ISSN 2454-5597

Knowledge-Humility-Excellence

ISFIRE WORKING PAPER SERIES

ON THE DYNAMICS OF INFLATION-STOCK RETURNS IN INDIA

Avishek Bhandari
Bandi Kamaiah

Working Paper-16
http://iire.in/ojs/index.php
Issue-November 2015

ABOUT US

ISF Institute of Research and Education (IIRE), a branch of **Inner Search Foundation, a public charitable trust.** It has been established to facilitate education and research in diverse fields. The aim of IIRE is to create integrated educational and research programs which enhance the capability, productivity and employment potential of individuals in their respective fields.

IIRE is a part of a multi-faceted, multi-disciplinary **ISF Group**, which has nearly two decades of experience, providing Consultancy, Business Management, Academic Management, Technical Management and Learning & Development solutions for various organizations. ISF Group believes in creating value for its customers and stakeholders by providing innovative services and solutions that are based on cutting edge research. The R&D activities of the Group are channelized with exclusive focus on leveraging innovation and creativity, of the scientific, technical and management resources across the globe. The group facilitates converting the generated body of knowledge into practical use through development of innovative products, services and solutions. There are three major verticals under the ISF Group:

1. **ISF Maritime Services** – *Provides services spanning the entire eco-system of the shipping industry*
2. **ISF HR Services** – *Provide organizational development and talent management services to organizations across industries*
3. **Inner Search Foundation** – *Guides individuals and helping organizations to expand their horizons and experiencing happy, healthy and fulfilling existence.*

For more information please log on to www.isfgroup.in

This page is intentionally blank

ON THE DYNAMICS OF INFLATION-STOCK RETURNS IN INDIA

Avishek Bhandari[1]
Bandi Kamaiah[2]

Abstract

In this paper, an attempt is made to examine the relationship between inflation and stock returns in India using spectral and time-frequency methods. Scale specific relation between inflation and stock returns is unraveled, allowing us to capture the relationship at varying investment horizons. The results based on monthly data from 1994:5 to 2014:11, obtained using spectral and wavelet techniques, reveal that there exist no significant pro-cyclical interdependencies between inflation and stock returns, implying that stock returns are no longer an adequate hedge against inflation.

***Keywords*:** Stock returns, Inflation, Coherence, Cross wavelets, Spectral density

***JEL Codes*:** C40, G12, E31, G10

[1] Research Fellow, School of Economics, University of Hyderabad, Hyderabad, 500046, India.
Email: bavisek@gmail.com
[2] Professor, School of Economics, University of Hyderabad, Hyderabad, 500046, India.
Email: kamaiahbandi@gmail.com

1. INTRODUCTION:

The relationship between stock returns and inflation has been the prime focus of researchers for many years. According to the Classical economists, real returns are independent of nominal variables such as money supply and inflation, where real returns are determined by real factors and independent of nominal magnitudes such as nominal money supply and inflation. This means that inflation should not affect real stock returns, implying that stock returns act as a hedge against inflation. Any increase in the inflation rate will lead to an increase in nominal returns without affecting the real return. Hence investors are fully compensated by this corresponding increase in nominal returns for any increase in the inflation rate. Thus, the classical tradition formulates a positive relationship between nominal stock return and inflation, also known as the Fisher's hypothesis. There are several studies which have validated this positive relation (Bodie,1976, Firth,1979, Gultekin,1983and Shanmugam and Misra,2008).

In the literature however, there are several studies which do not support the positive relationship between stock returns and inflation rate (Fama and Schwert,1977, Lintner, 1975, Fama ,1982; Geske and Roll, 1983). According to Fama (1981), real economic activity and demand for money are negatively influenced by rising inflation rates which in turn negatively influence economic activity, affecting future corporate profits, leading to a fall in stock prices. Here the transmission mechanism is through the impact on real economic activity caused by a rising rate of inflation. Recent studies concerning the relationship between stock returns and inflation seem to provide mixed evidences with regard to the hedging effectiveness of stock returns on inflation (Kim and Ryoo,2011, Oxman,2012, Rushdi *et al.*,2012).

It may be noted that, the relationship between stock returns and inflation is found to be dependent on time horizons with Fama's hypothesis holding for studies based on shorter time horizons and some evidence of Fisher effect at long time horizons (Firth, 1979, Gultekin, 1983, Anari and Kolari, 2001). However, most of the studies concerning inflation stock returns nexus focus only on short time horizons. This limited analysis concerning only short time-period leaves out the low frequency traders whose decisions concern long time horizons-. It is at odds with the heterogeneous market hypotheses where market consists of a diverse group of participants who trade at different frequencies based on their time horizon of interest. A complete study of the dynamics of inflation-stock return nexus therefore entails an analysis over both short and long term time periods. Moreover, an analysis which encompasses both time and frequency dynamics, thereby enabling one to capture information from both short and long time horizons- is pertinent, and made possible by the use of time-frequency methods and wavelets. The motivation behind this paper is to highlight the dynamic nexus between stock returns and inflation using time-frequency framework which gives both time and frequency information simultaneously. The present paper positions itself in this context and seeks to examine the inflation – stock returns nexus using time-frequency based wavelet methods.

Though there are quite a few studies on inflation–stock returns relationship which validated the Fisherian hypothesis over long time horizons (Schotman and Schweitzer,2000, Engsted and Tanggaard,2002), analysis of inflation-stock returns nexus across time and frequencies, using wavelet based methods, is only of recent phenomenon. Kim and in (2005) finds positive relationship at both shortest and longest time-scale and a negative relation at the intermediate time –scale. Wavelet methods used by Durai and Bhaduri (2009) detect a negative relationship between inflation and stock returns of India, only at a long time-scale. However, both the above mentioned wavelet analyses, carried out using the maximal overlap discrete wavelet transform (MODWT), fail to capture the overall dynamic evolution of the relationship between the two magnitudes. An analysis of the relationship between inflation and stock return of India, using continuous wavelet methods, is attempted in Bhanja *et al.* (2012). The study has come out with evidences in support of the Fisher effect, only for a limited time horizon of sixteen months.

Applications of continuous wavelet methods in analyzing economic and financial problems have gained popularity in recent times, where most of these studies (Vacha and Barunik,2012, Andries *et al.*,2014, Albulescu *et al.*, 2015, Tiwari *et al.*, 2015) reveal much more information than those based on discrete wavelet approaches. The dynamics of co-movements between interest rates, stock price and exchange rate in India, analyzed by Andries *et al* (2014) within the framework of continuous wavelets, reveals the existence of time-scale dependent lead-lag relationship between the three variables. Inflation co-movements of G7 countries were found to be of multi-scale in nature by Tiwari *et al.* (2015). This multi-scale information on co-movement of inflation rates was made much clearer using continuous wavelet coherence analysis.

Methods based on continuous wavelet transform (CWT) reveal much more information than what can be captured by discrete wavelet transform based approaches. Further, use of CWT based techniques enables one to detect regions of co-movement between two variables, with areas of high and low correlation, from a colour-coded two dimensional box plots spanning both time and frequencies. Such an analysis would not be possible with DWT based techniques as it cannot generate outputs encompassing a continuous range of time and frequencies. In view of the above, the present study employs continuous time wavelet techniques for analyzing the inflation-stock returns relationship.

With the exception of the study by Bhanja *et al.*, (2012) there are no studies which have highlighted the dynamics of stock returns-inflation nexus in India using time-frequency based CWT methods. The present paper is different from the earlier papers in one important respect namely, both spectral and wavelet methods are applied in the present study. The justification for this arises from the fact that diagnostics based on spectral analysis should ideally precede wavelet analysis.

2. METHODOLOGY:

Wavelet analysis begins with the consideration of a function known as the *mother wavelet*, which is given by,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad \text{………………..} \quad (1)$$

Where $a \neq 0$ and b are real constants. The parameter a is known as the scaling parameter which determines window widths, whereas the parameter b known as the translation parameter determine the position of the window. Unlike Fourier analysis, a number of mother wavelets can be chosen depending upon the problem at hand. Just like in Fourier analysis, where a function is expressed as a combination of sines and cosines to transform the function into the spectral domain, wavelets can be used to project a function onto the time-frequency domain.

The scaling parameter a is typically taken to be a power of two so that $a = 2^j$ for some integer j. The compressed wavelet captures the finer scale resolution (high frequency components are captured and well localized in time) of a given signal while the dilated wavelet (broad time window widths) captures low-frequency components of a signal by having a broad range in time. Thus scaling and translation, which allow adjustment of time window widths and their locations, are the most fundamental operations which enable go for higher and higher refinements in terms of time and frequency resolutions. Thus, the scaling and translation operations facilitate a given signal or function to be represented as a basis function which in turn allow for higher a refinement in the time resolution of a signal.

Since the large scale structures of a given signal in time are captured with broad time-domain wavelets, in which case the window width is broad (spread out in the time axis), the time resolution of the signal is very poor and captures only the low frequency components. However, finer and finer time resolution of the signal along with its high frequency components can be obtained by successive rescaling of the dilation parameter in time. The information at low and high scales is all preserved so that a complete picture of the time-frequency domain can be constructed. Ultimately, the only limit in this process is the number of scaling levels to be considered.

In the case of spectral analysis, a signal is taken and projected into the space of sines and cosines. Similarly, a function can be represented in terms of the wavelet basis. The wavelet basis can be accessed via the integral transform of the form

$$\int_t K\,(t,\omega) f(t) dt \qquad \text{………………..} \quad (2)$$

Where $K(t,\omega)$ is the kernel of the transform and $f(t)$is a time domain signal. The above equation represents any generic transform where a modification in the kernel gives the required transform. In the case of Fourier transform the kernel $K(t,\omega) = \exp(-i\omega t)$ represents the periodic oscillations. The key idea now is to define a transform which incorporates the mother wavelet as the kernel. Thus we define the continuous wavelet transform (CWT) as:

$$W_\psi[f](a,b) = \left(f, \psi_{a,b}\right) = \int_{-\infty}^{\infty} f\,(t)\,\overline{\psi}(t)\;dt \quad \text{………………..} \quad (3)$$

Where $W_\psi[f](a,b)$ is the CWT which is a function of the dilation parameter a and the translation parameter b, f and $\psi_{a,b}$ are as defined in equations (1) and (2). The CWT given in equation (3) should satisfy the following admissibility condition:

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\widehat{\psi(\omega)}|}{|\omega|} d\omega < \infty \qquad \text{……………. …..} \quad (4)$$

Where $\hat{\psi}(\omega)$, the Fourier transform of the wavelet is defined as:

$$\hat{\psi} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} e^{-i\omega t} \psi\left(\frac{t-b}{a}\right) dt = \frac{1}{\sqrt{|a|}} e^{-ib\omega}\, \hat{\psi}(a\omega) \qquad \text{…………….} \quad (5)$$

The wavelet transform given in equation (3) is well defined subject to satisfying the admissibility condition given in equation (4). An important property of the wavelet transform is its ability to construct new wavelet bases.

The working principle of wavelet transform is quite simple. A bunch of smaller signals are extracted from the main signal by translating (shifting time window location) the wavelet with parameter *b* over the entire time domain of the signal. Further, the scaling process is carried out where the same signal is processed at different frequency bands, or resolution, by scaling the wavelet window with the parameter *a*. This combination of translation and scaling allows for processing of signals at different times and frequencies which in turn allows to read the signal at different scales of time and frequency resolutions. The above process of analyzing a given signal or function at different scales of resolution is termed as multi resolution analysis.

Following Grinsted *et al.* (2004), the cross wavelet transform (XWT) of two time series say, x_n and y_n denoted by W^{XY} is defined as $W^{XY} = W^X W^{Y*}$, where * denotes complex conjugation. The absolute value of W^{XY}, is then defined as the cross wavelet power and the phase angle between x_n and y_n in the time frequency space is given by the complex argument $\arg(W^{XY})$. The paper uses Morlet wavelet as the mother wavelet for analysis[3].

[3]Torrence and Compo (1998) presents a detailed summary of bivariate wavelet analysis dealing with wavelet cross-spectrum and wavelet coherence.

However, results based on cross wavelet transform might lead to spurious correlations due to the leakage of power between the two individual continuous wavelet transforms. Wavelet coherency, which gives the measure of local correlation over both frequencies and time, does not possess this limitation as it is a normalized version of the cross wavelet transform. Wavelet coherency is defined as,

$$R_m(s) = \frac{|S(s^{-1}W_m^{XY}(s))|}{S(s^{-1}|W_m^X|^{\frac{1}{2}}S(s^{-1}|W_m^Y|^{\frac{1}{2}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (6)$$

Where S represents the smoothing operator, scale is represented by s and time by m, W_m^{XY} denotes the cross wavelet transform of X and Y, and, W_m^X *and* W_m^Y denotes the CWT of X *and* Y respectively.

The phase angle, which helps to understand the lead − lag relationship between the two time series X *and* Y, is given by

$$\varphi_{X,Y}=tan^{-1}\frac{\{W_m^{XY}\}}{\{W_m^{XY}\}}, \text{ where } \varphi_{X,Y} \in[-\pi, \pi] \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (7)$$

3. DATA SOURCE:

The data set consists of inflation rate calculated from the WPI series and stock returns calculated from the monthly closing price series of BSE SENSEX. The period of study ranges from May 1994 to November 2014. WPI series is considered for calculating the inflation rate as CPI based inflation rate does not include new consumption basket for agricultural and rural laborers as its base year is still 1986-87. The data for WPI is taken from the webpage of the Office of the Economic Adviser, Government of India, Ministry of Commerce and Industry, whereas the data for stock prices is taken from BSE webpage.

4. RESULTS:

The spectral density function[4] of stock returns and inflation rate calculated using the periodogram method with Daniell smoothing kernel is given in figure 1. We notice

[4] Methods based on Priestley (1981) are used for the computation of periodogram estimates.

common peaks at ω=1Δ=1/12, or one cycle per year (~12 months), and ω=0.5 Δ, or one cycle every two years (~24 months), where Δ=1/12 is inverse of the time period.

Figure 1: Power Spectral Density of Stock returns and Inflation rate

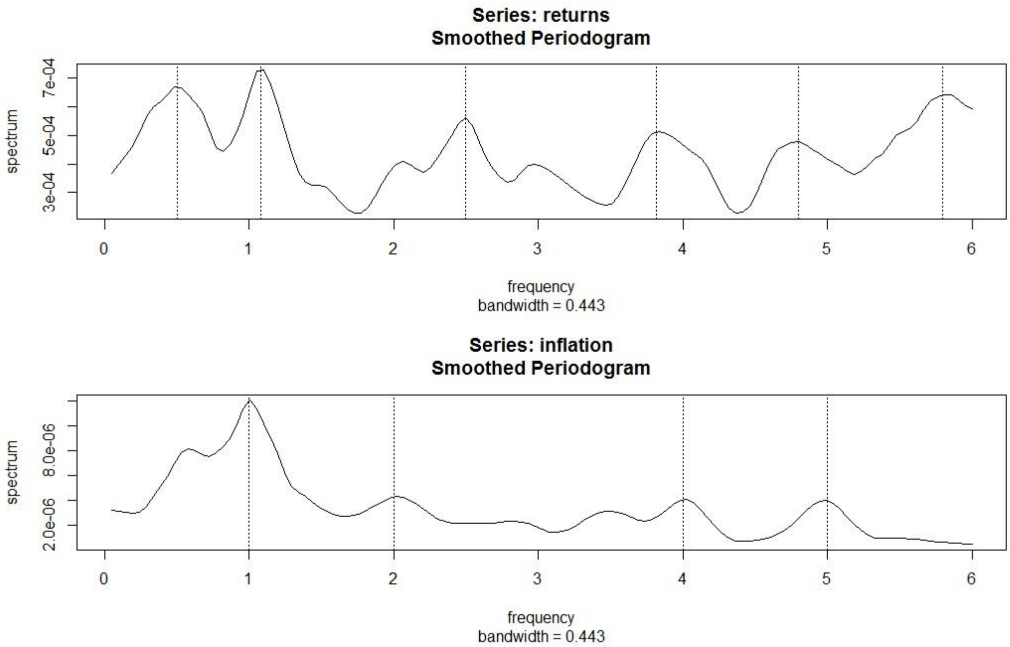
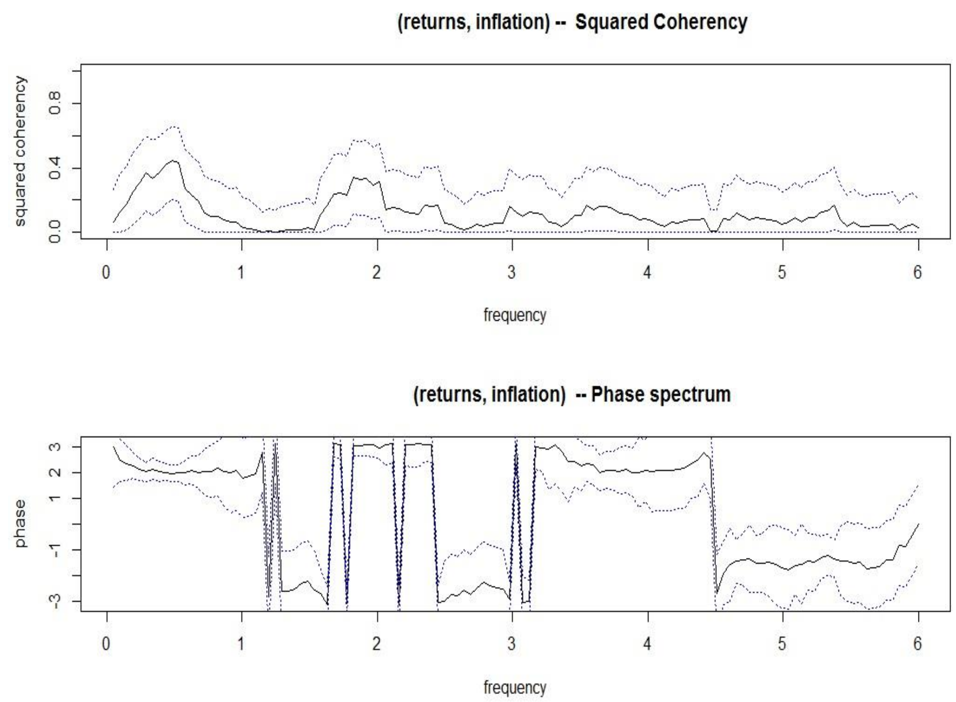


Figure.1. Periodogram of stock returns and inflation rate, n =246, where the frequency axis is labeled in multiples of Δ=1/12.

A quarterly cycle (of around 4.8 months) is also detected for stock returns where the spectrum peaks at frequency 3.82. The common peaks of the spectrum of stock prices and inflation rate seems more important as the frequencies around 1Δ and 0.5Δ contribute significantly to the overall variance. Hence we detect an annual cycle and a two-year cycle for both stock returns and inflation rate. However, we do not get the time domain information from the spectral density function as the time variable is integrated out when taking the Fourier transform, which makes it impossible to detect the time-point corresponding to the obtained frequency of significance.

Figure 2: Coherence between Stock returns and Inflation rate

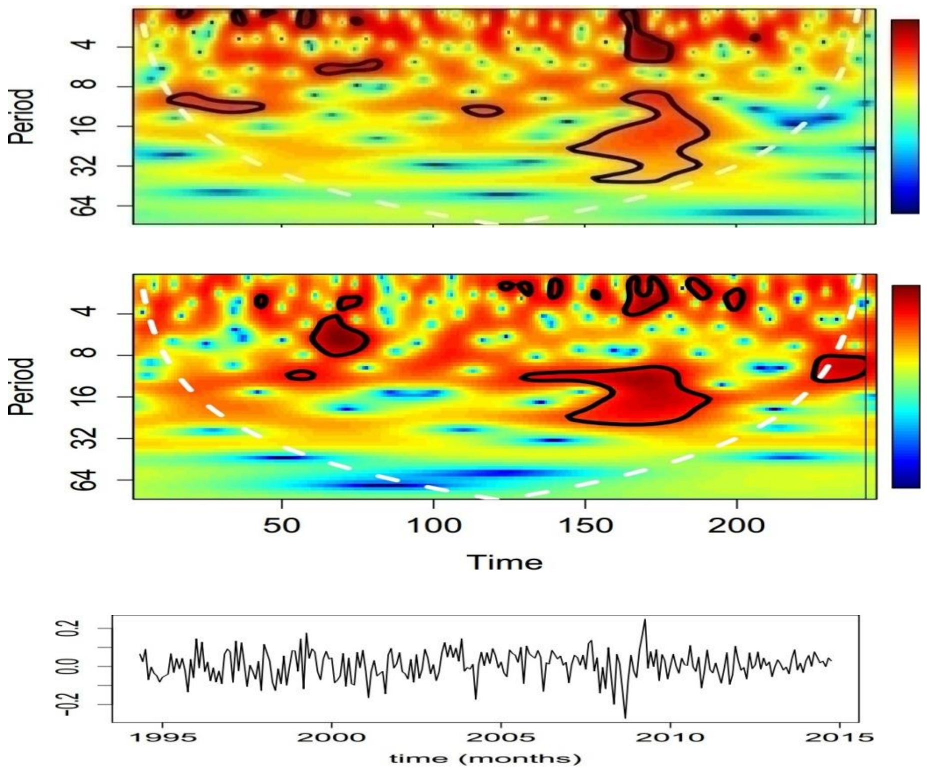


The relationship between stock returns and inflation is investigated using the coherency spectrum. Figure 2 gives the result of squared coherency and phase angle between the two series. The highest peak in the coherency spectrum occurs at frequency 0.5, *i.e.* ω=0.5 Δ, which corresponds to a period of about 24 months. The phase plot reveals that inflation leads stock returns around this low-frequency interval. However, the time interval where this phenomenon of inflation leading stock returns is not captured as spectral domain approaches loses time localization. Therefore, in order to capture simultaneous localization of information both in time and frequency, wavelet methods are implemented.

The stock returns and inflation series are decomposed using continuous wavelet transform (CWT) with Morlet wavelet as the mother wavelet. The wavelet power spectrum of stock returns (upper panel) and inflation (lower panel) are plotted in figure 3. The wavelet power is determined by the color codes where the power varies from deep blue (lowest) to deep red (highest). The significance of power is determined by the area inside the thick black lines. At higher frequencies, which capture the short run fluctuations, we observe some significant power at 0-4 month time scale for the BSE returns. This power occurs during the time period of 2008-2009 where stock returns experienced high volatility.

A significant power is detected for inflation at 4-8 month time scale during the time period of 1999-2000. The area with significant power increases as we move towards the higher time scale of 8-32 months, which captures the annual and two year cycle. This is also supported by the power spectral density of inflation in figure 1 where the peaks in the spectrum correspond to an annual and a 24 month cyclical behavior. However, we can see from the CWT plot that this cyclical activity, which is shown by the area within the significant confidence band, manifests only during the crisis period of 2007 to2010. This time localization was not captured by the periodogram based power spectral density estimates. We notice that the distribution of power for the inflation series is homogenous and stable across frequencies and time period, except for the period 2007 to 2010 where there is an increase in power.

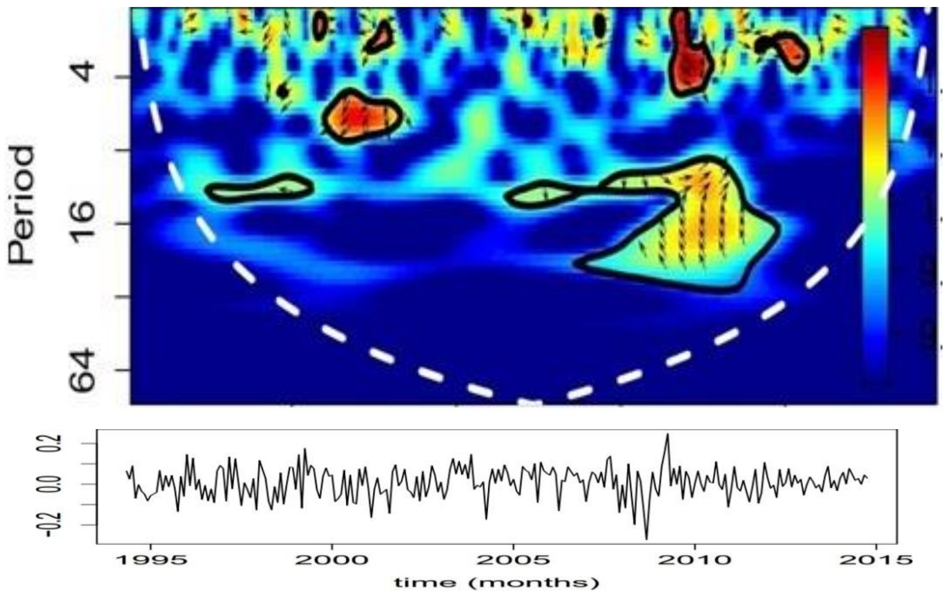
Figure 3: CWT of stock returns and inflation



The cross wavelet transform, which gives the measure of co-movement between two variables, is used to analyze the relationship between stock returns and inflation. It is evident from figure 4 that the relationship between stock returns and inflation varies with different wavelet scale and time period. A significant relationship between stock returns and inflation is observed at frequencies corresponding to the time scale of 4-8 months, during the time period between 1999 and 2002.

The direction of the phase arrows under the significant area leads us to conclude that the two series are out of phase with inflation leading stock returns. However, at this time-scale, we do not find any significant relationship during other time periods, where the two series seems to be independent of each other. As we move towards the higher time-scale of 8-16 and 16-32 months, we detect some significant relationship during the time period between 2007 to 2011 with inflation leading stock returns at 8-16 month time scale and stock returns leading inflation at 16-32 month time scale. Nevertheless, this relationship breaks down at other time periods where both series seems to be independent of each other. The sudden jump in power during 2007 to2011 can be attributed to the global financial crisis. The wavelet cross spectrum[5], however, does not provide a clear description of the relationship between these two series.

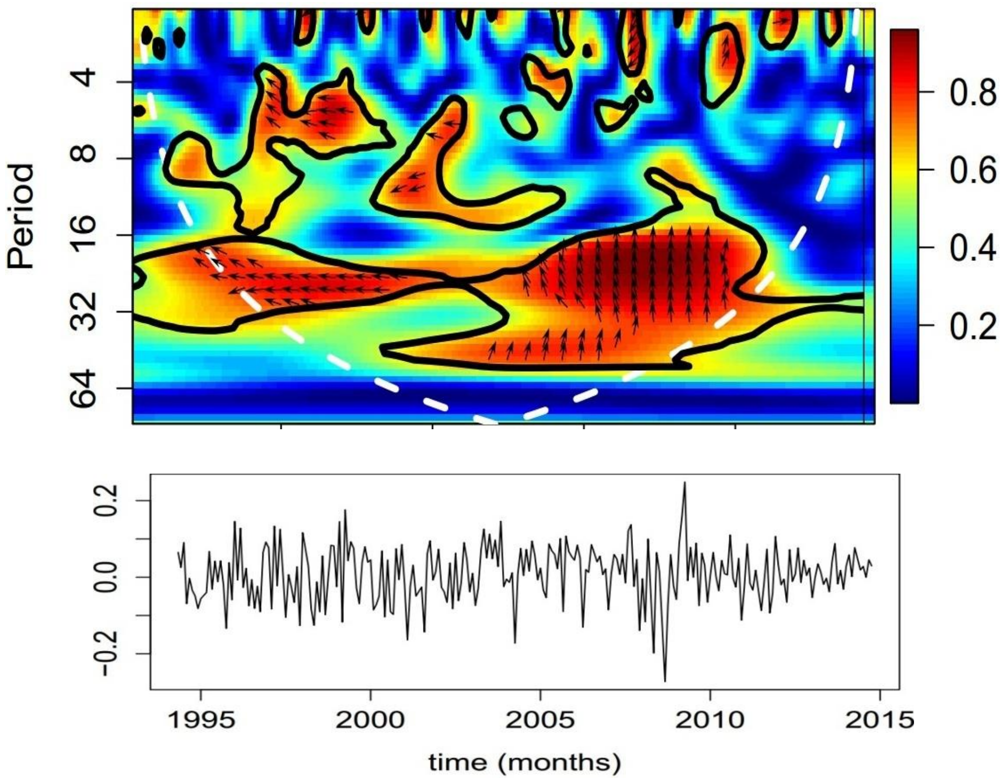
Figure 4: Cross-Wavelet spectrum of Stock returns and Inflation



[5]Wavelet cross spectrum is the non-normalized spectrum of the two series and therefore it might be contaminated by the leakages between the two individual power spectrum, which leaves a possibility for spurious correlation.

Wavelet coherence between stock returns and inflation, which's a normalized version of the wavelet cross spectrum, is given in figure 5. We observe significant coherence between the two series at frequencies corresponding to the time-scale of 4-8 month over the time period of 1997-2001, where stock returns and inflation are out of phase. Similar anti-cyclical behavior is observed at 16-32 month time scale over 1997-2002. There's a significant increase in power at 16-32 month time scale between 2004 and 2011. Some cyclical behavior is observed between 2004 and 2008 at the time scale of 32 to48 month where both the series are in phase with each other with inflation leading stock returns.

Figure 5: Wavelet Coherence between stock returns and inflation



However, this cyclical behavior is not observed at any other time periods and frequencies. Moreover, the overall relationship between the two series, barring the time period 2004-2007 corresponding to 32-48 month cycle, seem to be in anti-phase (counter-cyclic) with each other. This counter cyclical behavior can also be seen at lower time –scales with phase arrows in most of the significant areas pointing towards the anti-phase direction. Thus stock returns fail to serve as an inflation hedge in the Indian case except for the time period of 2004 to 2007 with around 48 month time-scale. The observed dynamic evolution of relationship between stock prices and inflation is well captured by wavelet based decomposition techniques where both time and frequency information is captured simultaneously. This simultaneous localization of information would not have been possible had we used any other traditional spectral and time-domain approaches.

5. CONCLUSIONS:

The main purpose of this paper is to study the inflation-stock returns nexus in India using the framework of continuous wavelet transforms. The study also highlights the superiority of wavelet based decomposition over the traditional Fourier based transformation techniques. The decomposition of stock returns and inflation across time and frequencies and the subsequent analysis using bivariate wavelet techniques could not reveal any significant cyclical relationship between the two series for most of the time-scale and periods. However, some cyclical relationship between stock returns and inflation for the limited period of 2004 to2007 over frequencies corresponding to the time-scale of 48 months has been detected. The overall behavior of the two series captured inside the significant bands, across most of the time periods and frequency, seems to be anti-cyclical in nature, suggesting that stock returns have not played the role of a hedge against inflation except for a brief period corresponding to the time-scale of forty-eight months.

REFERENCES:

Albulescu *et al.*, (2015). Contagion and dynamic correlation of the main European stock index futures markets: a time-frequency approach. *Procedia Economics and Finance*, 20, 19 – 27.

Anari, A. and Kolari, J., (2001). Stock Returns and Inflation. *Journal of Financial Research*, 24, 2, 587- 60.

Andries *et al.*, (2014). Analyzing time-frequency relationship between interest rate, stock price and exchange rate through continuous wavelet. *Economic Modelling* 41, 227-238.

Bhanja *et al.*, (2012). Are Stock Prices Hedge Against Inflation? A Revisit over Time and Frequencies in India. Central European *Journal of Economic Modelling and Econometrics*,4, 199-213.

Bodie, Z, (1976). Common Stocks as a Hedge against Inflation, *Journal of Finance,* 31, 259-270.

Durai S., Bhaduri S., (2009). Stock Prices, Inflation and Output: Evidence from Wavelet Analysis, *Economic Modelling,* 26, 1089-1092

Engsted T., Tanggaard C., (2002). The Relation between Asset Returns and Inflation at Short and Long Horizons, *Journal of International Financial Markets*, Institutions & Money 12, 101-118.

Fama E.F., Schwert G.W., (1977). Stock Market Returns and Inflation, *Journal of Financial Economics* 5, 115- 146.

Fama E.F., (1981). Stock Returns, Real Activity, Inflation and Money, *American Economic Review*,71, 545- 565.

Fama, E.F., (1982). Inflation, Output and Money. *Journal of Business*, 55, 201-231.

Firth, M., (1979). The Relationship Between Stock Market Returns and Rates of Inflation. *Journal of Finance*,34, 743-749.

Gencay, R. Selcuk, F. &Whitcher, B., (2002). *An Introduction to Wavelets and other Filtering methods in Finance and Economics*. Academic Press, San Diego.

Geske, R. and Roll, R., (1983). The Fiscal and Monetary Linkage between Stock Returns and Inflation. *Journal of Finance*,38, 1 - 33.

Grinsted *et al.*, (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series, *Nonlinear Processes in Geophysics*, 11, pp. 561–566.

Gultekin, N.B., (1983). Stock Market Returns and Inflation: Evidence from Other Countries. *Journal of Finance,* 38, 49-65.

Kim J., Ryoo H., (2011). Common stocks as a hedge against inflation: Evidence from century long US data, *Economics Letters* 113, 168-171.

Kim S., In F., (2005). The Relationship between Stock Returns and Inflation: New Evidence from Wavelet Analysis, *Journal of Empirical Finance*,12, 435-444.

Lintner, J., (1975). Inflation and Security Returns. *Journal of Finance*, 30, 259 – 280.

Oxman J., (2012). Price inflation and stock returns. *Economics Letters* 116, 385–388.

Priestley M. B., (1981). *Spectral Analysis and Time Series*, Academic Press, London.

Rushdi M, Kim J., Silvapulle P., (2012). ARDL bounds tests and robust inference for the long run relationship between real stock returns and inflation in Australia, *Economic Modelling* 29, 535-543.

Schotman P.C., Schweitzer M., (2000). Horizon Sensitivity of the Inflation Hedge of Stocks, *Journal of Empirical Finance* 7, 301-305.

Shanmugam K. R., Misra B.S., (2008). Stock Returns-Inflation Relation in India, *Working Paper*, Madras School of Economics.

Tiwari *et al.*, (2015). Analyzing Time-Frequency based Co-movement in Inflation: Evidence from G-7 Countries. *Computational Economics* 45, 91-109.

Torrence C., Compo G.P., (1998). A Practical Guide to Wavelet Analysis, *Bulletin of the American Meteorological Society* 79, 605-618.

Vacha, L. and Barunik, J., (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics*, 34, 241-247.

Published by:

ISF INSTITUTE OF RESEARCH AND EDUCATION
410, Gemstar Commercial Complex, Ramchandra Lane Ext, Kachpada,
Off Link Road, Malad (W), Mumbai 400 064,
India