Credit and Growth Cycles in India and US: Investigation in the Frequency Domain

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Abstract

In this paper, we investigate cyclical relationship between credit and growth cycles in India and US over the period 1994-2013 in the frequency domain. Originality of our contribution is in the use of Multitaper method of spectrum estimation which has the advantage of giving reliable estimates even in relatively short samples and provides jackknife confidence intervals of spectral statistics. Contrary to most studies which find credit cycles to be longer than business cycles, univariate spectrum to infer duration of series shows that credit and output cycles are similar in duration of approximately three years. We find that there is a strong coherence between credit and growth cycles in both India and US but the synchronization is relatively stronger in US. Lead lag relationship suggest that credit is a reliable leading indicator in US for a broad frequency range but in India, industrial production leads non-food credit and coherence is high only in the long run. This can be explained by difference in financial deepening and sophistication of financial sector in the two countries.

Keywords: Credit cycles, Business cycles, comovement, frequency domain

JEL codes: C14, E32, E51, E44

*I sincerely thank my advisor, Dr D.M. Nachane for his valuable suggestions and guidance at all stages of this study.

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1 Introduction

Understanding cyclical properties of key macroeconomic variables and interation with output has become important in the wake of recent financial crisis, both for early warning systems and macroprudential policies. The recent financial crisis and subsequent global recession has highlighed the role of credit and importance of studying interaction between real and financial aspects of economy. Characterizing cyclical properties of credit and its relationship with output is therefore essential in the context of designing early warning indicators of financial imbalances and macroeconomic policies.

Through historical analysis of financial crises, both qualitative (Kindleberger and Aliber, 2011) and quantitative (Reinhart and Rogoff, 2009), there seems to be strong relation between the real and financial aspects of the economy and credit booms have been found to precede financial crisis. Eichengreen and Mitchener (2003) trace the historical scholarship on the importance of credit and real economy and analyze depressions as credit booms gone wrong.

Keeping this is mind, our study aims to find answer to the following questions. Firstly, what is the duration of credit and growth cycle? How strongly are credit and growth cycles synchronized and what are the lead lag relations? Do monetary aggregates have any leading indicator properties for output? In each case, we compare results for India with US as both economies are different in the level of financial deepening and sophistication.

Answers to these questions are significant as strength of synchronization gives underpinnings to leading indicators in early warning systems and countercyclical policies. Additionally, difference in coherence over long, medium and short run implies that early warning indicators must take this information into account when choosing the forecast horizon. Spectral analysis of cyclical components in credit and output thus provides insight into the strength of interaction between real and financial aspects of economic fluctuations.

Our key contribution is the use of Multitaper method of spectrum estimation which is suited for cyclical analysis of short time series. To our knowledge, this is the first study using Multitaper spectrum estimation in the given context. Studies have so far used classical spectral techniques which require a long time series for consistent estimates, curb spectral leakage and for correct resolution of spectrum but Multitaper method uses a set of orthogonal tapers to reduce bias and variance of spectral statistics, also giving higher degrees of freedom which implies tighter confidence intervals. Other major advantages of this technique are that the Harmonic F-test can accurately test for periodic components of a time series and Jackknife confidence intervals are provided as measure of reliability of the spectral estimates.

We find empirical evidence of lead-lag relationship between credit and output in both India and US. Coherence and phase statistics show that there is strong synchronization between credit and output as proxied by bank credit and industrial production in both India and US. In India, this comovement is true only in the long run with IIP leading credit but relationship is stronger in US for both long and business cycle frequency range with credit leading industrial production. This difference may be attributed to nature of financial sectors in India and US which differ in relative dominance of financial markets and banks. As noted in Chakrabarti (2014) which gives an overview of financial sector in India, financial assets in India amounted to 228% of GDP in 2009, compared to 399% in US. US and UK are market dominated while countries like Germany and Japan see a larger role of banks. The study also notes that although India is better than other emerging market economies in terms of dominance of financial markets viz a viz banks, there is a big difference as compared to developed economies.

Empirical findings therefore support why studies have found credit based indicators useful in forecasting financial crises, specially in US but also suggests that the level of credit in the economy and the forecast horizon must be taken into account. In India, currency with public is found to be leading non-food credit at short frequency range and highlights its role as an important monetary policy variable to monitor and forward looking indicator.

The chapter is organized as follows: Section 2 reviews the literature on role of credit and money in business cycles. Section 3 covers the methodology of Multitaper spectrum and technical aspects with explanation of why this method is better than classical spectral techniques used now. Section 4 then gives details for data and the empirical results are discussed in Section 5. Section 6 concludes and discusses the implications of the findings.

2 Literature Review

Investigating nature of credit cycle[1] and build up of imbalances in the economy have led to recent set of papers trying to understand the cyclical nature of credit and its nexus with output and key macroeconomic variables.

> Financial system procyclicality refers to mutually reinforcing interactions between the real and financial sectors of the economy that tend to amplify the business cycles and that are often at the root of financial instability." (Drehmann, Borio, and Tsatsaronis, 2011).

Jordà, Schularick, and Taylor (2011) in a long run dataset spanning 1870-2008 for 14 developed economies find credit growth to the single best predictor of financial instability and that predictive ability increases on adding external factors. They also show that recessions are deeper when associated with crises. There key finding is that a high rate of credit expansion over five years is indicative of an increasing risk of a financial crises. Mendoza and Terrones (2008) find that unusually rapid expansion in real credit often ended in crises. Credit booms, defined as prolonged credit expansion in run up to crises, generally coincide with large cyclical variation in economic activity, with real output, consumption, investment, rising above the trend during buildup phase of credit boom. Eichengreen and Mitchener (2003) conclude that credit boom is the culprit behind financial crisis, particularly in EMEs.

Aikman, Haldane, and Nelson (2014) identify credit cycle as a real and distinct phenomenon from business cycle, both in amplitude and frequency and find that credit is a medium term cycle. Through comparison of variance in GDP and credit at business(2-8yrs) and medium(8-20) term frequencies using bandpass filter, it is claimed that credit has more variance at medium frequency range. Using probit models and peaks and troughs in credit cycle, they show that credit booms precede financial crises. [2] This study and Claessens, Kose, and Terrones (2012) conclude that financial cycles are longer and more pronounced than business cycles.

Recent literature on interaction of financial and business cycles are Jorda, Schularick, and

[1] The term credit cycle is used in a sense analogous to that of business cycles, i.e. alternating expansions and contractions of loans.

[2] Credit variable is defined as bank loans consisting of total domestic currency loans of banks and banking institutions to companies and households.

Taylor (2013), Karfakis (2013), Cardarelli, Elekdag, and Lall (2011), Chen, Kontonikas, and Montagnoli (2012) and Busch (2012). These studies examine the interaction between financial and business cycles and study the behaviour of credit booms and timing before and after recessions and financial crises.

Claessens, Kose, and Terrones (2012) studies interaction between business cycles and financial crises using turning point analysis over the period 1960 to 2010 using quarterly data on GDP, credit as aggregate claims on private sector by deposit money banks, housing prices index and equity prices for 21 advanced and 23 emerging market economies. Classical cycles of absolute rise and decline in the variables using Harding Pagan algorithm is used to avoid the trend cycle dichotomy. Multivariate regression is used to study interaction between output and financial cycles. Duration here refers to number of quarters between peak and trough and is 4 quarters for business cycle, 5, 6 and 8 quarters respectively in credit, equity and housing prices. For the upturn, the duration from trough to peak, is about 10 for credit, 18 for equity prices and 12 for housing prices. The study concludes that there are strong linkages between business and financial cycles and recessions associated with financial disruptions tend to be longer and deeper while recoveries associated with rapid credit growth tend to be stronger and emphasizes the importance of developments in the financial markets for the real economy.

Comovement of credit and business cycles in Germany has been studied in Busch (2012) over the time period 1971-2011 using quarterly data on four German loan aggregates, GDP growth, private investment and consumption expenditure using classical spectral analysis. Main findings of the study are that loans lag GDP by two to three quarters and there is strong comovement with GDP at 6 years.

Zhu (2011) examines credit and business cycles in US, Europe and Japan using time domain and frequency domain methods over the period 1950-2009(starting 1991 for Euro area) using quarterly data on real GDP, nominal bank credit, employment, investment and consumption. The study finds that credit output link in US is valid in the long run but weak over business cycles. This implies that there is no fixed relation which holds in all frequency ranges.

In the Indian context, Banerjee (2012) studies the lead lag relation between credit and growth cycles at aggregate, sectoral and industry level for the periods 1950-51 to 1979-80, 1980-81 to 1990-91 and post-1991. The study recommends that the absence of causality from credit to output growth in the post-reforms period emphasizes need for more directed flow of and easy access to credit to all sectors for monetary policy to have the desired impact on output growth in the economy.

Role of credit and money in amplifying economic fluctuations

To elucidate the pattern which leads to credit boom and financial crises, and how credit behaves during different phases of business cycles, we briefly sum up sequence of events leading upto financial crisis and recession as described in detail in Kindleberger and Aliber (2011).

The sequence of events highlights the expansion of money supply and credit which feeds the lending boom in periods of economic growth. As noted by Kindleberger, *markets will create new forms of money in periods of boom.*

Economic outlook changes because of some exogenous shock to the macroeconomy which increases profits in atleast one important sector. Investors flock to it and a boom ensues which is fed by an expansion in bank credit through new banks, financial innovations and credit instruments which in turn enlarges the total money supply. Urge to speculate increases effective demand for goods and financial assets which puts pressure on capacity to increase production and financial assets. This results in increase in price, and profit opportunities which further increases investment. At some point, investment for use gives way to buying and selling for profits. This phase can be termed as "euphoria" or"overtrading" and overestimation of profits and mania are halted by bursting of bubble at some time that leads to financial crises. International dimension plays an important role by increasing money supply on which higher pyramids of credit can be supported.

Credit booms and expansion of money supply therefore, do have a role in amplifying economic fluctuations and are the main reason for financial instability.

Empirically, credit and monetary aggregates in US have been found to be decoupled after second world war in study by Jorda, Schularick, and Taylor (2013). They find that real monetary growth, as measured by M2 may be used as measure of financial cycle. [3]

Drehmann, Borio, and Tsatsaronis (2011) say that although money and credit are two sides of a simplified balance sheet, their relationship with asset prices is different. This may imply

[3] Note that in this study, we consider money as a form of credit.

that although money may be considered as a form of credit, its behavior viz a viz financial stability may be different.

Money supply has been found to anticipate growth in real output as proxied by IIP in India by Nachane and Dubey (2011) and therefore suggests that relationship between money and output needs to be studied more closely not only for its role as a leading indicator, but also as an instrument of monetary policy.

More importantly, although many studies find a strong correlation between growth in money supply and output, this link may differ across frequency ranges i.e. relation might differ in short, medium and long run.

Financial accelarator is one of mechanisms that leads to credit booms where shocks to asset prices get amplified through balance sheet effects. New lending amplifies asset prices leading to higher asset demand. Overoptimism about future earnings boosts asset valuations and artificially enhances the net worth of firms which is unsustainable beyond a point. Gourinchas (2001). Phenomenon of financial accelarator occurs due to information asymmetry and incentives facing borrowers and lenders.

Tsatsaronis (2005) gives more detailed explanation of impact of financial variables on the macroeconomy and that of real economy on financial strength of individual sectors through income and profits, which subsequently transfers to creditworthiness of economic players. The study emphasizes the importance of understanding joint dynamics of these processes and interaction with business cycles as key to assess build up of financial vulnerabilities.

Hume and Sentance (2009) reviews the theories for credit and financial cycles and how the recent global credit boom poses questions for the current economic theory and models. Austrian school was among the first to put credit at the heart of business cycle theory. Minsky's"financial instability hypothesis" which states the endogenous cycle theory, that the capitalist economies are inherently unstable. Irrational economic behavior like anchoring, overoptimism, herding and persistent biases are the explanations of behavioural economics for the patterns seen in financial crises and accounts of economic historians.

We now describe the methodology of Multitaper method of spectrum estimation to study the cyclical relationship between credit, money and output.

3 Methodology

To understand how Multitaper method improves on classical spectral methods, basic concepts of spectral estimation are summarized and then it is explained how Multitaper method reduces spectral leakage and variance. Jackknife confidence intervals, Thompson F-test and cross-spectrum analysis are then discussed.

3.1 Spectral Analysis

A concise review of spectral analysis is presented here to help understand the main features of Multitaper spectrum method. Details of spectrum analysis are covered in Percival and Walden (1993), Priestley (1981), Jenkins and Watts (1998), Chatfield (2003) and Brockwell and Davis (2002).

Consider the case of a discrete parameter, real valued, stationary and ergodic process x_t, with zero mean and purely continuous spectra, where *Spectral Density Function(sdf)* or *spectrum* is denoted by $S(.)$. Basic problem of spectrum analysis is to estimate sdf correctly given a finite sample of time series and additionally, to increase accuracy when analyzing series of short length.

Let $x_1,\ldots,x_N$ be a sample of length N from a zero mean, real valued stationary process X_t, with sdf $S(.)$ defined over the interval $[f_{-N}, f_N]$ where $f_N \equiv 1/2\Delta t$ is the Nyquist frequency and Δt is the sampling interval between observations.

There are two approaches to estimate the spectrum: directly by taking Fourier transform of the data and indirectly by first computing the autocovariance function and then calculating spectrum as weighted Fourier transform of the covariance function. Discussion is limited to direct spectrum estimates of which periodogram is the starting point.

Periodogram is computed as scaled squared modulus of the Fourier transform of the data.

$$\hat{S}_{pdgm}(f) = \frac{1}{N}\left|\sum_{t=0}^{N-1} x(t)e^{-2\pi i f t}\right|^2$$

Problem with periodogram estimates is that they are biased and inconsistent for practical purposes: biased as there are inaccuracies in locating significant peaks in the spectrum and inconsistent as variance of estimates does not converge as the data length becomes infinite (Percival and Walden, 1993).

Since our purpose is to detect peak in the spectrum correctly, it is important to understand the source of bias in spectral estimates. Consider a finite length, stationary stochastic process $x(t)$ By Cramer's Spectral Representation theorem

$$x_t = \int_{1/2}^{1/2} e^{2\pi i f t} dZ(f)$$

i.e. we can express x_t as a linear combination of sinusoids at different frequencies f with random amplitude at frequency f generated by the increment $dZ(f) = Z(f + df) - Z(f)$, where $Z(f)$ is an orthogonal process. Expected value of squared magnitude of this random amplitude defines the sdf i.e.

$$S_x(f)\,df = E[|dZ(f)|^2], \qquad f \in [-1/2, 1/2]$$

Fourier transform of process $x(t)$ is given by

$$X(f) = \sum_{t=0}^{N-1} e^{-2\pi i f t} x(t) \quad = \int_{-1/2}^{1/2} K(f - f\prime)\,dX(f), \quad f \in [-1/2, 1/2]$$

which can be represented as

$$X(f) = \int_{-1/2}^{1/2} \frac{sinN\pi(f - \nu)}{sin\pi(f - \nu)} dZ(\nu) \tag{1}$$

and is referred to as the basic equation of spectrum estimation (Thomson, 1982).

Equation (1) is a convolution of true spectrum with Fejér kernel which implies that there is a smearing of the true spectral density function because of finite Fourier transform.

Bias in periodogram is attributable to Fejér kernel in the Fourier transform convolution, as it has not only a major lobe at frequency f but also sidelobes of significant magnitude at neighbouring frequencies. This implies that values of the spectrum at a frequency far removed from the frequency f can affect the expected value of the spectrum at f. This phenomenon of transfer of power from one region of the sdf to another via the kernel of convolution is known as *Spectral leakage across frequencies*.[4]

For correct resolution of spectrum, effort is that frequencies in the immediate neighbourhood of f_0 (frequency under consideration) have greater weight than those away from f_0. A spectral

[4]This aspect is also causes distortions in filtering operation as discussed in technical notes to chapter 2.

window consists of a central lobe centred at frequency zero which controls the resolution of the spectrum and also has several side lobes centred at other frequencies. Ideally, the sidelobes should be as small as possible to minimize leakage.

Bias in spectrum occurs due to shape of the spectral window in two ways: Firstly, width of main lobe which affects bandwidth resolution and smooths out spectral features. i.e. missed peaks if the main lobe is too wide. Secondly, through amplitude of side lobes which cause detection of spurious peaks. Bias problem is therefore about tradeoff between size of main lobe which determines resolution of the spectrum and that of sidelobes which cause spectral leakage.

We discuss solutions to reduce bias and inconsistency in periodgram to demonstrate how Multitaper method is able to reduce bias without increasing variance.

Bias in spectrum estimates can be reduced with *tapering*.[5] Tapering consists of multiplying the data sequence $x(t)$ by a function $h(t)$ called *taper* or *fader* or *data window* at the endpoints of the series to make it fall off to 0 gradually.

$$\tilde{s}_\tau = h(t)x(t)$$

Fejér kernel is associated with the default taper

$$h(t) = \begin{cases} 1 & \text{if } 0 \le x \le 1 \\ 0 & \text{otherwise} \end{cases}$$

Thus, whether or not to taper is rather a question of which taper to use. Fourier Transform of the taper is referred to as *Spectral window* [6].

$$H(f) = \sum_{t=0}^{N-1} h(t)e^{-2\pi i f t}$$

The key idea of tapering is therefore to make the start and end point of the series the same to make it a complete signal. Taper function is chosen in such a way that it has lower sidelobes than the Fejér kernel by making the values of taper h_t go to zero more smoothly rather than

[5]Other technique of reducing bias is *Prewhitening* which works by decreasing dynamic range of the time series.

[6]Fejér Kernel is the spectral window associated with the periodogram

sudden change in rectangular or default taper. A good taper has low amplitude for different frequencies and is high for neighbourhood frequencies.

One of the methods to reduce variance in perodogram estimates is Welch Overlapped Segment Averaging(WOSA). Time series is broken into a number of contiguous non-overlapping blocks, computing a periodogram for each block and then averaging them to get the overall spectral estimator. Welch extended this idea in two ways; using taper on each data block to reduce bias and allowing the blocks to overlap which he showed leads to reduction in the variance. Overlapping compensates for the loss of data due to tapering and recovers some of the information concerning the acvf contained in the pairs of values spanning adjacent non-overlapping blocks. The parameters to choose are the block size and the amount of overlap. Although this method is efficient only when long time series are available, we have discussed it in brief as it motivates the idea behind multitaper estimates discussed in the next section.

Main problem in spectrum estimation however, is the tradeoff between bias and variance. Bias in power spectrum estimation arises because of sidelobe leakage which is reduced by data tapers. On the other hand, tapering causes reduction in effective sample size and thus leads to increase in variance. The next section explains how Multitaper method addresses this problem.

3.2 Multitaper Method of Spectrum Estimation

Essence of Multitaper method(MTM) is to use a set of orthogonal tapers designed to prevent leakage and spectrum estimates using all tapers are then averaged to reduce variance of estimates.

Key component of MTM to reduce bias is the use of multiple orthogonal tapers as basis functions for expressing time series in fixed bandwidth $(f-w, f+w)$ centred at frequency f. Tapers are based on *Slepian sequences* or *dpss (Discrete Prolate Spheroidal Sequences)* which have maximum energy concentration in the bandwidth $2w$ under finite sample size constraint. This property implies that the sidelobes have low energy and thus reduces bias without increasing variance.

Slepian sequences or dpss are a family of orthogonal data tapers with optimal spectral window properties i.e. spectral window will have large amplitude when $|f-f'|$ becomes small for neighbouring frequencies. i.e. leakage in spectrum estimate at frequency f for frequencies $f \neq f'$ is minimized.

Basic idea of dpss is to choose a frequency W, where $0 < |W| \leq 1/2$ and maximize the fraction of energy of $H(f)$ at frequencies from $(-W, W)$. i.e. Slepian sequences have the maximum energy in bandwidth W. In mathematical form, $\lambda(N, W)$ is the amount of energy at $\hat{S}(f)$ that comes from $(f - w, f + w)$ and $1 - \lambda$ as the amount which causes bias and comes from outside the band.

$$\lambda(N, W) = \frac{\int_{-w}^{w} |H(f)|^2 \, df}{\int_{-1/2}^{1/2} |H(f)|^2 \, df}$$

To maximize λ, $H(f)$ is appropriately chosen by solving the set of equations detailed in Percival and Walden (1993), which leads to solving the matrix eigenvalue problem of the form

$$\lambda_k v_n^k = \sum_{m=0}^{N-1} \frac{sin 2\pi W(n-)}{\pi(n-m)} v_m^k \text{for} \quad 0 \leq n \leq N-1$$

Solutions are eigenvalues $1 > \lambda_0 > \lambda_1 > \ldots > \lambda_{N-1} > 0$ and associated eigenvectors $v_k(t; N, W)$ are called the dpss which are used as tapers in Multitaper spectrum estimation.

Eigenvalues are bounded between zero and one, with the first $K \approx 2NW$ of them large, i.e. nearly one and rest nearly zero. Eigenvector with largest eigenvalue is the best possible taper for suppression of spectral leakage. First $2NW - 1$ tapers are typically used and as they are orthogonal, estimates based on them are statistically independent of each other and can be combined to give more reliable estimates.

Given a particular bandwidth W, compute the eigencoefficients

$$y_k(f) = \sum_{t=0}^{N-1} x(t) v_k(t) e^{-2\pi i f t}$$

Generally, $k = 1, \ldots, K$ where $K = 2NW - 1$. From these eigencoefficients, we get K eigenspectra

$$\hat{S}_k(f) = |y_k(f)|^2$$

Multitaper spectrum estimate is then calculated by a simple average of these eigenspectum which reduces variance in the spectrum estimate.

$$\bar{S}(f) = \frac{1}{K} \sum_{k=1}^{K} \hat{S}_k(f)$$

Thomson (1982) recommends adaptive weighing procedure to reduce the bias even further.

$$\hat{x}_k(f) = d_k(f) y_k(f)$$

where weights $d_k(f)$ are chosen to reduce bias from spectral leakage. Weights used are

$$d_k(f) = \frac{\sqrt{\lambda_k} S(f)}{\lambda_k S(f) + (1 - \lambda_k)\sigma^2}$$

where σ^2 is variance of the sample $x(t)$. As $S(f)$ is not known, the weights are calculated iteratively using average of $\hat{S}_0(f)$ and $\hat{S}_1(f)$ as the starting point. Convergence is rapid and only a few iterations are necessary.

For each increment in K, variance decreases but spectral leakage increases. K is typically chosen to be $2NW - 1$ or $2NW$ based on the number of available spectral windows with eigenvalues close to one. Only the first few terms of the dpss have desirable bias properties after which the modest decrease in variance can be offset by poor bias of the corresponding eigenspectra.This is because the sidelobe level of the Slepian tapers increases as K increases beyond the Shannon's number($2NW$) and the rate of decrease in variance becomes slower than that implied by the uncorrelatedness of the terms.

Choice of *Time Bandwidth parameter* NW is important and based on consideration of bias-variance tradeoff. Choice of $2W$, the bandwidth determines amount of smoothing and is selected to reduce bias without distorting the spectrum. Typically, NW is fixed to a small number (3 or 4) and then number of tapers is chosen by visual inspection and some trial and error to obtain reasonable spectral resolution. It may seem that taking more terms in the average may improve the estimate but that is not true in Multitaper technique.

In summary, Multitaper method consists of first selecting a resolution bandwidth $2W$ keeping the variance versus bias trade-off in mind. Prolate spheroidal sequences must then be computed to work as tapers. The K eigenspectra are then computed for $K = 0$ to $K - 1$ with $K \leq 2NW\Delta t$ and averaged to get the final estimate. For computing jackknife confidence intervals, $\hat{S}_k(f)$ are used as K independent estimates of the spectrum.

3.3 Jackknifing Multitaper Spectrum Estimates

There are two ways to estimate confidence intervals for statistical estimates, first being the asymptotic error bar and other is using resampling techniques like jackknife and bootstrapping when the underlying probability distribution is not known.

For large N, the data process may be assumed to be asymptotically normally distributed under general circumstances and thus the spectrum estimates are asymptotically distributed according to χ^2_{dof}. Note that degrees of freedom depend on the number of tapers and amount of zero padding.

However, if the series does not satisfy stationarity and Gaussianity assumption, which is the case for most real data series, empirical distribution constructed using jackknife method can be employed. A set of spectrum estimates are obtained by leaving one data taper at a time. As the dpss tapers used are orthogonal, these estimates are therefore independent. A variance stabilizing transformation like logarithm for spectrum and arctanh for coherence is used to approximate empirical distribution by a Gaussian distribution. Error bars can then be calculated based on variance of this approximation for required critical values (Mitra and Pesaran, 1999).

More precisely, as elucidated in Thomson (2007), consider a sample of K independent observations, $x_i, i = 1, \ldots, k$, sampled from distribution characterized by parameter θ which needs to be estimated.

We calculate estimate of θ based on all the data and from K subsets obtained by deleting one entry at a time. i.e. $\hat{\theta}_{\setminus i} = \hat{\theta}[x_1 \ldots, x_{i-1}, x_{i+1}, \ldots x_K]$ for $i = 1, \ldots, K$ where $\setminus i$ denotes set notation for without. Averaging over the K-delete one estimates,

$$\theta_{\setminus \bullet} = \frac{1}{k} \sum_{i=1}^{k} \hat{\theta}_{\setminus i}$$

and jackknife variance of $\hat{\theta}_{all}$ is

$$\hat{v}ar(\hat{\theta}_{all}) = \frac{K-1}{K} \sum_{i=1}^{K} (\hat{\theta}_{\setminus i} - \theta_{\setminus \bullet})^2$$

When parameter of interest is spectral density, take $\theta_{\setminus j} = ln\hat{S}_{\setminus j}(f)$ i.e. omit the j^{th} eigencoefficient at each frequency which implies drop one taper at a time. The variance estimates are then given by

$$\hat{V}_J(f) = \frac{K-1}{K} \sum_{i=1}^{K} [ln\hat{S}_{\setminus j}(f) - ln\hat{S}_{\setminus \bullet}(f)]^2$$

Jackknife is a useful tool in estimating variance of complicated estimated procedures without overly restrictive Gaussian assumption. Given the use of orthogonal tapers, eigenspectrum are independent and therefore jackknifing of spectrum estimates can be done in Multitaper method in a straightforward manner.

3.4 Testing for periodicity : Harmonic F-statistics

Harmonic F-statistic helps to determine significance of peaks in the spectrum which correspond to periodic or quasi-periodic phenomenon. Null hypothesis being tested is that the spectrum is smooth and there are no periodic components in the series. Thomson (1982) and Percival and Walden (1993) discuss this method in detail and only summarizing the main idea here.

Consider the case of one sinusoid embedded in coloured noise as it can be extended for multiple sinusoids. Let $x(t)$ be a time series with sample size N. Assuming that there is a line component at frequency f_0 where $\eta(t)$ is not restricted to be white noise,

$$x(t) = A\cos(2\pi f_0 t + \phi) + \eta(t)$$

Following simplified format used by Pesaran (2008), multiply both sides of equation by a dpss taper $w_k(t)$ and bandwidth parameter $2w$. Taking the Fourier transform of the equation then gives

$$\tilde{x}_k(f) = \mu U_k(f - f_0) + \mu^* U_k(f - f_0) + N_k(f)$$

where $\mu = Aexp(i\phi)$ and $U_k(f), N_k(f)$ are the Fourier transforms of $w_k(f)$ and $\eta(t)$ respectively. Linear regression equation at $f = f_0$ becomes $x_k(f) = \mu U_k(0) + N_k(f_0)$.

Solving for μ,

$$\hat{\mu}(f_o) = \frac{\sum_{k=1}^{K} U_k(0)\tilde{x}_k(f_0)}{\sum_{k=1}^{K} |U_k(0)|^2}$$

F-statistic with $(2, 2k-2)$ degrees of freedom, where k is the number of tapers used, is then given by

$$F(f) = \frac{(K-1)|\hat{\mu}(f)|^2 \sum_{k=1}^{K} |U_k(0)|^2}{\sum_{k=1}^{K} |\tilde{x}_k(f) - \hat{\mu}(f)U_k(0)|^2}$$

and as standard, is interpreted as ratio of explained vs unexplained contribution to the variance.

Important feature of F-test is that it is accurate in detecting periodic components even in short time series as it does not depend on the amplitude of the peak. However, it must be interpreted with the following caveat in mind.

As noted by Thomson (1990),

> It is important to remember that in typical time series problems hundreds of thousands of uncorrelated estimates are being dealt with; consequently one will encounter numerous instances of the F-test giving what would normally be considered highly significant test values that, in actuality, will only be sampling fluctuations. A good rule of thumb is not to get excited by significance levels less than $1 - 1/N$.

Therefore, in empirical results, Harmonic F-statistics is plotted with respect to frequency and a peak is deemed to be statistically significant only if it exceeds the threshold of 1-1/N where N is sample size.

3.5 Cross Spectrum Analysis

To determine relationship between two series as a function of frequency, we study coherence and phase spectral statistics which measure strength of comovement and the lead lag structure in the frequency domain. Cross-spectrum is Fourier transform of cross-correlation and is a complex valued quantity which gives information regarding degree of synchronization between two time series.

Let X_t and Y_t be two time series with a sample size N. Cross correlation function of two series is given by

$$\hat{\rho}_{xy}(k) = \frac{1}{N}\sum_{i=0}^{k} X(i)Y(i+k)$$

Cross spectrum is its fourier transform

$$\hat{S}_{xy}(f) = \frac{1}{N}\sum_{k=1}^{N} \hat{\rho}_{xy}(k\Delta t)\exp(-jfk\Delta t)$$

Coherence is the frequency domain analog of correlation coefficient. High value of covariance can be due to high level of synchronization between the two series at that frequency or due to high power in the spectrum of any of the individual series at a particular frequency.

Coherence is therefore defined just like correlation as

$$\hat{\gamma}_{xy} = \frac{|\hat{S}_{xy}|^2}{|\hat{S}_{xx}|^2|\hat{S}_{yy}|^2}$$

where denominator is product of autospectral density of X_t and Y_t i.e. normalizing the cross-spectrum using auto-spectrum of each series which helps in isolating only those frequencies for which there is high synchronization. [7]

Phase is a statistic which measures lead-lag relation between two comoving series. It is valid only when there is a significant coherence in the pair of series. Relative phase is uniformly distributed over the range $-\pi$ to π. If the processes X and Y are uncorrelated, then no particular relative phase relationship is to be expected at any frequency. Phase shift can be estimated precisely only when coherence is high (Priestley, 1981, p. 670). This explains the erratic discontinuities seen the graph of phase when coherence is low.

Cross spectrum as a complex valued quantity is written as $S_{xy} = \hat{c}o_{xy}(f) + i\hat{q}u_{ij}$ where co is referred to as the co-spectrum and qu as quadrature spectrum. Phase is defined as

$$\hat{\theta}_{xy} = arctan(-\frac{\hat{q}u_{xy}(f)}{\hat{c}o_{xy}(f)})$$

When phase is a straight line segment over a subset of frequencies, the slope indicates which series is leading. Note that phase sign reverses depending on the order in which series are inputted in computations. Therefore phase estimates must be interpreted with caution. Interpretation of phase is described further when discussing the empirical findings.

Finally, major advantages of using multitaper method of spectrum estimation are as follows: It defines resolution of estimators in a natural non-subjective way i.e. $2W$ which is a difficult concept to determine for spectral estimators in general. Resolution of spectrum is therefore naturally defined as 2W. We thus have an estimate of how fine the spectral peaks are and tradeoff between bias and variance is easier to quantify.

It is a method of computing direct spectral estimate with more than just two degrees of freedom which noticeably shrinks the width of confidence intervals for an sdf at a particular frequency. Jackknifing makes it possible to obtain an internal estimate of the variance without any distributional assumption. The technique also offers a unified approach to estimating both mixed spectra and sdf and can be naturally extended to spectral estimation

[7] For computing confidence intervals of Coherence, arctanh transform is used to stabilize variance.

of time series with missing and irregularly sampled data and for multidimensional spectra. Thompson F-test is a highly accurate way of testing for periodicity and finding the significant cyclical components in a time series.

MTM is better than traditional methods like WOSA as it can be applied without details like choice of block length and amount of overlapping. Also, unlike WOSA, multitapering uses the entire data series and thus problem of information loss and choice of overlapping percentage of the data are avoided. Different tapers are chosen usually from the family of dpss. Each taper is applied to the full data record and periodogram is computed. Thus, information in the series is being used more efficiently for multitaper estimates.

Haykin, Thomson, and Reed (2009) finds MTM to be a robust spectrum estimation technique in simulation studies and also summarizes studies comparing MTM with other spectrum estimation methods. The study concluded MTM to be close to the optimum maximum likelihood procedure and better than using periodogram with Hamming tapers. Bronez (1992) compares WOSA and MTM on three performance measures leakage, variance and resolution and evaluate the performance on each of the measures while keeping the other two equal. The study recommends the use of MTM whenever a nonparametric estimator is appropriate.

In conclusion, MTM has many advantages for spectral analysis of economic time series which are generally of short length. Classical spectral estimates obtained with short time series have drawback of spectral leakage which biases the results. Multitaper method suggested by Thomson (1982) allows one to reduce spectral leakage and gives improved consistency at the same time by using multiple orthogonal tapers on the data. Therefore MTM is better choice of method to compute spectrum and has been shown to work well with short time series.

4 Data

Time series data on output, credit and monetary aggregates at monthly frequency for the period 1994:04 to 2013:03. Variables under study for India are IIP, M0, M1, M3, MCWP(Currency with Public) and NFC(Non Food Credit). For US, they are USIIP (Industrial Production) and USTBKC (Bank Credit of All Commercial Banks), M1 and M2. [8]

[8] 1. Nominal Bank credit in India is the sum of NFC (Non Food credit) and Food credit. As Food credit is governed by external factors like monsoon, market surplus and Govt procurement and allocated by Food

All series have been seasonally adjusted using X-13-ARIMA and log transformed. Nominal series are converted to real by using price index. Presence of outliers may distort spectrum estimates and therefore the series are adjusted for outliers.

Starting year for the study is chosen as 1994 as the structure of Indian economy has changed after introduction of liberalization reforms of 1990s and there are studies like Dua and Banerji (2001a) which suggest that leading indicators started working in India after the introduction of these market reforms. It is also the year of base change and thus avoids problem that might come from splicing the series for just two years of data if we start from 1992 onward.

A note on the choice of reference variables

Industrial production is used as reference cycle to measure business cycles in India and US. Although IIP has limitations as proxy for overall economic activity, it is the best alternative to GDP available at monthly frequency enabling a longer time series required by econometric technique of spectral analysis. Additionally, industrial growth is an important driver of economic growth and reflects the real production output of the country.

Studies characterizing financial cycle and credit cycle generally take bank credit to private sector as reference variable but this data is available through BIS(Bank of International Settlements) database only at quarterly frequency. Since we are using data at monthly frequency for a longer time series to conduct analysis in the frequency domain, we restrict reference variable for credit cycle to Non Food credit in India and Bank credit of All Commercial Banks in US.

HP filter as the method of detrending

Since spectral analysis is valid for stationary series, we need to use a detrending method to remove stochastic trends. Note that this implies the study of growth cycles.

First differencing is commonly used method to make economic time series stationary. However, $(1-L)$ differencing filter enhances the high frequency components while reducing the low frequency components and causes phase shift (Baxter and King, 1999). Additionally,

Corporation of India, it has not been included in the definition of credit for the Indian economy. NFC is therefore used as measure of credit in India.

2. M1 and M2 are considered for US as they are the monetary aggregates monitored by Fed and M3 was discontinued in 2006.

unit root tests do not give a clear idea on the order of differencing required to make the series stationary. Since the number of times the series is differenced will influence the results for further analysis, we prefer to use HP filter which removes unit roots upto fourth order.

An important point to note when using HP filter for detrending is the choice of smoothing parameter. Results using $\lambda = 14400$ and 400000 are different in terms of cyclical length calculated as amount of smoothing determines the separation between trend and cycle. Azevedo (2002) note that although the results are dependent on the choice of smoothing parameter, the order of the cycles detected remain the same when using the same value of λ across series. Importantly, results for synchronization are not affected as coherence normalizes the cross-spectrum with spectral mass of each series and results for coherence are almost similar for difference choices of HP smoothing parameter.[9]

5 Empirical Results

We estimate univariate spectrum of output and credit variables to determine the duration of growth and credit cycles and then calculate the cross-spectrum to find the degree of synchronization and lead lag relationship between credit and output, credit and money, money and output and output in India and US.

The key questions for which we seek answer are: Firstly, what is the duration of credit and output cycle in India and US? Second, is there a strong comovement among the real and credit variables? Third, can money be a good leading indicator of credit or output ? In each case, we compare results with US as both economies differ in the nature and structure of financial sector.

5.1 Univariate Spectrum Results

Peak in the spectrum at a particular frequency means that it makes maximum contribution to the variance in the series, from which it can be inferred that there is a cycle of duration corresponding to that frequency in the data.

Main consideration in spectral analysis is the choice of bandwidth which determines the resolution of peaks and small bandwidth is preferred to reduce bias. In MTM, there is an

[9] Drehmann, Borio, and Tsatsaronis (2012) use $\lambda = 400000$ to capture medium term cycles. We present results using both these series for comparison. Note that the choice of this parameter determines the cyclical component being extracted. RBI (2006) uses λ as 129600 to get cycles of length 5 years.

additional choice regarding number of dpss tapers to balance the bias variance tradeoff. Percival and Walden (1993) gives some rules of thumb for choosing the amount of tapering required. The log spectrum of the series must have similar variance throughout. If tapering reduces variability in the spectrum in the high frequency range, then it indicates the need for using tapers. The number of tapers is increased till the point when the variability decreases. Changes in the spectrum are also sensitive to the presence of outliers and robustness of results must be tested in series adjusted for outliers.

Different combinations of NW, the time bandwidth parameter and K, number of tapers were tried and only results for NW = 4, K = 8 are presented in Table 1 with HP-14400 detrended series and in Table 2 when series was made stationary with HP-400000. This combination of NW and K has been found to be a reasonable value using rules of thumb mentioned above and keeping in mind computation of bivariate statistics which require NW and K to be the same for each pair of series. [10]

The duration of cycle in years in presented using frequency at which peak occurs in the spectrum and the jackknife confidence intervals. With $\lambda = 14400$, IIP has been found to have a cycle of 2.7 years while NFC has duration of 3.3 years. Both USIIP and USTBKC are found to have cycle of length 2.9 years. With $\lambda = 400000$, Thompson F-test detects cycles of length approx 7 years in both US IIP and US Bank credit while period corresponding to the peak in the spectrum is 21 years for both the series. However, note that confidence intervals are too wide from which it appears that the choice of smoothing parameter is not valid.

Notable point however is that the length of business and credit cycles has been found to be of similar length in contrast to studies like Drehmann, Borio, and Tsatsaronis (2012), Aikman, Haldane, and Nelson (2014) and Claessens, Kose, and Terrones (2011) who use band pass filter and turning point methodology and find credit to be much longer than business cycles in both amplitude and frequency. This may be due to difference in the choice of reference variable for credit and use of band pass filters.

Using IIP as the reference cycle, our study finds growth cycles of length 2.7 years or 32.4 months using standard value of smoothing parameter of HP filter. Comparison of this finding with other empirical studies in India over comparable time period is as follows. Bordoloi and Rajesh (2007) use probit models to study growth rate cycles in the monthly

[10] Results are presented for outlier adjusted series. Note that only the results for M0 are affected by the outlier adjustment.

industrial index and find the average duration of cycles to be 28 months for the time period 1980-2006 using Bry Boschan method. RBI (2006) gives chronology for growth and growth rate cycles with IIP and non-agricultural GDP as the reference series. The average duration was found to be 36 months for growth cycles in IIP data and 21 months for the growth rate cycles for the period 1993-2006. For quarterly non-agricultural GDP, the average duration of growth cycle is 10 quarters and for growth rate cycle is 9 quarters for the reference period. The RBI (2002) report establishes chronology for growth rate cycles using IIP as the reference series. Nilsson and Brunet (2006) find average length of growth cycles in industrial production to be 38 months long for the period 1978-2004. Dua and Banerji (2001b) use Bry and Boschan method to detect cyclical turning points in the coincident index constructed using NBER methodology for classical and growth rate cycles from 1964-1997 and find the length of business cycles to be over 6 years.

Graphs of univariate spectrum for all the series along with jackknife confidence intervals are shown in Figure 1. Left hand side of the graphs show the multitaper spectrum and the right hand side shows Thompson F-statistic with dashed lines drawn at 95% and 99% level of significance. In a sample of N = 228 observations, only those frequencies for which this statistic is more than 1-1/N = 99.56% are considered statistically significant.

The x-axis corresponds to frequency in cycles/year which means that cycles of duration more than one will have a peak in the interval (0,1) as frequency = 1 means 1 cycle per year. Frequency = 2 corresponds to cycles of 6 months and spectrum in the range (2, 6) corresponds to cycles of less than 6 months. Nyquist frequency is 1/2 as the sampling interval is one, which implies that shortest distinguishable cycle is of 2 months. [11]

Thompson F-test for cyclical periodicity with $\lambda = 14400$ detects very short cycles which maybe present in the data due to short term volatility. From this it can be inferred that some denoising procedure is necessary to remove this noise and therefore, results from this test cannot be applied mechanically in the economic series. Filtering the series using $\lambda = 400000$ however might be removing some of the noise and in this case, Thompson F-test detects cycles of length about 7 years for USIIP and USTBKC.

[11] 1. If the maximum of the spectrum occurred at frequency 0 for some series, then it corresponds to cycle of 85.3 years. Since this seems unreasonable, shifted the index to 5 which corresponds to 17 years. It only points to a limitation of using short time series as cannot distinguish between low and very low frequency components.
2. Time series have been centered i.e. converted to zero mean using an expansion on the Slepian sequences if the bandwidth parameter (nw) and number of tapers (k) is specified.

Table 1: HP-14400 filtered Time Series, Outlier Adjusted : Spectrum Statistics for frequency at which SDF is maximum

.id	Tapers	Idx	Freq	Period	Period(Ftest)	SDF	Lower	Upper	CI.length	Fstats
iip	nw,k=4,8	32	0.36	2.7	0.44	3	1.8	5.5	3.7	8.1
m0	nw,k=4,8	27	0.3	3.2	0.38	0.23	2.4	8.4	6	12
m1	nw,k=4,8	40	0.46	2.1	0.47	0.14	1.1	2.9	1.8	14
m3	nw,k=4,8	49	0.56	1.7	0.44	0.098	0.88	2	1.2	5.8
mcwp	nw,k=4,8	36	0.41	2.4	0.61	0.15	1	2.9	1.8	12
nfc	nw,k=4,8	26	0.29	3.3	0.81	0.17	1.9	5.3	3.4	11
usiip	nw,k=4,8	29	0.33	2.9	0.27	0.0096	2.3	6.8	4.5	7.3
usm1	nw,k=4,8	28	0.32	3	0.69	0.091	1.4	7.5	6.1	8.5
usm2	nw,k=4,8	32	0.36	2.7	0.43	0.026	0.65	1.8	1.1	16
ustbkc	nw,k=4,8	29	0.33	2.9	0.19	0.0055	0.73	2.2	1.4	19

Table 2: HP-400000 filtered series, Outlier Adjusted : Spectrum Statistics for frequency at which SDF is maximum

.id	Tapers	Idx	Freq	Period	Period(Ftest)	SDF	Lower	Upper	CI.length	Fstats
iip	nw,k=4,8	8	0.082	11	0.44	0.23	6.8	28	21	7.7
m0	nw,k=4,8	7	0.07	12	0.38	0.22	11	30	20	11
m1	nw,k=4,8	8	0.082	11	0.37	0.086	9.1	28	19	7.7
m3	nw,k=4,8	5	0.047	17	8.5	7.9	8.8	19	10	17
mcwp	nw,k=4,8	9	0.094	9.5	0.61	0.15	2.9	8	5.1	13
nfc	nw,k=4,8	8	0.082	11	0.17	0.065	24	61	37	9
usiip	nw,k=4,8	4	0.035	21	7.1	13	15	28	14	17
usm1	nw,k=4,8	5	0.047	17	7.8	17	21	38	17	9.9
usm2	nw,k=4,8	8	0.082	11	0.43	0.026	2.1	9	7	15
ustbkc	nw,k=4,8	5	0.047	17	7.1	7.7	7.8	21	13	10

From the univariate spectrum graphs, we observe that the Thomson F-test does not always agree with the peak in the spectrum.[12] Cyclical duration according to Thompson F-test are also given in the results table but it detects cycles of less than a year using the rule to select only frequencies with more than 99.56% statistical significance. For example, in case of IIP, the shape of spectrum suggests a period of 2.7 years while the Ftest shows a significant cyclical component of duration 0.44 months. This discrepancy can be explained by presence of high frequency components or noise present in economic data which is biasing

[12]There might be a mismatch in the shape of spectrum and results from F-test in the case where there is no fixed periodicity. Economic cycles phenomenon are not strictly periodic but do have strong periodic tendencies.

the detection of dominant frequency. Therefore, unless the series is denoised properly, we rely on economic theory and shape of multitaper spectrum to infer periodicity.

5.2 Bivariate Spectrum Results

There are two main bivariate spectral statistics, coherence and phase, which together capture the strength of synchronization and lead lag relationship between the two series.

The maximum of the coherence and the corresponding phase statistics for each pair of series are presented in Table 3. The frequency range to find the maximum has been restricted from 0 to 2 as we are interested in strength of comovement for cycles of atleast 6 months. This table gives the maximum coherence, the jackknife confidence intervals, the frequency yielding the maximum coherence and the corresponding phase statistics and error estimates. Table 4 shows the average of coherence and phase in long, medium and short run and here maximum coherence is as measured over the entire frequency range. Here, long run refers to cycles more than 8 years, medium run refers to cycles between 1 to 8 years and short run refers to cycles less than 1 year.

Table 3: HP-14400 Outlier adjusted :
Bivariate Spectral Statistics for frequency at which coherence is maximum

	Freq	Coherence	Lower CI	Upper CI	Phase	Lower CI	Upper CI
iip & nfc	0.023	0.64	0.28	0.85	-0.26	-0.49	-0.025
iip & mcwp	0.035	0.3	0.01	0.66	3.1	2.2	-2.3
iip & m0	0.07	0.75	0.45	0.9	-0.3	-0.63	0.026
iip & m1	0.12	0.71	0.37	0.89	-1.6	-1.9	-1.2
iip & m3	0.57	0.48	0.14	0.75	-1.9	-2.4	-1.4
m0 & m1	1.9	0.46	0.23	0.66	0.044	-0.61	0.7
m0 & m3	0	0.23	0.16	0.81	0	0	0
m0 & mcwp	0.63	0.33	0.087	0.58	0.25	-0.93	1.4
m0 & nfc	1.8	0.2	0.025	0.65	1.6	0.89	2.4
m1 & m3	0.82	0.82	0.67	0.91	-0.36	-0.56	-0.17
m1 & mcwp	0.88	0.89	0.76	0.95	-0.025	-0.28	0.24
m1 & nfc	1.9	0.48	0.0067	0.85	0.18	-0.72	1.1
m3 & mcwp	0.84	0.79	0.34	0.95	0.45	0.19	0.7
m3 & nfc	1.9	0.55	0.33	0.72	-0.13	-0.88	0.62
mcwp & nfc	0.79	0.65	0.46	0.79	-0.25	-0.64	0.14
usiip & ustbkc	0.11	0.68	0.4	0.85	1.1	0.77	1.3
usiip & usm1	0.47	0.84	0.64	0.94	-3	3	-2.6
usiip & usm2	0.46	0.88	0.76	0.94	-3.1	3	-2.8
usm1 & usm2	0.43	0.84	0.53	0.95	-0.068	-0.23	0.098
usm1 & ustbkc	0.71	0.33	0.11	0.55	-0.67	-1.7	0.32
usm2 & ustbkc	0.75	0.69	0.22	0.91	-0.14	-0.49	0.22
iip & usiip	0.46	0.68	0.41	0.84	0.36	-0.028	0.75
iip & ustbkc	0.93	0.78	0.4	0.93	-2.8	-3.1	-2.6
nfc & ustbkc	0.95	0.053	0.17	0.52	-1.2	2.6	1.2

Table 4: HP-14400 Outlier adjusted:
Bivariate Spectral Statistics : Average over frequency ranges

	Freq	Max.Coh	Avg.Long	Avg.Med	Avg.Short	Max.Phase	Phase.Long	Phase.Med	Phase.short
iip & nfc	0	0.76	0.46	0.086	0.12	0	-0.58	-0.31	0.25
iip & mcwp	5.7	0.55	0.34	0.21	0.17	-2.3	-2.1	-1.5	0.45
iip & m0	0.07	0.75	0.53	0.32	0.12	-0.3	-0.023	-0.061	-1.4
iip & m1	0.12	0.71	0.4	0.44	0.17	-1.6	-2	-1.4	0.079
iip & m3	0.57	0.48	0.084	0.25	0.15	-1.9	-0.5	-2.1	0.46
m0 & m1	2.3	0.55	0.2	0.19	0.18	-1.2	-2.6	-0.52	-2
m0 & m3	2.3	0.54	0.21	0.1	0.14	-1.1	-0.46	-1	2.2
m0 & mcwp	5	0.5	0.13	0.18	0.14	0.27	0.66	0.12	-1.5
m0 & nfc	5.1	0.68	0.068	0.11	0.12	1	-1.1	0.8	-3.1
m1 & m3	0.82	0.82	0.18	0.49	0.45	-0.36	-1.1	-0.66	0.16
m1 & mcwp	0.88	0.89	0.45	0.59	0.2	-0.025	-0.17	-0.082	1.6
m1 & nfc	2.1	0.89	0.27	0.24	0.29	0.018	1	0.53	0.29
m3 & mcwp	0.84	0.79	0.32	0.44	0.2	0.45	0.89	0.3	0.78
m3 & nfc	2	0.85	0.092	0.25	0.44	-0.1	-2.8	1.1	0.085
mcwp & nfc	0.79	0.65	0.26	0.34	0.17	-0.25	1.6	0.39	1.7
usiip & ustbkc	0.11	0.68	0.49	0.46	0.16	1.1	0.69	1.8	-1.9
usiip & usm1	0.47	0.84	0.21	0.44	0.18	-3	-3.1	-2.8	3
usiip & usm2	0.46	0.88	0.34	0.48	0.16	-3.1	2.8	-3	-2
usm1 & usm2	0.43	0.84	0.43	0.68	0.32	-0.068	-0.72	-0.16	-2.6
usm1 & ustbkc	3.2	0.52	0.11	0.21	0.22	2.9	-2.6	-1.5	-0.52
usm2 & ustbkc	0.75	0.69	0.04	0.31	0.18	-0.14	-0.67	-1.1	2.2
iip & usiip	0.46	0.68	0.37	0.47	0.15	0.36	-0.033	0.48	-0.15
iip & ustbkc	0.93	0.78	0.25	0.32	0.13	-2.8	0.72	2.4	-0.24
nfc & ustbkc	2.3	0.59	0.08	0.11	0.13	-2.5	0.95	0.23	-1.4

Graphs 2 show the coherence and phase statistics for each pair of series. The graphs on the left hand side are for coherence and on the right hand side for the phase. The dashed lines show the 95% jackknife confidence intervals. Note that phase makes sense only when the coherence is high. Thus, the estimates and confidence intervals are tight only in cases where coherence is atleast 0.5. The dotted line in coherence graphs refers to coherence equal to 0.4. The graphs show the coherence and phase modulo 2pi between pair of series in the frequency range 0 to 2.

Estimating a significant phase shift requires high coherence estimates as the sampling error of phase estimate is negatively correlated with coherence. The higher the coherence, the more precisely the phase shift can be estimated (Priestley, 1981). [13]

Phase diagrams for each pair of series given in Figure 2 can be interpreted as follows. For each pair, the first series in the figure title is designated as the input series. There is a lead lag relation only when there is straight line segment with non zero slope. A negative slope in the phase diagram corresponds to a leading input series. If the straight line segment has a positive slope,the output series leads. If there is no slope, it implies that the series move contemporaneously. If the phase is along 0 or 2pi, the movements are in same direction and if it falls along odd multiples of 2pi, then the series move contemporaneously but in the opposite direction. (Hilliard, 1979).

These are the conclusions that can be drawn from these tables and graphs with regards to the following questions : [14]

Is there a strong synchronization between real and credit variables in India and US ?

We find that the coherence of credit-output relation is strong, specially at the low frequencies. Strength of coherence is higher in US than India and the lead lag relations in US are that credit leads industrial production and vice versa in India. Coherence between IIP and NFC is 0.64, 95% CI[0.28, 0.85](Confidence Interval) at frequency 0.023 with average coherence highest in the long run frequency range (0.46). Phase is -0.26 radians with CI [-0.49, -0.025].

[13]Sharp discontinuities in the graph for phase are because of converting the phase to radians and taking modulo 2pi.

[14]Results for bivariate spectrum are using $\lambda = 14400$.
Note that although results for HP filter with different values of lambda affect the cyclical length found in univariate analysis, the results for coherence are not affected as coherence normalizes the cross spectrum with spectrum of each of the series.

For US, industrial production and bank credit are strongly synchronized with a coherence of 0.68, CI[0.4, 0.85] at freq 0.11 and average coherence highest in the long run (0.49) and substantial coherence in the medium run as well (0.46). Phase at frequency of maximum coherency is 1.1 radians with CI[-0.77, 1.3].

In the phase diagram for IIP and NFC, phase is linear segment with negative slope which implies that IIP is the leading series. Phase between USBKC and USIIP is decreasing in the long run, which implies that USBKC is leading USIIP. This may be explained on the basis of difference in sophistication of financial systems in the two economies. US is a market based economy while in India, banks are dominant sources of credit (Chakrabarti, 2014) which alters the accessibility of credit in the two economies. One of explanations for this finding is that in India, an increase in IIP suggests that the firms are producing more and thus more profitable which makes them credit worthy. Firms with more profitability are able to borrow more which implies that level of output determines credit obtained and thus IIP leads NFC in India.

Significant cross country differences in the credit output relation has implications for both the theoretical underpinnings and empirical analysis of the relationship. i.e. Is there a single model which fits data well at all frequencies or are there distinct data generation processes in different frequency bands?

We find that for India, average coherence is highest in the low frequency range, 0.43 but weak in the business cycle and high frequency, 0.86 and 0.12. region. For US however, average coherence is comparable in long and medium run, 0.53 and 0.46 respectively but low in the high frequency region (0.18).

This in contrast to Zhu (2011) who finds that in US credit output relationship is valid in the long run but weak over business cycles. The study uses real GDP, nominal Bank credit, employment, real fixed investment and real private consumption at quarterly frequency for the time period 1950 to 2009 for US and Japan and since 1991 for Euro Area and examines the relationship in the frequency domain using spectral analysis. However, conclusion that credit output relation varies over frequency range and across countries and is significant only in the long run agrees with findings of our study from bivariate Multitaper spectrum.

How are the Indian and US series related ?

IIP has a strong coherence with both USIIP and USTBKC with bulk of average coherence in the medium run. On the other hand, there is little coherence between NFC and USIIP or USTBKC.The phase between IIP and USIIP is 0.22 radian with a 95% confidence interval of [-0.04, 0.49]. Between IIP and US IIP, there is slight upward slope which implies that USIIP is leading or that IIP is lagging.

This finding gives strength to the use of USIIP as an early warning indicator of recessions in India and is in agreement with studies like Nachane and Dubey (2013) which argue for cyclical coupling of the two economies.

What is the relationship between money and credit variables ?

For India, NFC is most strongly correlated with MCWP, with a coherence of 0.76, CI [0.33, 0.93] at frequency 0.71. From the graphs, it is evident that coherence is atleast 0.4 in frequency range corresponding to approximately one to two years where phase is a straight line with negative slope implying that MCWP is leading NFC. Coherence between M3 and NFC is high at 0.61 but the series are contemporaneous. For M1, coherence is 0.52 but the lead lag relation is not that clear.

From this we may infer that MCWP is a useful indicator as it is leading NFC in the frequency range of 1 to 2 years. Given that India is a demand driven economy, primarily dependent on domestic markets, a plausible explanation is that when MCWP is high, consumers have more money to spend which increases demand and since production depends on domestic demand, increase in production thus leads to increase in credit.

In US, M1 and bank credit seem to be countercyclical in the long run and contemporaneous in the short run. M2 seems to be contemporaneous in frequency bands where coherence is atleast 0.4.

What is the relation between money and output ?

In India, there is high coherence between IIP and M0 and M1 in frequency range (0,2) but not with M3 and MCWP. Coherence for the pairs IIP and M3, M0 and M3, M0 and MCWP, M0 and NFC, NFC and USTBKC is below 0.5 Between M1 and M3, the phase is decreasing in the range 0.5 to 1 but increasing in range 1.2 to 2 i.e. there is a phase reversal in medium run to short run i.e. M1 leads M3 in the short run but lags M3 in the short run. IIP and M1 have high coherence in the long to medium run where the phase is an almost straight line of about -1 radians which means that series are countercyclical.

Figure 1: Multitaper Spectrum Estimates and Thompson F-statistics, nw = 4, k = 8

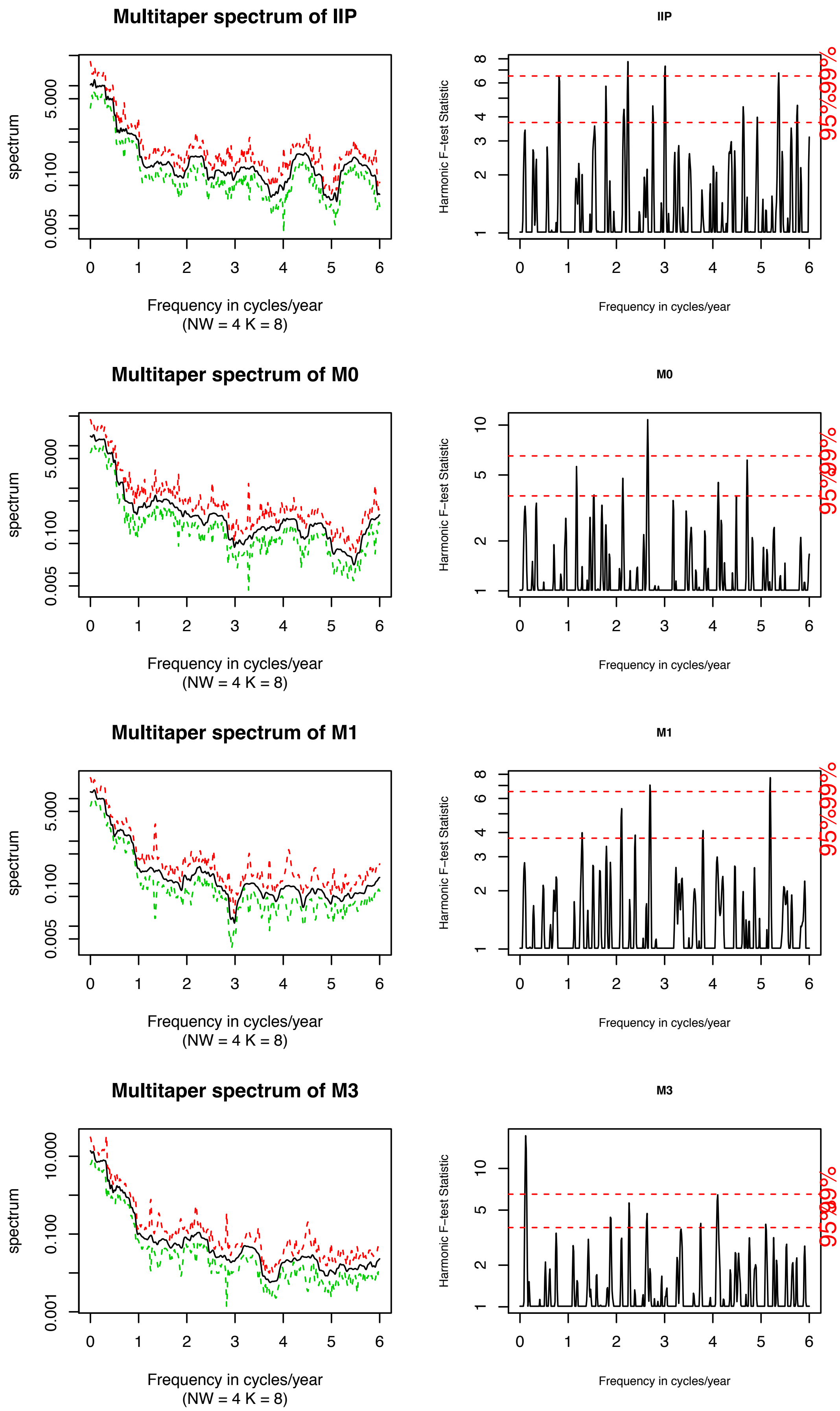


Figure 1: Multitaper Spectrum Estimates and Thompson F-statistics, nw = 4, k = 8

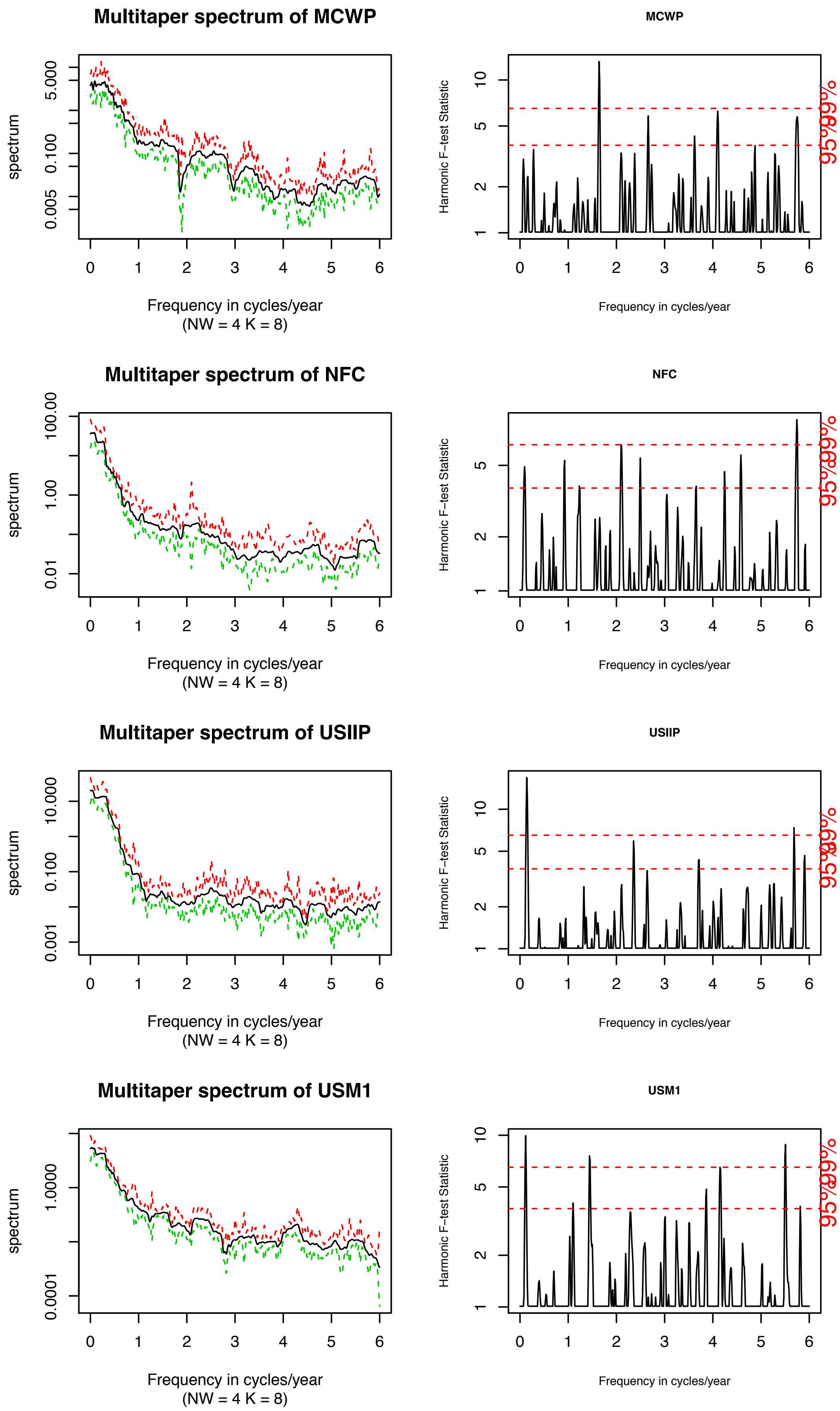


Figure 1: Multitaper Spectrum Estimates and Thompson F-statistics, nw = 4, k = 8

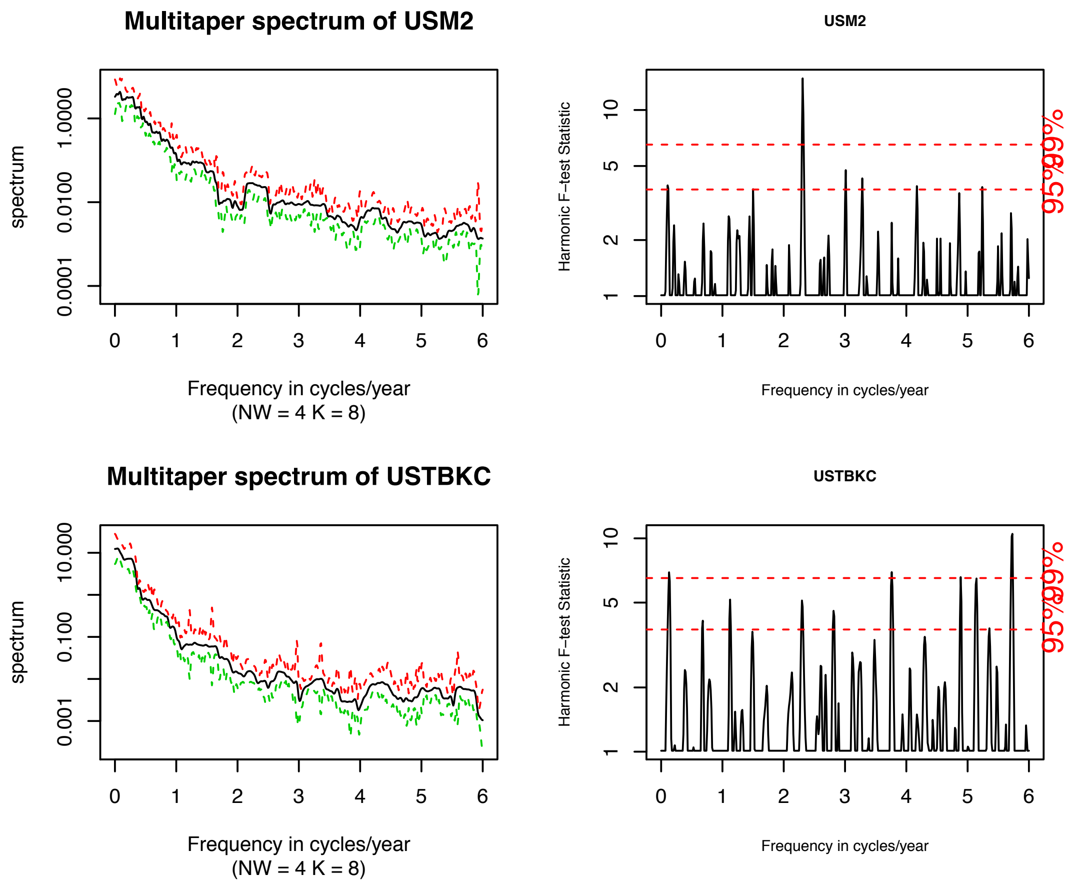


Figure 1: Multitaper Univariate Spectrum and Thompson F-statistics, NW = 4, K = 8. Dotted lines show jackknife confidence intervals.

Figure 2: Coherence and Phase Bivariate Multitaper Estimates, nw = 4, k = 8

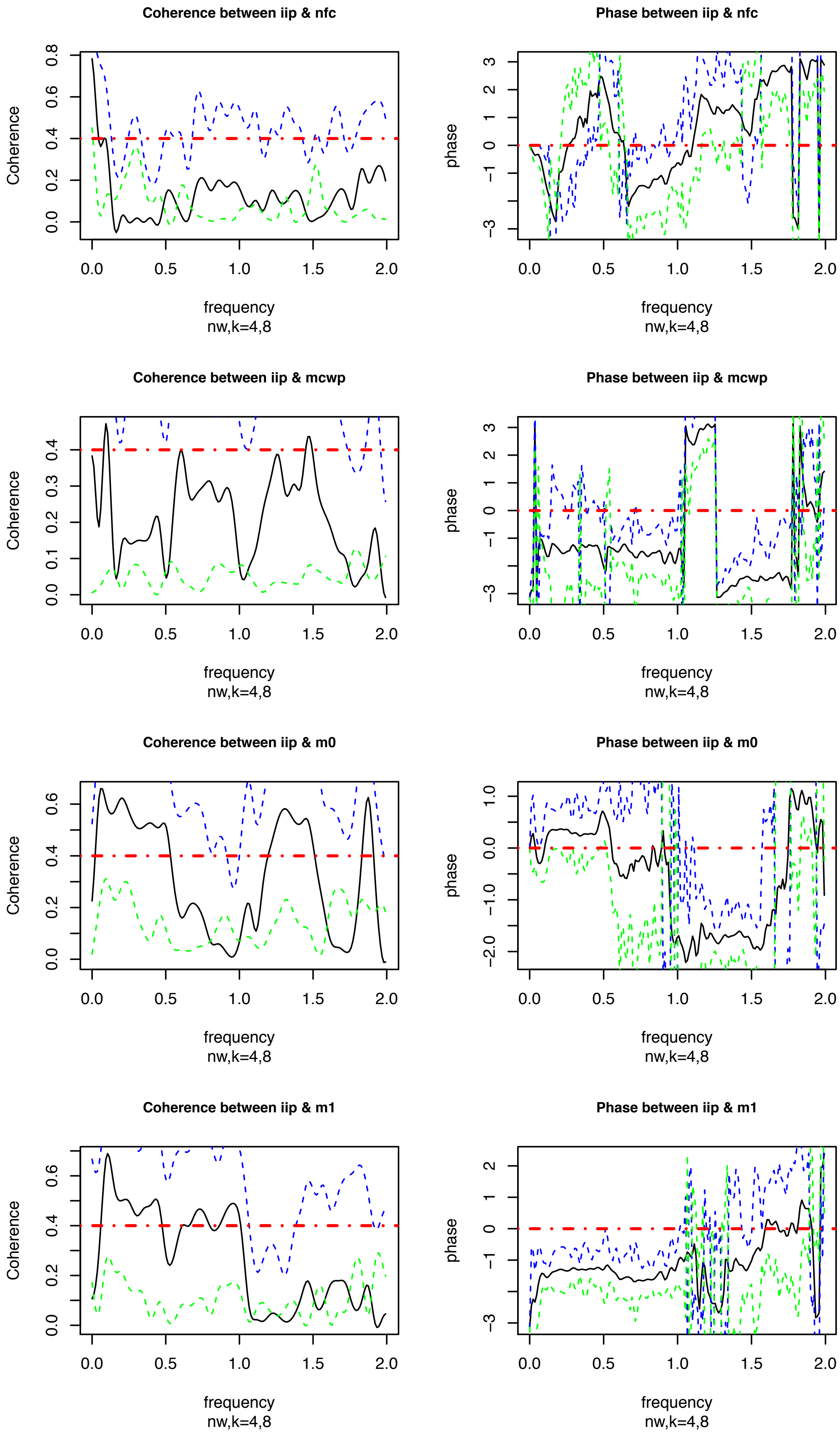


Figure 2: Coherence and Phase Bivariate Multitaper Estimates, nw = 4, k = 8

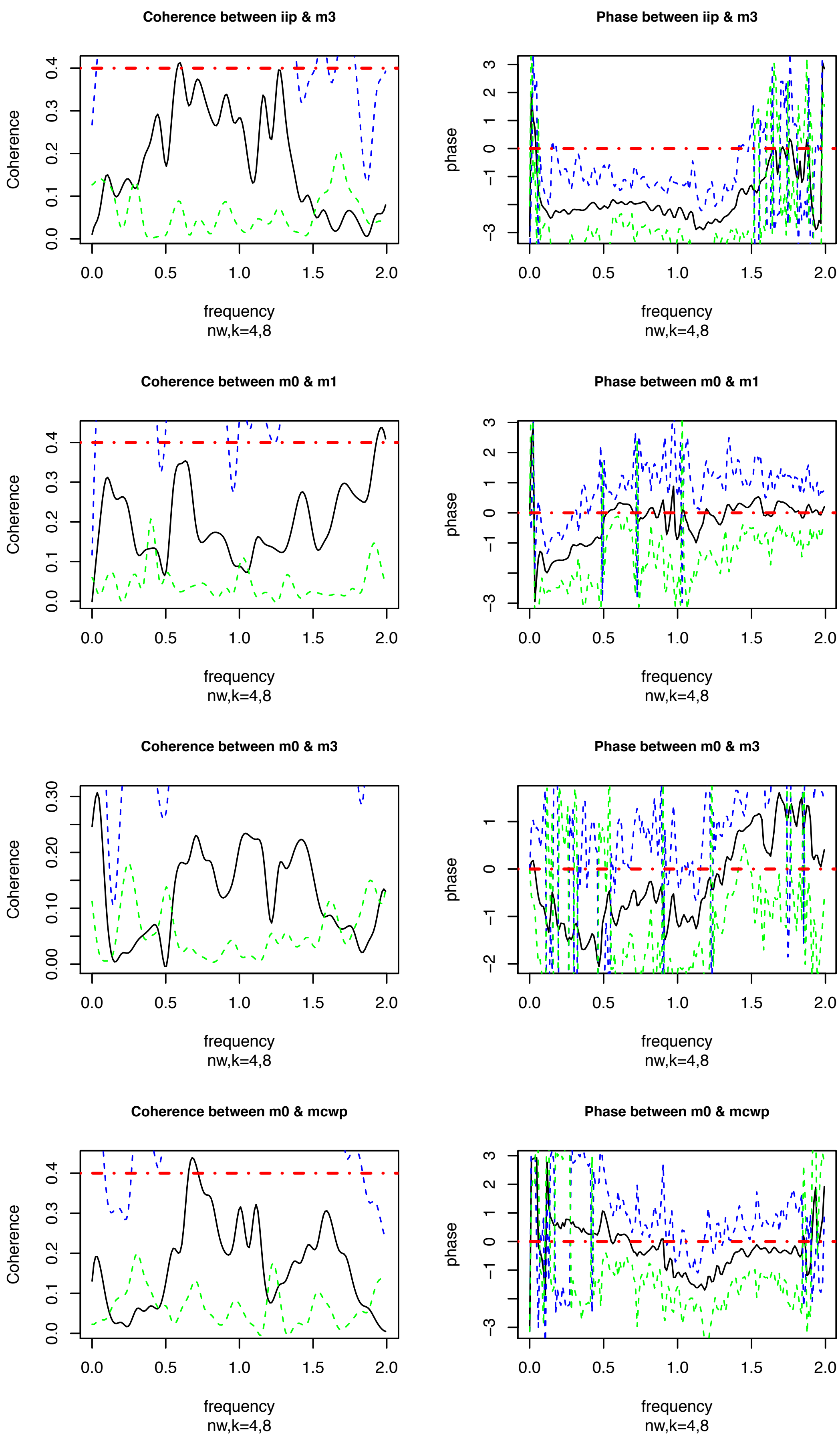


Figure 2: Coherence and Phase Bivariate Multitaper Estimates, nw = 4, k = 8

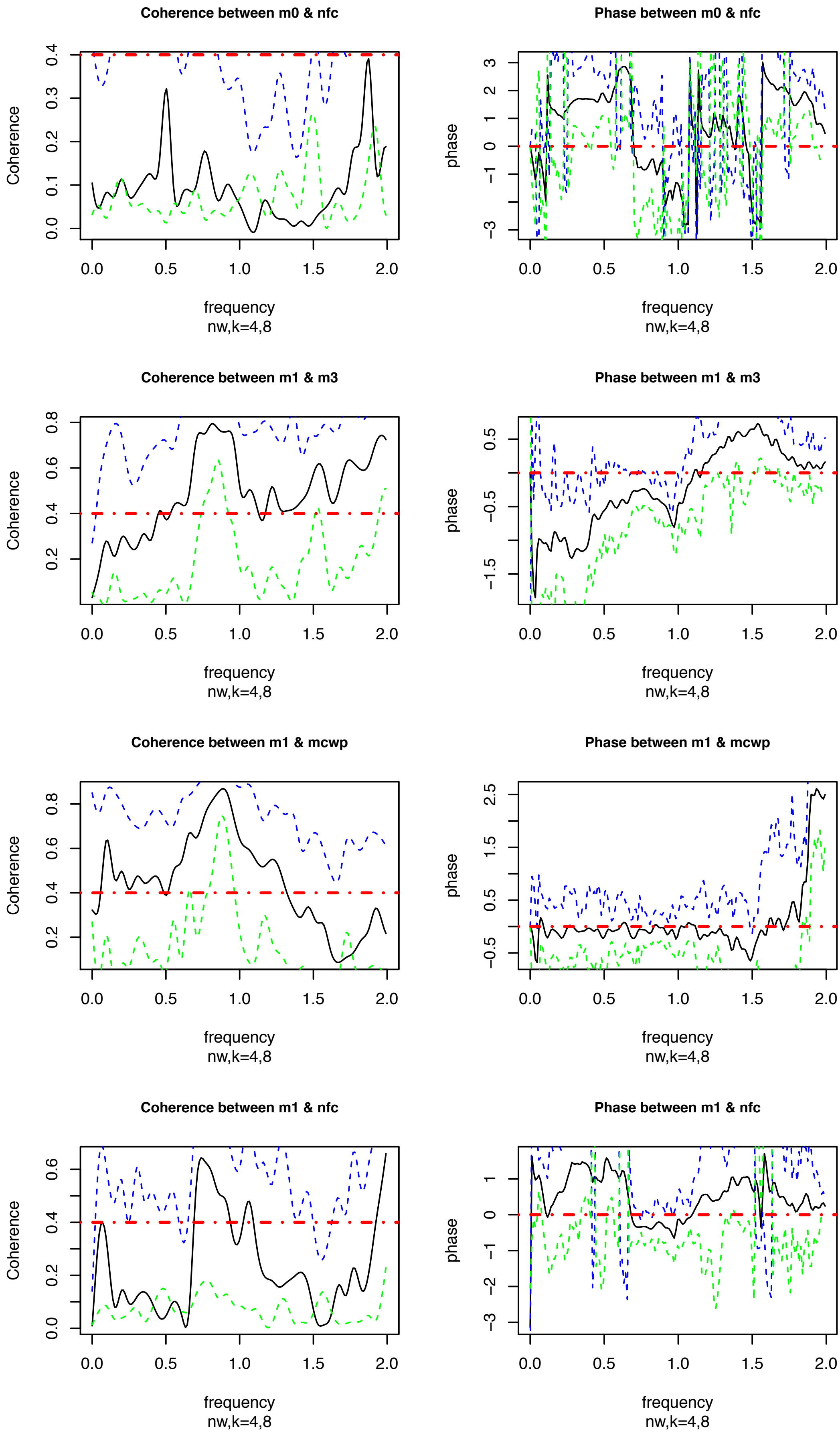
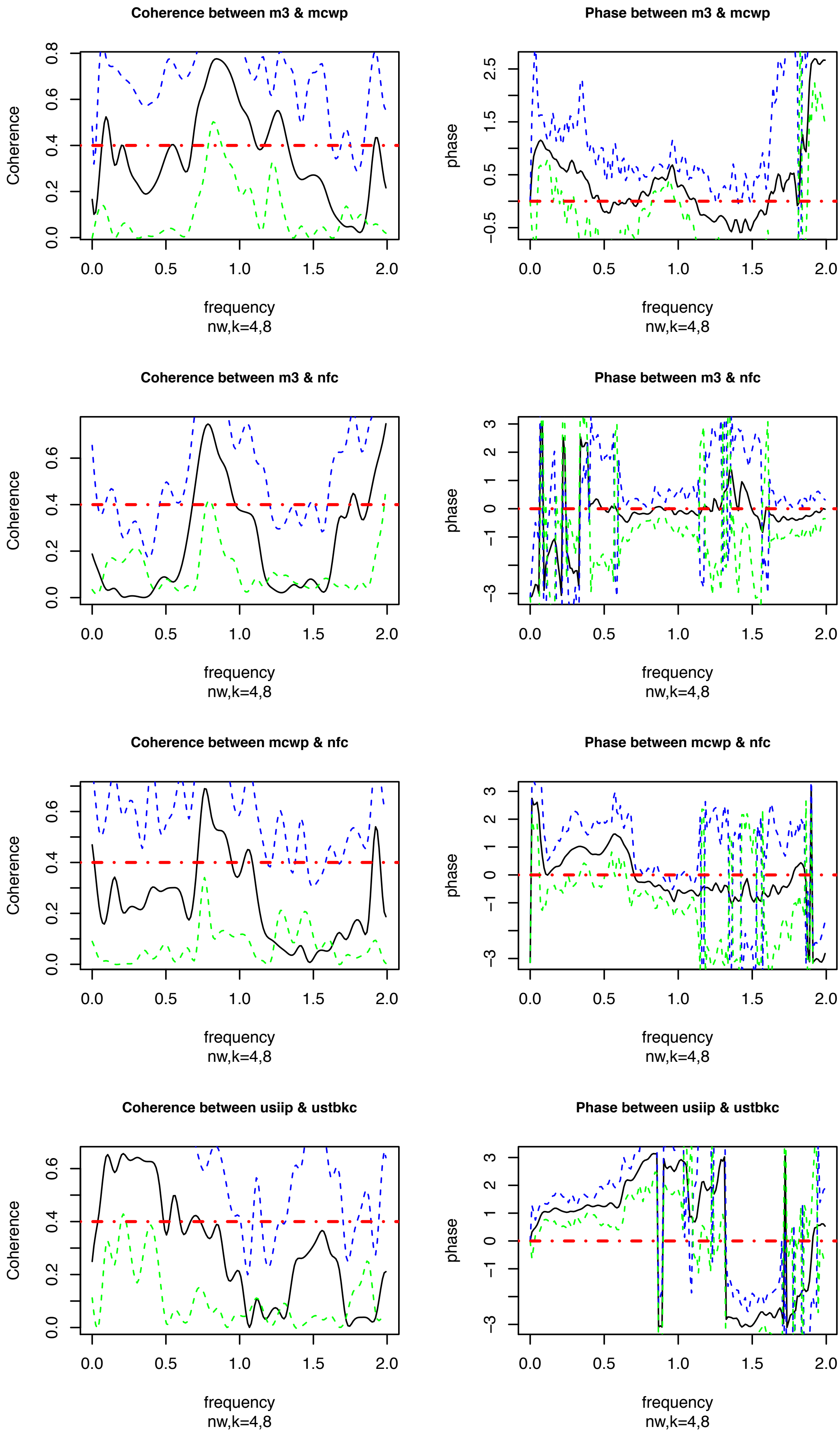


Figure 2: Coherence and Phase Bivariate Multitaper Estimates, nw = 4, k = 8



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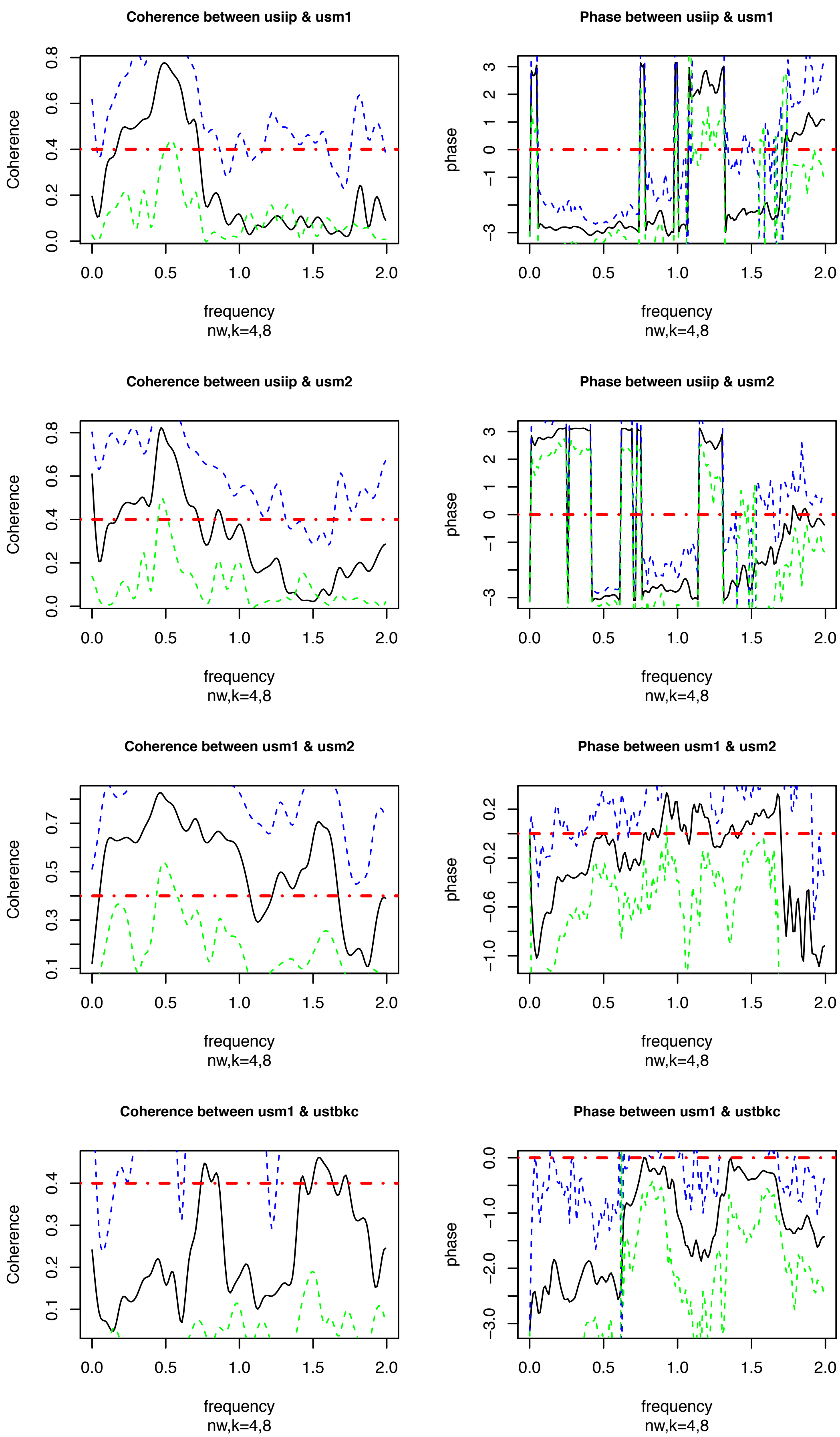

Figure 2: Coherence and Phase Bivariate Multitaper Estimates, nw = 4, k = 8

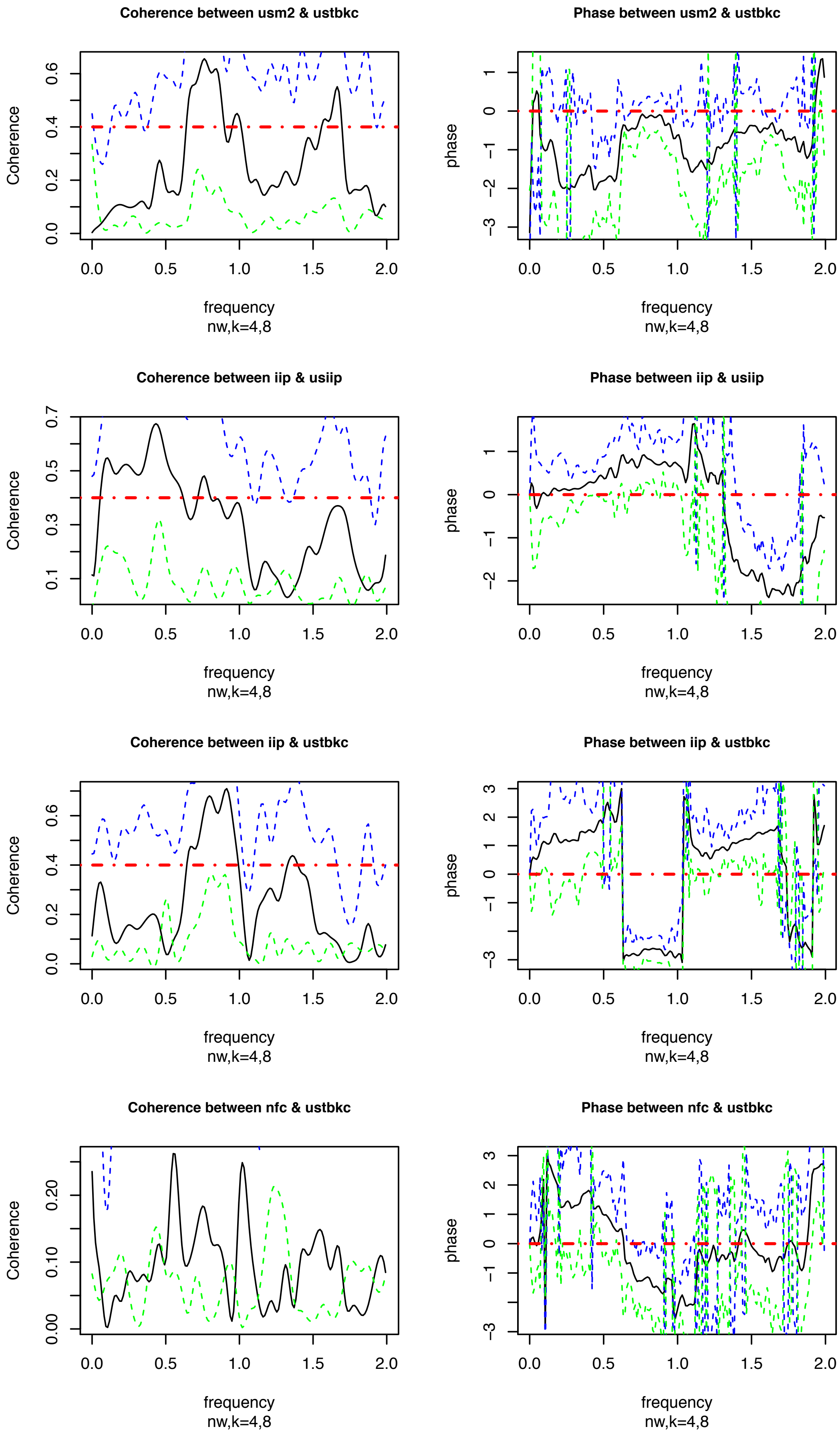

Figure 2: Coherence and Phase Bivariate Multitaper Estimates for NW = 4, K = 8, nFFT = 1024. Dotted lines show the jackknife confidence intervals

6 Conclusions

Objective of this chapter was to understand the cyclical properties of credit and relationship of Indian economic time series in the frequency domain. Given the short length of economic time series, Multitaper method of spectrum estimation was used which reduces spectral leakage and thus gives better results than classical methods of spectral analysis. The cyclical duration of real and financial series was estimated using representative reference series for credit and output.

One of the most intriguing finding from the Multitaper spectrum is that credit cycles are of approximately the same length as that of output cycles. Paper has clearly shown that choice of smoothing parameter when using HP filter to make the series stationary needs to selected with caution as a very high value of λ might lead to erroneous conclusions regarding duration of credit and business cycles. Further work which helps denoise the series correctly and use of Thompson F-test then will give a more accurate picture of the periodicity of the series.

Strength of synchronization and the lead lag relations for each pair of series was computed using coherence and phase along with reporting of the jackknife confidence intervals. Overall we found a high coherence between USIIP and credit variables in the US economy but for India, coherence between IIP and NFC is high only in very long run. Empirical findings show that credit leads output in US but reverse holds for India as the financial sector in the two economies are very different. This suggests that features of country be taken into account when examining relationship between credit and output.

For US, strong synchronization between credit and output gives credence to role of credit and its impact on the real economy. It is also important from the point of view of monitoring credit booms as precursors of financial crises and setting policy targets.

Relatively short length of time series available is the major limitation in detecting cycles of longer period. Although multitaper method is applicable for short time series, more reliable results may be obtained in case of countries with longer time series but is difficult in the case of economic data. Choice of NW and K is subjective and results are sensitive to this choice. The bias variance tradeoff in selecting the number of tapers and time bandwidth parameter is based on inspection of graphs and involves an element of judgement. The results of duration of a series must be interpreted keeping this in mind. The detailed tables of duration for selected combinations of NW and K show that the cyclical duration can vary from 2 to 16 years but the graphs and confidence intervals give a reasonable idea of whether that is valid choice.

Another limitation which we want to address in the next stage of research is the discrepancy in the results from maximum in spectral density and Thompson F-test graphs which suggests that there might be high frequency components which are biasing the results. These components may be due to the agrarian fluctuations or otherwise. The presence of these components maybe tested and removed by denoising the series. The F-test can then be more reliable in indicating the more dominant low frequency.

Further study on the choice of detrending method is required as it has a major impact on the results of spectrum estimation. First differencing as a way to remove the stochastic trends also removes the low frequency cyclical components of interest . More research into methods which make the series stationary without creating spurious cycles is much needed. Comparison of such methods and more clarity on ways to remove stochastic trends will make spectral results more reliable.

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