility spillover has succeeded in establishing the magnitude of various types of volatility spillover between various sectors but apparently failed to look in to the issue that why it is happening, and it could be basically due to the limitations of the time domain approach, unless one has a clear picture about the idiosyncratic behavior of variables under consideration and how they have been interacting with each other over a period time, it will be difficult to address this issue. In this regard, we attempt to capture the interactions between the variables by employing continuous wavelet tools and see why volatility transmission happening between these variables.

The wavelet tools are gaining importance in the economic literature and it is being widely used to capture the undercurrents of the relationship between any two time series. Moreover, all economic time series can be considered as the sum total of various components operating on various frequencies. Hence, many idiosyncratic behaviors of the data can be traced out by examining the behavior of the time series at different frequencies which may be left unnoticed or uncaptured in a usual time domain framework ([Aguiar-Conraria and Soares, 2011](#)). But

apparently most of the previous studies were carried out in time domain treating oil as a gross variable, which may lead to the loss of vital information (Mork, 1989). Various time scales give better understanding of the dynamic relationship between the variables under scrutiny and some interesting relationship may exist at different frequencies². In recent times, the continuous wavelet transform and its associated tools gathered wide popularity [see for e.g. Jagric and Ovin (2004), Raihan *et. al.* (2005), Crowley and Mayes (2008), Aguiar-Conraria *et. al.* (2008)].

As mentioned earlier, India follows more or less a regulated retail oil price policy for more than two decades. Therefore by the day to day price fluctuations in the international crude oil markets are not expected to influence the macroeconomic variables unless it is reflected in the domestic retail oil price. However, there are some noteworthy studies that tried to examine the oil-macroeconomic relationship in the Indian context. For instance, Bhattacharya and Bhattacharya (2001) observed that a 20 percentage point hike in oil prices would result in a hike in inflation by 1.3 percentage points and a reduction in industrial output by 2.1 percentage points. Similarly, the Federation of India Chambers of Commerce (FICCI, 2005) suggests that if the oil price was double and persistent for two years it would have enhanced inflation by 7.9 percentage points and pulled down the GDP growth by 4.9 percentage points. Further, De Gregorio *et. al.* (2007) find that doubling the oil price would lead to a 7.9 percentage points increase in the consumer price index (CPI) and their study rejects the presence of any structural breaks in the oil- macroeconomy relationship in the Indian case. Likewise, Mandal *et. al.* (2012) find evidence for enhanced pass-through to domestic inflation and output, especially after 2002 when domestic and international oil prices have become more synchronized. In this context, Ghosh (2009) shows that there exists unidirectional causality between

²For example, at higher frequencies oil price may act as a supply shock and affect the industrial production, whereas, at the lower frequencies oil shocks may affect industrial production through a demand effect, (Naccache, 2011; Tiwari, 2013).

crude oil import and economic growth in the long-run; hence it is less likely that a dip in the Indian crude oil import would affect its economic growth in the long-run. Similarly, [Tiwari et. al. \(2013\)](#) find nonlinear and linear causal relationships between the oil price and the real effective exchange rate of Indian rupee, but only at higher time scales.

Apparently, there are no significant studies that examine the volatility spillover between oil price shocks and stock returns in the Indian context. However, the studies mentioned above clearly indicate that oil price shocks do affect various macroeconomic variables directly or indirectly. Hence, this study intends to probe into the volatility spillover between oil price returns and stock returns in the Indian context by employing a bivariate GARCH model and further, to check the reason behind this spillover transmission, various tools of continuous wavelet transform have been applied.

THE METHODOLOGY

Bivariate GARCH Specification

The BEKK representation for the bivariate GARCH (1, 1) model can be written as:

$$H_{t+1} = C' C + B' H_t B + A' \varepsilon_t \varepsilon_t' A \tag{1}$$

Where H_t represents the conditional variance-covariance matrix and C is a 2×2 lower triangular matrix with three parameters. Matrix B depicts the extent to which the present conditional variances are related to past conditional variances. A is a 2×2 square matrix of parameters that captures the effects of lagged shocks or events on volatility. The total number of estimated parameters for the variance equations in this case will be eleven. The conditional variance for each equation can be derived by expanding the variance system H_t as follows:

$$h_{11,t+1} = c_{11}^2 + b_{11}^2 h_{11,t} + 2b_{11}b_{12}h_{12,t} + b_{21}^2 h_{22,t} + a_{11}^2 \varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2 \varepsilon_{2,t}^2 \quad (2)$$

$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2 h_{22,t} + a_{12}^2 \varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2 \varepsilon_{2,t}^2 \quad (3)$$

The above equations measure the spillover effects and volatility transmissions across the variables over a period of time. Similarly, the coefficients of the equations (2) and (3) are non-linear function of the elements in the BEKK-GARCH equation (1). Hence, the standard errors for these coefficients should be derived from the first order Taylor expansion around its mean following [Kearney and Patton \(2000\)](#). The estimates of the above equations can be obtained by maximizing the following likelihood function:

$$L(\theta) = -T \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T (\ln |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad (4)$$

where the notation T symbolizes the number of observations, θ is the estimated parameter vector and N represents the number of variables in the estimated system and the errors in the estimation process are assumed to be normally distributed. Simplex algorithm is used to obtain the initial starting values for the estimation and then the final parameters of the mean and variance –covariance matrix with the respective standard errors are simultaneously estimated by using BFGS (Broyden-Fletcher-Goldfarb- Shanno) algorithm³.

As mentioned earlier, we have also used wavelet tools to examine the relationship between oil and financial sector. The application of wavelet tools help us to understand the relations that may exist between the variables of our interest at different frequencies. In fact, the

³BFGS is powerful in solving unconstrained optimization problems.

macroeconomic time series can be decomposed into different combinations of components operating at different frequencies. In essence, wavelet analysis examines the relation between the variables in two dimensions namely location in time and frequency. The frequency can be considered as temporal length or time horizons. Thus, using wavelet tools we are able to examine the spectral characteristics of a series as a function of time⁴. In this context, the wavelet transform has the ability to perform “natural local analysis of a time-series in the sense that the length of wavelets varies endogenously: it stretches into a long wavelet function to measure the low-frequency movements; and it compresses into a short wavelet function to measure the high-frequency movements” (Aguilar-Conraria and Soares, 2011).

In this study, we apply Continuous Wavelet Transform (CWT) to examine the time frequency dependencies between oil and stock market. Specifically, we have utilized continuous wavelet tools such as wavelet power spectrum and wavelet coherency. The wavelet power spectrum depicts the evolution of the variance of a time series at various time frequencies, wavelet coherency shows the correlation coefficient in various frequency bands and wavelet phase difference provides information about the delay between the oscillations of two time series.

The Continuous Wavelet Transform⁵

A wavelet is a function with an average value of zero. A Wavelet function is localized in both frequency and time and it can be characterized by how it is localized in time and frequency. Basically a wavelet transform decomposes a time series into some basis wavelets, obtained by scaling and translating the mother wavelet. There are two kinds of wavelet

⁴The idea of wavelet transform is similar to Fourier transform. Under Fourier analysis the time series is decomposed into linear combinations of sinusoids. However, under Fourier transformation the time information of a time series is lost as the sine wave function has a specific frequency but infinite duration in time. Similarly, Fourier transform requires the series to be stationary (Roueff and von Sachs, 2011).

⁵Please refer [Aguilar-Conraria and Soares \(2014\)](#) for a detailed survey of CWT.

transform: (i) discrete wavelet transforms (DWT); (ii) continuous wavelet transforms (CWT). This study employs CWT.

The CWT of a given time series $x_t \in L^2 \mathbb{R}$ is defined as a convolution type:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x_t \psi_{\tau, s}^*(t) \quad (5)$$

Where $L^2 \mathbb{R}$ denotes the set of square integrable functions, $\psi_{\tau, s}^*(t)$ is the complex conjugate function of wavelet basis $[\psi_{\tau, s}(t)]$. Basis wavelets $\psi_{\tau, s}(t)$ are obtained from a mother wavelet (ψ)⁶ by scaling and translating ψ and can be expressed as follows:

$$\psi_{\tau, s}(t) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t - \tau}{s}\right), \quad s, \tau \in \mathbb{R}, s \neq 0 \quad (6)$$

where s is a scaling factor that controls the width of the wavelet and τ is a location parameter that controls where the wavelet is centered. The CWT maps the original series into a function of s (which determines the position of wavelet in frequency domain) and τ (determine the position of wavelet in time domain). We can visualize the changes in the amplitude of x_t over a period of time by changing the scale parameters (s) along a localized time index or location parameter (τ) [Torrence and Compo, 1998]. If we have a discrete time series with uniform time steps δt , i.e. ($x_t, t=0, 1, \dots, T-1$), then the expression given in equation 6 becomes:

$$W_m^x(s) = \frac{\delta t}{\sqrt{s}} \sum_{t=0}^{T-1} x_n \psi^* \left[\left(t - m \right) \frac{\delta t}{s} \right], \quad m = 0, 1, \dots, T - 1 \quad (7)$$

⁶The mother wavelet must have zero mean i.e. $\int_{-\infty}^{\infty} \psi(t) dt = 0$ and its square must integrate to unity i.e. $\int_{-\infty}^{\infty} \psi^2(t) dt = 1$. It must also satisfy the admissibility condition given as $0 < C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|}{|\omega|} d\omega < \infty$, where C_ψ is the admissibility constant and $\psi(\omega)$ denotes the Fourier transform of the mother wavelet $\psi(t)$. The Fourier transform of mother wavelet is defined as $\psi(\omega) = \int_{-\infty}^{\infty} \psi(t) e^{-i\omega t} dt$.

The wavelet literature proposes various kinds of mother wavelets. In this study we apply one of the popular and commonly used mother wavelets (Morlet wavelet) introduced by Goupillaud, *et. al.* (1984). A simplified version of Morlet wavelet is given as follows:

$$\psi_{\eta}(t) = \pi^{-1/4} e^{int} e^{-t^2/2} \quad (8)$$

where $\pi^{-1/4}$ ensures its unity energy and $e^{-t^2/2}$ ensures that the admissibility condition is satisfied for this wavelet (See footnote 6). A Morlet wavelet (with $\eta = 6$) is commonly used for feature extraction purposes since it balances the time and frequency localization. Moreover, Aguiar-Conraria and Soares (2014) observes that I) the Morlet wavelet can be treated as an analytic wavelet⁷ II) the conversion from scale to frequencies are easier for Morlet wavelets, since its peak frequency, energy frequency and central instantaneous frequency are equal iii) given $\eta = 6$, the relationship between frequency (f) and scale is given as follows $f = \frac{6}{2\pi s} \approx \frac{1}{s}$. Thus we can decompose a time series x_t into joint time frequency plane where the longer (shorter) wavelet scale corresponds to the higher (lower) frequency under this scheme. Since we can calculate the amplitudes and phases of a Morlet wavelet, we can easily estimate the wavelet power spectrum, wavelet coherency and phase difference.

Wavelet Power Spectrum

We define the wavelet power spectrum (WPS) of a series x_t as $|W_x(\tau, s)|^2$. It can be considered as the localized variance or volatility of x at each scale or frequency. Similarly the global wavelet power spectrum (GWPS) can be obtained by taking average over all times and can be defined as:

⁷ To measure the time evolution of frequency transients we need to use complex analytic wavelets which can separate the phase and amplitude components of a time series. The analytic wavelet have $\psi(\omega) = 0$ for $\omega < 0$, where $\psi(\omega)$ denotes the Fourier transform of the mother wavelet.

$$\int_{-\infty}^{\infty} |W_x(\tau, s)|^2 d\tau \quad (9)$$

We may also define the cross wavelet transform (XWT) of any of two time series x_t and y_t as $W_{xy}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s)$ in which W_x and W_y are the wavelet transforms of x_t and y_t and * denotes complex conjugation. Analogous to wavelet power we can define cross wavelet power as:

$$|W_{xy}(\tau, s)|^2 = |W_x(\tau, s)|^2 |W_y^*(\tau, s)|^2 \quad (10)$$

The cross wavelet power can be considered as the local variance of x_t and y_t at each time and frequency.

Wavelet Coherency and Phase -Difference

[Aguilar-Conraria et. al. \(2008\)](#) defines Wavelet Coherency as “the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series”. Analogous to Fourier coherency, let us define the complex wavelet coherency as follows:

$$C_{xy} = \frac{S(W_{xy}(\tau, s))}{\sqrt{S(|W_x(\tau, s)|^2)S(|W_y(\tau, s)|^2)}} \quad (11)$$

where S is a smoothing operator in both time and scale. Without smoothing the coherency is equal to one at all time and scales. Smoothing is done by a convolution in time and scale⁸. The absolute value of complex coherency is called as wavelet coherency and can be defined as:

$$R_{xy} = \frac{|S(W_{xy}(\tau, s))|}{\sqrt{S(|W_x(\tau, s)|^2) \cdot S(|W_y(\tau, s)|^2)}} \quad (12)$$

⁸See [Cazelles et. al. \(2007\)](#) and [Torrence and Compo \(1998\)](#) for details.

Thus wavelet coherency is the ratio of the cross-spectrum to the product of the spectrum of each series. This can be interpreted as the local correlation between two time series both in time and frequency. Zero coherency means no co-movement between the two time series and coherency equal to one indicates a strong co-movement between them. The statistical significance of the estimated wavelet coherency is tested using Monte Carlo simulation methods.

The wavelet coherency as defined above doesn't distinguish between negative and positive co-movements. The information on positive and negative co-movements and the lead-lag relationship between two time-series can be examined using the phase of the wavelets. The phase (or the phase-angle) of a given time series, ϕ_x shows its position in the pseudo-cycle of the series⁹. Then the Phase difference between the two time series ϕ_{xy} characterize the phase relationship and shows their relative position in the pseudo-cycle. The Phase difference is given as follows:

$$\phi_{xy} = \tan^{-1} \left(\frac{\Im\{S(W_{xy}(\tau, s))\}}{\Re\{S(W_{xy}(\tau, s))\}} \right), \phi_{xy} \in [-\pi, \pi] \quad (13)$$

Where \Im and \Re are the imaginary and real parts of the smooth power spectrum. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency and a phase difference of π (or $-\pi$) indicates an anti-phase relation. More specifically if $\phi_{xy} \in \left[0, \frac{\pi}{2}\right]$ then the series move in-phase (positively co-move), with x_t leading y_t . On the other hand, if $\phi_{xy} \in \left[\frac{\pi}{2}, \pi\right]$ then the series move out of phase (negatively co-move) with y_t is leading x_t . Similarly, if $\phi_{xy} \in \left[-\pi, -\frac{\pi}{2}\right]$ then the series is negatively co-move with

⁹The Phase difference is nothing but the angle of a complex wavelet coherency. Note that the complex wavelet coherency can be written in polar as $C_{xy} = |C_{xy}|e^{i\phi_{xy}}$

x_t leading y_t and if $\phi_{xy} \in \left[-\frac{\pi}{2}, 0\right]$ then the series move in phase with y_t leading x_t .

EMPIRICAL RESULTS AND DISCUSSION

The empirical analysis has been conducted using seasonally adjusted monthly data for the sample period January 2000 to December 2012. The Indian crude oil basket¹⁰ has been taken as a measure of oil price and the data has been collected from the website Index Mundi. The S&P CNX NIFTY has been chosen as a proxy for stock market index and the data has been collected from the National Stock Exchange (NSE) website.

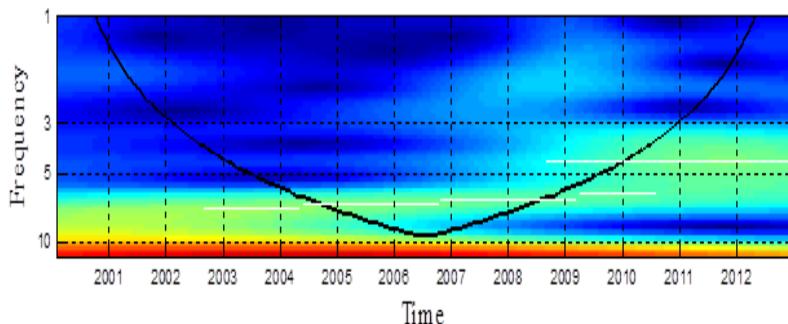
To begin with, we obtain the power spectrum of crude oil price to identify whether there is any structural break in the historical data. The wavelet power spectral estimates are displayed in [Fig. 1](#) with time on the horizontal axis and period of cycles on the vertical axis. The power is measured by colors, which ranges from blue (low power) to red (high power). The regions outside the thick black line are called Cone of Influence (COI)¹¹. We can identify the cycle of period of the series by spotting green/yellow color regions. The white lines in the green/yellow color regions give the maxima of the undulations of the wavelet power spectrum and it shows the precise estimates of cycle period. However, the shift in the white line suggests that the cycle is not continuous and there seems to be a break in the green/yellow spot around Oct 2008. Specifically, there is a shift in the cycle of period from roughly 7 year periodicity to 4 year periodicity during this period. More precisely, the 4 year periodicity seems to be very important in explaining the total

¹⁰The composition of Indian Basket of Crude represents average of Oman and Dubai for sour grades and Brent (Dated) for sweet grade in the ratio of 69.9:30.1 for 2013-14.

¹¹The estimates of power spectrum in the region of COI should be interpreted carefully, because the CWT, as observed by [Aguilar-Conraria and Soares \(2011\)](#), underestimates the wavelet power spectrum in the beginning and at the end of the sample period.

variance of the series since Oct 2008. This can, perhaps, be due to the recent financial crisis and it may be treated as an evidence for a structural break in the variance of the series during that period.

Fig. 1: Wavelet Power Spectrum of Indian Crude Oil Basket



The findings of [Claessens *et. al.* \(2010\)](#) reiterate the significance of this particular break date as some of the emerging as well as major crude oil importing countries like China, Brazil and South Africa were largely exposed to the global financial meltdown during this period. Moreover, it was during the third quarter of the same year some of the prominent multinational conglomerates like Fannie Mae and Freddie Mac, Goldman Sachs, Morgan Stanley, Lehman Brothers and AIG confronted the most severe phase of the financial crisis including bankruptcy. Also, [Fan and Xu \(2011\)](#) have found almost similar break date; their findings suggest the presence of a structural break in June 2008.

Further to check the robustness of the break date obtained from the wavelet power spectrum, the chow break point test has been carried out and the results are presented in [Table 1](#). The F-statistics and likelihood ratio statistics reject the null hypothesis of no structural break in October 2008 as the p-values are 0.00.

The information in [Table 2](#) is descriptive statistics for each of the return series during pre and post break period. The mean of oil and stock return are same for both pre and post break periods, whereas the standard deviation of these series are slightly higher in the post break period. Further the estimates of other sample moments (Skewness and kurtosis) for pre and post break period indicate that the distributions of these series have negative Skewness and fat tails. Similarly, the Ljung–Box Q statistics up to twelve lags indicate that the null of no autocorrelation in both series can be rejected during pre and post break periods. As each of the return series was found to be leptokurtic (i.e. they have the characteristics of fat tails) each of the mean equations were to be tested for the existence of ARCH effect.

Table 1: Chow Break Point Test: October 2008

F-statistic	112.05 (0.00)
Log likelihood ratio	85.29 (0.00)

Note: Values in the parenthesis are probability values.

Table 2: Descriptive Statistics

	Pre-break		Post-break	
	Oil	Stock	Oil	Stock
Mean	0.01	0.01	0.01	0.01
Median	0.02	0.02	0.02	0.01
Maximum	0.12	0.16	0.14	0.18
Minimum	-0.26	-0.27	-0.22	-0.27
Std. Dev.	0.05	0.06	0.07	0.07
Skewness	-1.43	-1.02	-1.26	-0.56
Kurtosis	9.11	6.28	5.04	6.55
Q(12)	24.09 (0.00)	21.83 (0.03)	33.92 (0.00)	20.03 (0.00)
Sample Period	<i>01-2000 to 10-2008</i>		<i>10-2008-12-2012</i>	

Note: Q(12) is the Ljung-Box statistic for serial correlation in return series. The values in parentheses are probability values.

To this end, we estimate the following mean equation for each return series:

$$R_{it} = \mu_i + \alpha R_{it-1} + \varepsilon_{it} \quad (14)$$

Where R_{it} is the return of series between time $t - 1$ and t , μ_i stands for a long term drift coefficient and ε_{it} is the error at time t . After estimating equation (14) the residuals were tested for the existence of ARCH effects using ARCH LM test proposed by Engle (1982) and found the presence of ARCH effects in variables under consideration (the results are not produced here). Since ARCH effect was evident, we can use the BEKK parameterization of the bivariate GARCH model which is capable of capturing the transmission of volatility among different series as well as the persistence of volatility within each series.

The Bivariate GARCH Results

As mentioned above, this study has estimated a bivariate GARCH model with BEKK parameterization for pre and post break periods separately. The estimates of variance equation for pre and post break periods respectively are reported in [Tables 3 and 4](#). The conditional variance for oil price returns at time $t + 1$ is denoted by $h_{11,t+1}$ (hereafter, the oil equation) and the conditional variance for stock returns at time $t + 1$ by $h_{22,t+1}$ (hereafter, the stock equation). Similarly $h_{12,t}$ stands for the conditional covariance between the oil price returns and stock returns at time period t . The unexpected shocks or 'news' emerging from the oil market or stock market, subscripted by the numbers 1 and 2 respectively, shall be captured by the squared error terms ε_{1t}^2 and ε_{2t}^2 . Similarly, the impact of 'news' through indirect effects is represented by the cross product of error terms ($\varepsilon_{1t}\varepsilon_{2t}$).

There is no evidence for direct or indirect volatility spillover from stock returns to oil sector in the pre break period as the coefficients of $h_{22,t}$ and $h_{12,t}$ are statistically insignificant in the oil equation ([Table 3](#)). Similarly, direct and indirect news effects from stock market to oil sector are not significant during this period. This result makes sense since the

Indian stock market is so thin to exert pressure on the global crude oil markets.

Table 3: Oil Price Returns and Stock Returns

(Pre-Break:01-2000 to 10-2008)

$h_{11,t+1} = 0.03 + 0.04h_{11,t} - 0.02 h_{12,t} + 0.17h_{22,t} + 0.33\varepsilon_{1,t}^2 - 0.07 \varepsilon_{1,t}\varepsilon_{2,t}$ $+ 0.01\varepsilon_{2,t}^2$
$h_{22,t+1} = 0.02 + 0.05h_{11,t} + 0.26h_{12,t} + 0.41h_{22,t} + 0.03\varepsilon_{1,t}^2 + 0.29\varepsilon_{1,t}\varepsilon_{2,t}$ $+ 0.22\varepsilon_{2,t}^2$

Note: t statistics are given in brackets (critical values of t- statistics for 10% and 5% levels of significance are 1.65 and 1.96 respectively).

Table 4: Oil Price Returns and Stock Returns

(Post-Break 11-2008 to 12-2012)

$h_{11,t+1} = 0.01 + 0.11h_{11,t} - 0.20 h_{12,t} + 0.11h_{22,t} + 0.70\varepsilon_{1,t}^2 + 0.02\varepsilon_{1,t}\varepsilon_{2,t}$ $+ 0.01\varepsilon_{2,t}^2$
$h_{22,t+1} = 0.02 + 0.09h_{11,t} + 0.25h_{12,t} + 0.18h_{22,t} + 0.16\varepsilon_{1,t}^2 + 0.89\varepsilon_{1,t}\varepsilon_{2,t}$ $+ 0.77\varepsilon_{2,t}^2$

Note: t statistics are given in brackets (critical values of t- statistics for 10% and 5% levels of significance are 1.65 and 1.96 respectively).

However, that the stock returns are indirectly affected by the volatility and the news emanating from the oil sector (see the statistically significant coefficients of $h_{12,t}$ and $\varepsilon_{1,t}\varepsilon_{2,t}$ in the stock equation). Similarly, the significant coefficients on $h_{22,t}$ and $\varepsilon_{2,t}^2$ indicate that the stock returns are directly affected by its own volatility and news. Yet, there is no direct volatility spillover transmission from oil sector to stock returns in the pre break period as the coefficient of $h_{11,t}$ is statistically insignificant and there is no significant direct news effect on the stock returns from the oil sector (see the insignificant coefficient of $\varepsilon_{2,t}^2$ in the stock equation).

Thus, estimates of bivariate GARCH models for the pre break period indicate that volatility from the oil sector was transmitted to Indian stock market mainly through indirect effects whereas, there is no evidence for reverse spillover effects as such.

The estimates of bivariate GARCH model for the post-break period which includes the global financial crisis and subsequent periods are given in the [Table 4](#). The results indicate that the volatility of oil price returns are affected by it's on past volatility (see the significant coefficient on $h_{11,t}$ in the oil equation). Similarly, the oil price returns are directly affected by its own shocks as the coefficient of $\varepsilon_{1,t}^2$ is statistically significant. However, there is no evidence for direct and indirect channels of volatility transmission and news effect from the stock market to oil prices for this period, as the coefficients on $h_{22,t}$, $h_{12,t}$, $\varepsilon_{2,t}^2$ and $\varepsilon_{1,t}\varepsilon_{2,t}$ are statistically insignificant in the oil equation.

Whereas, estimates of the stock equation indicate that the equity sector has become more vulnerable to the volatility spillover from the oil price returns during the post-break period. Specifically the volatility of stock returns are directly affected by returns of oil price volatility since the coefficient of $h_{11,t}$ is statistically significant. The shocks from the oil sector also seems to have a significant direct impact on stock return volatility, but only at 10% level of significance. Apparently, none of the direct channels appeared to be significant during the pre-break period. Further, the significant coefficients on $h_{12,t}$ and $\varepsilon_{1,t}\varepsilon_{2,t}$ suggest that stock return volatility is affected indirectly by volatility and the immediate shocks (news) from the oil market. Compared to pre-break period, the bivariate GARCH results clearly indicate that the magnitude of the volatility spillover has become stronger during the post-break period.

The results from bivariate GARCH models can be further substantiated by checking the covariance between the two variables in the frequency domain. Exploring the relationship between the variables in

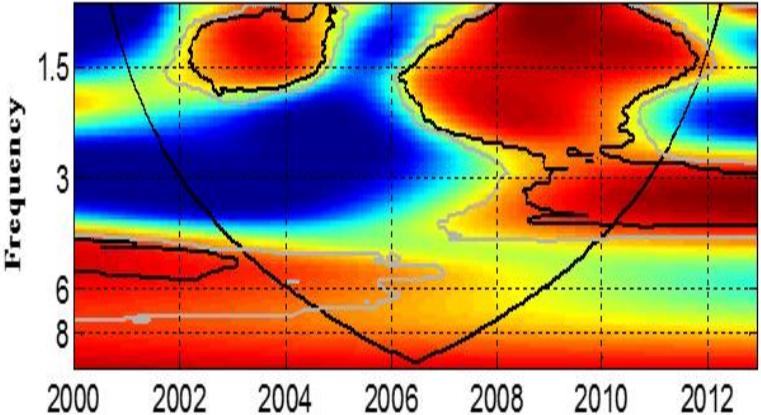
frequency domain will be helpful in understanding the dynamics of relationship in time and across frequencies. The wavelet analysis can be considered as a robustness check for the volatility spillover results generated by employing the bivariate GARCH model. Further, wavelet tools are capable of capturing the presence of the structural breaks and transitory elements in the oil and stock relationship. For this purpose we employ various continuous wavelet tools like wavelet coherency and phase difference.

Results from Wavelet Analysis

The wavelet coherency, which provides a picture of co-movement of oil price returns and stock returns, is presented in [Figure 2](#)¹². Time is plotted on the horizontal axis and frequency in the vertical axis. The wavelet coherency picture shows the strength of co-movement of the variables in time and frequency space. The colour code differs from red to blue. The red color area in the picture indicates high power and high coherency whereas blue colour indicates low power and low coherency. Statistically significant areas at 5% (10%) significance level are indicated by black (grey) lines in the area with warmer colors (red or yellow). Similarly, the cone of influence (COI) is designated by a U shaped black line.

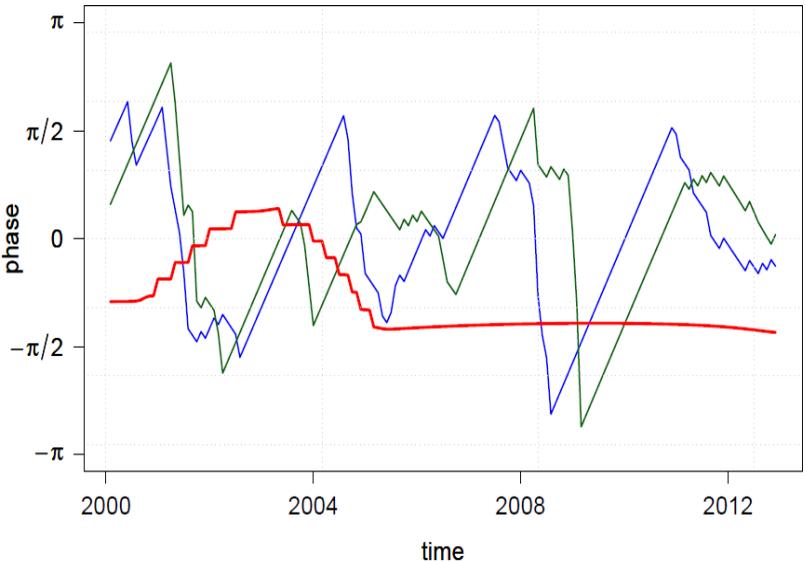
¹² All the results and graphs in this section was generated using Matlab toolbox called ASToolbox written by Luis Aguiar Conraria and Maria Joana Soares (available at <https://sites.google.com/site/aguiarconraria/joanasoares-wavelets/the-astoolbox>)

Figure 2: Wavelet Coherency between Stock Market Returns and Oil Price Returns.



Notes: The black (grey) contour designates the 5% (10%) significance level based on an ARMA (1, 1) null. The colour code varies from blue (low power) to red.

Figure 3: Phases and Phase-difference of Oil and Stock Returns: 1.5 ~ 4 Frequency band)



From the wavelet picture, it can be observed that there are significant regions of coherency at different frequency bands. It is interesting to note that at low frequencies (corresponding to 4 ~ 8 frequency band) we observe statistically significant coherency only in the pre-break period. However, at higher frequency bands we have statistically significant coherency during both pre and post break periods. Specifically, there is a statistically significant region of coherency in the 2 ~ 1 frequency bands between 2002 and 2005 during the pre-break period. However, the coherency in the short run frequency bands is stronger during the post break period. There is evidence for significant coherence between oil price returns and stock returns in the short run cycles (corresponding to 1~3 frequency band) during the 2006 - 2012 period. Also the coherence between these variables seems to be stronger during 2008 to 2012 in the 3 ~ 4.5 frequency band. These results in general indicate the dominance of high frequency elements in the oil and stock relationship especially during the post break period.

The phase oscillations and the phase difference of oil and stock returns are plotted in [Figure 3](#). The plot of phase-difference helps us to identify the strength of co-movement and lead-lag relationships between these variables at different frequencies. Since the oil and stock returns are most coherent in high frequency bands, we limit our focus on the phase-difference of these variables on 1.5 ~ 4 frequency band. The green line represents phase of oil returns, the blue line represents the phase of stock returns and the red (bold) line indicates the phase-difference between oil and stock returns.

The variables can be considered to be in-phase (positively correlated) if the phase- difference line lies between $\frac{\pi}{2}$ and $-\frac{\pi}{2}$. Similarly, if the phase- difference lies between 0 and $-\frac{\pi}{2}$ or $\frac{\pi}{2}$ and π then the oil price returns leads the stock returns. From [Figure 3](#) it is evident that the stock returns and oil price returns are positively correlated in the

specified frequency band as the red line indicating phase-difference consistently lies between $-\frac{\pi}{2}$ and $\frac{\pi}{2}$. Further, we can say that oil price returns leads the stock returns for most of the time period except for a short period during 2002 and 2005). Moreover, the phase-difference clearly shows that the coherence between oil and stock prices was strong during the post break period in high frequency bands. We haven't reported the phase- difference plot for the 4 ~ 8 frequency band as the coherency between these variables were not statistically significant for most of the period (see [Figure 2](#)). However, the phase-difference line between oil and stock was close to zero for both the time periods at this frequency band.

In general, the estimates of wavelet coherence and phase-difference substantiate the results from BEKK- GARCH models. The wavelet analysis validates the structural break identified by chow test and wavelet power spectrum. Further, the results of wavelet coherence and phase-difference clearly indicate a strong coherence between oil price and stock return during the post- break period, especially at the higher frequency band. Apparently BEKK-GARCH also indicates presence of direct and indirect volatility transmission from oil to stock returns during the post break period. The high coherence of oil and stock return at high frequency bands indicate the temporary nature of volatility transmission between these markets and can be attributed to the financial crisis during that period. Thus, the result from both bivariate GARCH and continuous wavelet analysis implies that the developments in the world crude oil prices do affect Indian stock markets even though the oil prices are regulated in India. Hence, the financial market participants can use changes in oil prices as indicators of future changes in Indian stock markets.

CONCLUDING REMARKS

This paper examined the transmission of shocks and volatility between returns of the oil sector and the Indian stock market. Monthly data from April, 2000 to December, 2012 has been used in empirical estimation. The sample has been divided into two periods as evidence derived from the wavelet power spectrum of oil price and chow test suggested a break in the oil price data around October 2008. Comparing with some of the previous literature and considering historical events, it is evident that the structural break obtained by employing the wavelet power spectrum has strong economic and historic validation. The dynamics oil and stock returns relationship is examined using bivariate GARCH models in time domain and continuous wavelet tools in frequency domain. The empirical results suggest that, after the outbreak of the global financial crisis, there has been significant escalation in the magnitude of volatility spillover between oil price returns and the Indian stock market returns. Apparently, the wavelet coherency picture indicates that during the post-break period the coherence relationship among the two variables has become stronger at high frequency bands.

This study is novel as it combines both time and frequency domain approaches under a common theoretical platform to probe into the changes in the magnitude of volatility spillover between crude oil price returns and the Indian stock market returns. Interestingly, results from both wavelet and bivariate GARCH models complement each other and helps to get a clearer picture of the dynamics between oil price and stock returns.

Our results are important in order to understand the dynamic interaction between crude oil prices and stock markets. It suggests that, the financial market participants can utilize information emanating from the international crude oil price volatility to predict the expected volatility in the Indian stock market returns and formulate their investment decisions accordingly.

REFERENCES

- Aguiar-Conraria, L. and M. J. Soares (2011), "Oil and the Macroeconomy: Using Wavelets to Analyze Old Issues", *Empirical Economics*, 40(3), 645-655.
- Aguiar-Conraria, L., and M. J. Soares (2014), "The Continuous Wavelet Transform: Moving Beyond Uni and Bivariate Analysis", *Journal of Economic Surveys*, 28(2), 344-375.
- Aguiar-Conraria, L., N. Azevedo and M. J. Soares (2008), "Using Wavelets to Decompose the Time-Frequency Effects of Monetary Policy", *Physica A: Statistical Mechanics and its Applications*, 387(12), 2863-2878.
- Apergis, N., and S. M. Miller (2009), "Do Structural Oil-Market Shocks Affect Stock Prices?", *Energy Economics*, 31(4), 569-575.
- Basher, S. A., and P. Sadorsky (2006), "Oil Price Risk and Emerging Stock Markets", *Global Finance Journal*, 17(2), 224-251.
- Basher, S. A., A.A., Haug and P. Sadorsky (2012), "Oil Prices, Exchange Rates and Emerging Stock Markets", *Energy Economics*, 34(1), 227-240.
- Bernanke, B. S., M. Gertler, M. Watson, C. A. Sims and B. M. Friedman (1997). "Systematic Monetary Policy and the Effects of Oil Price Shocks", *Brookings Papers on Economic Activity*, 91-157.
- Bhattacharya, K., and I. Bhattacharyya (2001), "Impact of Increase in Oil Prices on Inflation and Output in India", *Economic and Political Weekly*, 4735-4741.
- Brown, S., and M. K. Yücel (2002), "Energy Prices and Aggregate Economic Activity: An Interpretative Survey", *The Quarterly Review of Economics and Finance*, 42(2), 193-208.
- Burbidge, J., and A. Harrison (1984), "Testing for the Effects of Oil-Price Rises Using Vector Auto Regressions", *International Economic Review*, 459-484.

- Cazelles, B., M. Chavez, G.C. de Magny, J. F. Guégan and S. Hales (2007), "Time-dependent Spectral Analysis of Epidemiological Time-series with Wavelets", *Journal of the Royal Society Interface*, 4(15), 625-636.
- Chen, S. S. (2010), "Do Higher Oil Prices Push the Stock Market into Bear Territory?" *Energy Economics*, 32(2), 490-495.
- Claessens, S., G. Dell'Ariccia, D. Igan and L. Laeven (2010), "Cross-country Experiences and Policy Implications from the Global Financial Crisis", *Economic Policy*, 25(6), 267-293.
- Cong, R. G., Y. M. Wei, J. L., Jiao and Y. Fan (2008), "Relationships between Oil Price Shocks and Stock Market: An Empirical Analysis from China", *Energy Policy*, 36(9), 3544-3553.
- Crowley, P. M., and D. G. Mayes (2008), "How Fused is the Euro Area Core?: An Evaluation of Growth Cycle Co-Movement and Synchronization Using Wavelet Analysis", *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 2008(1), 63-95.
- Cunado, J., and F. Pérez de Gracia (2003), "Do Oil Price Shocks Matter? Evidence for Some European countries", *Energy Economics*, 25(2), 137-154.
- Cunado, J., and F. Pérez de Gracia (2005), "Oil Prices, Economic Activity and Inflation: Evidence for Some Asian Countries", *The Quarterly Review of Economics and Finance*, 45(1), 65-83.
- Davis, S. J., and J. Haltiwanger (2001), "Sectoral Job Creation and Destruction Responses to Oil Price Changes", *Journal of monetary economics*, 48(3), 465-512.
- De Gregorio, J., O. Landerretche and C. Neilson (2007), "Another Pass-through Bites the Dust? Oil Prices and Inflation", *Economica*, 155-208.
- DeLong, J. B. (1997), "America's Peacetime Inflation: The 1970s" In C. D.Romar and D. H. Romar (Eds) *Reducing inflation: Motivation and Strategy* (pp. 247-280). University of Chicago Press.

- Engle R. F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the U.K. inflation", *Econometrica*, 50, 987-1008.
- Fan, Y., and J. H. Xu (2011), "What has Driven Oil Prices Since 2000? A Structural Change Perspective", *Energy Economics*, 33(6), 1082-1094.
- Federation of Indian Chambers of Commerce and Industry (2005), "Impact of High Oil Prices on Indian economy".
- Ferderer, P. J. (1996), "Oil Price Volatility and The Macroeconomy", *Journal of macroeconomics*, 18(1), 1-26.
- Ghosh, S. (2009), "Import Demand of Crude Oil and Economic Growth: Evidence from India", *Energy Policy*, 37(2), 699-702.
- Gisser, M., and T. H. Goodwin (1986), "Crude Oil and The Macroeconomy: Tests of Some Popular Notions: Note", *Journal of Money, Credit and Banking*, 18, 95-103.
- Goupillaud, P., A. Grossmann and J. Morlet (1984), "Cycle-octave and Related Transforms in Seismic Signal Analysis", *Geoexploration*, 23(1), 85-102.
- Hamilton, J. D. (1983), "Oil and the Macroeconomy Since World War II", *The Journal of Political Economy*, 228-248.
- Hamilton, J. D. (2003), "What is an Oil Shock?", *Journal of Econometrics*, 113(2), 363-398.
- Hamilton, J. D. (2009), "Understanding Crude Oil Prices", *The Energy Journal*, 30(2).179-206
- Hamilton, J. D., and A. M. Herrera (2004), "Comment: Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy", *Journal of Money, Credit and Banking*, 265-286.
- Huang, R. D., R. W. Masulis, and H. R. Stoll (1996), "Energy Shocks and Financial Markets", *Journal of Futures Markets*, 16(1), 1-27.

- Jagric T., and R. Ovin (2004), "Method of Analyzing Business Cycles in a Transition Economy: The Case of Slovenia", *The Developing Economies*, 42(1), 42-62.
- Jones, C. M., and G. Kaul (1996), "Oil and The Stock Markets", *The Journal of Finance*, 51(2), 463-491.
- Kearney, C., and A. J. Patton (2000), "Multivariate GARCH Modeling of Exchange Rate Volatility Transmission in the European Monetary System", *Financial Review*, 35(1), 29-48.
- Kilian, L., and C. Park (2009), "The Impact of Oil Price Shocks on the U.S Stock Market", *International Economic Review*, 50(4), 1267-1287.
- Li, H., and E. Majerowska (2008), "Testing Stock Market Linkages for Poland and Hungary: A multivariate GARCH approach", *Research in International Business and Finance*, 22(3), 247-266.
- Mandal, K., I. Bhattacharyya and B. B. Bhoi (2012), "Is the Oil Price Pass-through in India Any Different?", *Journal of Policy Modeling*, 34(6), 832-848.
- Malik, F., and B. T. Ewing (2009), "Volatility Transmission between Oil Prices and Equity Sector Returns", *International Review of Financial Analysis*, 18(3), 95-100.
- Malik, F., and S. Hammoudeh (2007), "Shock and Volatility Transmission in the Oil, US and Gulf Equity Markets", *International Review of Economics and Finance*, 16(3), 357-368.
- Masih, R., S. Peters and L. De Mello (2011), "Oil Price Volatility and Stock Price Fluctuations in an Emerging Market: Evidence from South Korea", *Energy Economics*, 33(5), 975-986.
- Miller, J. I., and R. A. Ratti (2009), "Crude Oil and Stock Markets: Stability, Instability, and Bubbles", *Energy Economics*, 31(4), 559-568.
- Mork, K. A. (1989), "Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results", *Journal of Political Economy*, 740-744.

- Mussa, M. (2000), "The Impact of Higher Oil Prices on the Global Economy", International Monetary Fund. Available at <http://www.imf.org/external/pubs/ft/oil/2000>.
- Naccache, T., (2011), "Oil Price Cycles and Wavelets", *Energy Economics* 33, 338–352
- Olson, M. (1988), "The Productivity Slowdown, the Oil Shocks, and the Real Cycle", *The Journal of Economic Perspectives*, 2, 43-69.
- Papapetrou, E. (2001), "Oil Price Shocks, Stock Market, Economic Activity and Employment in Greece", *Energy Economics*, 23(5), 511-532.
- Raihan, S. M., Y. Wen and B. Zeng (2005), "Wavelet: A New Tool for Business Cycle Analysis", *Federal Reserve Bank of St. Louis Working Paper Series*, (2005-050).
- Roueff, F., and R. von Sachs (2011), "Locally Stationary Long Memory Estimation", *Stochastic Processes and their Applications*, 121(4), 813-844.
- Sadorsky, P. (1999), "Oil Price Shocks and Stock Market Activity", *Energy Economics*, 21(5), 449-469.
- Tiwari, A. K. (2013), "Oil Prices and the Macroeconomy Reconsideration for Germany: Using Continuous Wavelet", *Economic Modelling*, 30, 636-642.
- Tiwari, A. K., A. B. Dar, and N. Bhanja (2013), "Oil Price and Exchange Rates: A Wavelet Based Analysis for India", *Economic Modelling*, 31, 414-422.
- Torrence, C., and G. P. Compo (1998), "A Practical Guide to Wavelet Analysis", *Bulletin of the American Meteorological Society*, 79(1), 61-78.

MSE Monographs

- * Monograph 17/2012
Monitorable Indicators and Performance: Tamil Nadu
K. R. Shanmugam
- * Monograph 18/2012
Performance of Flagship Programmes in Tamil Nadu
K. R. Shanmugam, Swarna S Vepa and Savita Bhat
- * Monograph 19/2012
State Finances of Tamil Nadu: Review and Projections A Study for the Fourth State Finance Commission of Tamil Nadu
D.K. Srivastava and K. R. Shanmugam
- * Monograph 20/2012
Globalization and India's Fiscal Federalism Finance Commission's Adaptation to New Challenges
Baldev Raj Nayar
- * Monograph 21/2012
On the Relevance of the Wholesale Price Index as a Measure of Inflation in India
D.K. Srivastava and K. R. Shanmugam
- * Monograph 22/2012
A Macro-Fiscal Modeling Framework for forecasting and Policy Simulations
D.K. Srivastava, K. R. Shanmugam and C. Bhujanga Rao
- * Monograph 23/2012
Green Economy – Indian Perspective
K.S. Kavikumar, Ramprasad Sengupta, Maria Saleth, K.R.Ashok and R.Balasubramanian
- * Monograph 24/2013
Estimation and Forecast of Wood Demand and Supply in Tamilnadu
K.S. Kavi Kumar, Brinda Viswanathan and Zareena Begum I
- * Monograph 25/2013
Enumeration of Crafts Persons in India
Brinda Viswanathan
- * Monograph 26/2013
Medical Tourism in India: Progress, Opportunities and Challenges
K.R. Shanmugam
- * Monograph 27/2014
Appraisal of Priority Sector Lending by Commercial Banks in India
C. Bhujanga Rao
- * Monograph 28/2014
Fiscal Instruments for Climate Friendly Industrial Development in Tamil Nadu
D.K. Srivastava, K.R. Shanmugam, K.S. Kavi Kumar and Madhuri Saripalle
- * Monograph 29/2014
Prevalence of Undernutrition and Evidence on Interventions: Challenges for India
Brinda Viswanathan.

MSE Working Papers

Recent Issues

- * Working Paper 85/2014
Unravelling India's Inflation Puzzle
Pankaj Kumar and Naveen Srinivasan
- * Working Paper 86/2014
Agriculture and Child Under-Nutrition in India: A State Level Analysis
Swarna Sadasivam Vepa, Vinodhini Umashankar, R. V. Bhavani and Rohit Parasar
- * Working Paper 87/2014
Can the Learnability Criterion Ensure Determinacy in New Keynesian Models?
Patrick Minford and Naveen Srinivasan
- * Working Paper 88/2014
Perspectives on Valuation of Biodiversity
Suneetha M S
- * Working Paper 89/2014
Testing the Expectations Trap Hypothesis: A Time-Varying Parameter Approach
Naveen Srinivasan
- * Working Paper 90/2014
Analyzing the Pathway to Improve Tiger Conservation in India
Zareena Begum, I and Amanat K. Gill
- * Working Paper 91/2014
A New Approach to Construct Core Inflation
Sartaj Rasool Rather, S. Raja Sethu Durai and M. Ramachandran
- * Working Paper 92/2014
Energy Use Patterns And Firm Performance: Evidence From Indian Industries
Santosh Kumar Sahu
- * Working Paper 93/2014
Women's Malnutrition In India: The Role Of Economic And Social Status
Shikha Dahiya and Brinda Viswanathan
- * Working Paper 94/2014
Asymmetric Price Adjustment - Evidence For India
Sartaj Rasool Rather, S. Raja Sethu Durai and M. Ramachandran

* Working papers are downloadable from MSE website <http://www.mse.ac.in>

§ Restricted circulation