

CONSUMER CONFIDENCE AND SECTORAL STOCK RETURNS IN CHINA: EVIDENCE FROM MULTI-RESOLUTIONS WAVELET AND GRANGER COHERENCE ANALYSES

Sameer Al Barghouthi

Al Falah University

Saba Qureshi*

University of Sindh

Ijaz Ur Rehman

Al Falah University

Faisal Shahzad

COMSATS Institute of Information Technology

Fiza Qureshi

Universiti Malaya

ABSTRACT

We empirically examine the dynamic relationship between consumer confidence and sectoral returns at diverse time periods in China using monthly data over the period of 1992-2016. Using Wavelet coherence, we find evidence of sectoral returns leading consumer confidence and the interconnection is robust across medium and long run horizons. However, there is no consistent stability in direction of this linkage. Further, the study investigates the causal connection among variables at various time spans using granger coherence. Empirical findings confirm that sectoral returns as a predictor of consumer confidence thus signaling the projective contents of changes in the consumer confidence. The causal relation is significantly stronger in the long term and is notably dominated by deviating causality sways. The results have useful implications for institutional investors, speculators and portfolio managers.

Keywords: Consumer Confidence; Sector Returns; Wavelet Coherence; Granger Coherence.

1. INTRODUCTION

Over the last few decades, the role and development of stock markets has significantly increased across the world economies and market capitalization has witnessed many-fold surge across world stock markets. A developed stock market plays an important role in the financial market and hence contributes to the economic growth and development (Sajjad et al. 2012; Shahbaz et al. 2016b). The development of capital markets has attracted the attention of research to look into linkages of stock markets and real economy. Resultantly, financial economics literature has recorded a handful of studies noting the ability of stock markets to forecast economic growth. In fact, recent financial

* Corresponding Author: Institute of Business Administration, University of Sindh, Jamshoro, email: qureshisaba1990@gmail.com

economics literature considers stock market as a leading indicator of real economy (see for instance, Næs et al. 2011)¹. There are three well-known channels discussed in the theoretical literature that distinguish causal relationship between stock market and real economy namely, wealth effect (consumption-smoothing hypothesis), Investment, and balance sheet channel where credit market imperfection and related consequences are discussed (see for instance, Poterba, 2000; Barnett and Sakellaris, 1998; Bernanke et al. 1999). More recently, consumer's mood and their opinion also provide an indirect link to stock market². For instance, Ludvigson, (2004) noted that real economic activities and consumer confidence are highly correlated. More specifically, consumer confidence plays important role in the business cycles fluctuations. Blanchard (1993) for instance noted that the consumer confidence may be a cause of correlation between large negative consumption shocks and 1990-1991 recessions.

Since consumer confidence plays a substantial role in the level of economic activities such as consumption and expenditure, hence it is natural to anticipate that consumer confidence also plays a role in the stock market. The intuition behind the role of consumer confidence in stock market follows that, when investors' anticipate fear of worsen economy, they also anticipate the stocks will fall too and they will lose money. This kind of anticipation pushes the investors to sell their stocks and may cause the market to fall (Chen, 2011). In this vein, several studies have empirically examined the link between consumer confidence and investors behavior in the stock market. For instance, Otoo (1999) noted a strong contemporaneous correlation between consumer sentiments and changes in equity values. Jansen and Nahujs (2003) noted a positive correlation between change in the consumer sentiments and 9 out of 11 EU stock markets. Fisher and Statman (2003) noted that consumer confidence is positively correlated with high stock returns, but low stock returns follow high consumer confidence. Lemmon and Portniaguina (2006) conclude that returns of small stocks are forecasted by the consumer confidence and low level of institutional ownership. In a cross- countries setting, Sum (2014) shows that change in consumer confidence has a stronger effect on stock market returns as compared to the change in business confidence. Yacob and Mahdzan (2014) show that consumer sentiments hold significant predictive power driving the volatility of stock market. Ferrer et al. (2016) on the contrary noted that the CCI-stock market relationship is not universally positive. The role of consumer confidence in the stock returns can potentially be linked with the market efficiency phenomenon indirectly. For instance, financial theory suggests that, investors behave rationally in the stock market, however in reality; investors do not entirely act rationally owing to psychological factors that lead to anomalies in the market (Aftab et al. 2016).

Our interest is to empirically examining the role of consumer confidence in stock returns of China's stock market. Since early 1990s, the stock market in china has developed swiftly and in two decades, stock market in china has emerged as largest Asian stock market in term of market capital. The increasing importance of the China Stock market suggest that variations in the stock prices might have a significant and direct effects on China's economy (Hau, 2011). According to a Credit Suisse survey, consumer confidence in China has sharply increased from a year ago and Wage earners are expecting a real growth of 6.1 percent in their income over the next Six months³.

Our study departs from earlier studies and, therefore makes three-fold contributions to the existing literature. First, while earlier studies consider the impact of consumer confidence on the aggregate

¹ See for instance, Rehman et al (2016)

² Inflation also plays a significant role of the real economic activities in a sense that in order to fulfill consumption commitment; investors pull out some of their fund, and therefore affect asset prices. Shahbaz et al (2016a) noted that Inflation creates uncertainty and hence affects investment thus causing decline in the economic activity.

³ <http://www.scmp.com/business/markets/article/2083192/chinas-consumer-confidence-sharply-higher-2017-says-credit-suisse>

stock market, we examine the impact of consumer confidence on sectoral stock returns. Second, earlier studies use traditional approaches to examine the relationship between these two variables; we take advantage of Wavelet Coherence, Multi Resolution Wavelet, and Granger Coherence approaches. This approach ignores reduced data issues across long horizons and reveals term relationships between variables at different frequencies. Third, unlike other studies, we use Granger Coherence method at time and frequency domains to examine the causality between consumer confidence and sectoral stock returns.

The rest of the paper is organized as follow. Section 2 outlines the data and methodology of the study. Section 3, reports and discusses the results. Section 4 presents the conclusion and implications of the study.

2. DATA AND EMPIRICAL STRATEGIES

Monthly data on consumer confidence (CCI) and sector stock indices for China is used through the sample period of February 1992-February 2016 and has been collected from Thomson Reuter's DataStream. The analysis for 15 sector indices include Oil and gas, Basic material, Chemical, Basic resources, Industrial and mining, Construction, Aerospace and defense, Financial, Food and beverages, Health care, Retail, Personal and households, Technology, Travel and leisure and Utilities. However, the data time span for Technology, Oil and gas and Aerospace and defense commences from 1997, 1998 and 2000 respectively because of data unavailability. We exclude other indices since they are less representative and the constitution is complex. For empirical strategies, we take advantage of Wavelet methodology to examine the relationship between consumer confidence and sectoral stock returns. The details of Wavelet methodology are discussed below.

2.1. A brief note on Wavelet Analysis

Wavelet analysis disintegrates the data into numerous time scales which is generally more desirous than Fourier analysis owing to the fact that it can be crumbled more and further it does not demand stationarity in the series⁴. Consequently the said analysis depends on two main stream functions. Father wavelet represented as ' ϕ '; explains the inclination of a signal with considerably low frequencies whereas the mother wavelet ' τ ' represents the inclination of a signal with high frequencies in the trend.

The wavelet series estimate of a time series ' x_t ' is given by:

$$x(t) = \sum_k s_{J,K} \varphi_{j,k}(t) + \sum_k d_{J,K} \varphi_{j,k}(t) + \sum_k d_{J-1,K} \varphi_{j-1,k}(t) + \dots + \sum_k d_{1,K} \varphi_{1,k}(t) \quad (1)$$

Where ' J ' is the number of multi resolution scales, and k ranges from 1 to number of coefficients in the specified approximation. The $s_{J,K}, d_{J,K}, \dots, d_{1,K}$ are the wavelet transform coefficients. J is the maximum integer such that 2^J is less than the number of data points. The wavelet coefficients estimate the analogous wavelet function location in the series and also find out the influence of the analogous wavelet function to the approximation sum. The coefficients can be estimated by the following integrals:

⁴ For detailed discussion on wavelets, see for e.g.; Chui (1992), and Strang and Nguyen (1996), Schleicher (2002).

$$S_{J,k}(X) \approx \int_{-\infty}^{\infty} \varphi_{j,k} y(x) dx \tag{2}$$

$$D_{j,k(x)} \approx \int_{-\infty}^{\infty} \tau_{j,k} y(x) dx \quad (j = 1, 2, \dots, J) \tag{3}$$

Where $S_{j,k}$ signifies the smooth coefficients that confine the trend, while the higher frequency alternations are captured by the detail coefficients such as $d_{j,k} \dots d_{1,k}$ and which also represent increasing finer scale deviations from the smooth trend. The sum of the smooth signal $S_{j,k}$ and the detail signals is expressed by the wavelet series approximation of the original time series x_t given the coefficients.

$$x_t = S_{J,k} + D_{j,k} + D_{j-1,k} + \dots + D_{1,k} \tag{4}$$

Analogues to short run fluctuations elucidated by shocks mounting at time scale 2^i is denoted by D_j which represents the highest frequency component and similarly, mid and extendedly long run fluctuations are represented by rest of constituents at time scale 2^j . The data is decomposed into six levels since the study uses monthly data hence establishing $J=6$. D_j is then proceeded by average term and long term disparity as $2^1 = 2$ months, $2^2 = 4$ months. $2^6 = 64$ months.

2.2. Wavelet Power Transformation and Bias Correction

The wavelet decomposition is remedying and problem resolving of the issues which seems biased and impartial. In this regard problem may arise when approaching low frequency swings in wavelet power and cross power spectrum (Veleda et al, 2012). The issue of impartiality is rectified for consumer confidence and stock returns rates following Ng and Chan (2012). To present the wavelet coherence and power spectrum the standard approach of contour plot is used. Coherence power, time and period are its major facets, where, the vertical axis and horizontal axis shows the period and time respectively. The extent of similarity is indicated by range of colors from blue to red (low to high state of similarity).

2.3. Wavelet Coherence Transformation

It seems more optimum rely on Wavelet coherence to evaluate the joint interactive coherence among different variables. It is a useful tool which considers frequency, space and time intervals, thus differentiates possible relationships among two time series. Specifically, wavelet coherence locates correlation analysis by revealing infrequent periodic correlations between the series. The significance of the correlation relationship of two time series explains the coherence of cross wavelet of the series in time frequency space. This method implements the wavelet coherence analysis for the studies identifying relationships, even at intervals where high coherence occurs to cross wavelet power which illustrates areas with high common power; therefore, wavelet coherence is comparatively more useful. Nevertheless, the wavelet power spectrum of the two time series shows only minimal power (Aguar-Conraria and Soares, 2011; Grinsted et al., 2004). Based on the cross wavelet spectra and the auto-wavelet power, the wavelet coherence is defined as the cross spectra normalized by the two related auto-spectra. The wavelet coherence of the time series is expressed as

$$R_n^2(s) = \frac{|\nabla(s^{-1} w_n^{xy}(s))|^2}{\nabla(s^{-1} |w_n^x(s)|^2) \nabla(s^{-1} |w_n^y(s)|^2)} \tag{5}$$

Where, $R_n^2(s)$ and ∇ indicates the squared value of wavelet coherency and a smoothing operator, respectively. This smoothing operator is defined as, $\nabla(W) = \nabla_{scale} (\nabla_{time} (Wn(s)))$. ∇_{scale} and ∇_{time} represents the smoothing along the wavelet scale axis and smoothing in time, respectively. The properties of the correlation, that depicts strong or weak dependence between the two non-stationary time series over a particular period is described by the value of wavelet coherence, in wave function, which ranges between 0 and 1 (Akoum et al., 2012).

Phase-difference is defined as the angle of the arrow of the wavelet coherence ϑ_{XY} , which entails that phase lead of X over Y . Furthermore, phase and anti-phase is showed by same and reverse direction, respectively. The movement of the two time series which move together at the certain time frequency is implied by Zero phase-difference. Anti-phase relation is expressed by π or $-\pi$ expresses an. If $\vartheta_{XY} \in (0, \pi/2)$, then the Y leads X in the time series, conversely if $\vartheta_{XY} \in (-\pi/2, 0)$, then the time series is led by X . In case of arrows pointing to right down or left up the first variable is the leading one. Whereas, the arrows in the wavelet coherence explain that the second variable is leading if pointing towards right up or left down.

The time period in the wavelet coherence is plotted on horizontal axis and scale or frequency is plotted on vertical axis. To identify the areas that reveal wavelet coherence the analysis is conducted in these axes. Through warmer colors in the graph, significant interdependence between the series is shown. The lower dependence among frequencies and time is associated with colder colors on the other side. To estimate the significance level of wavelet coherence, the Monte Carlo method is used.

2.4. The Discrete Wavelet Transformation

The discrete sample wavelets transformation is based on two mechanisms known as wavelet filter and scaling filter symbolized by $h_l, l = 0, K, L - 1$ and $g_l, l = 0, K, L - 1$ ⁵. The matrix of DWT is constructed by the wavelet filters (a high-pass filter) $\{h_l\}_{l=0}^{L-1}$ and the scaling filters (low-pass filter) $\{g_l\}_{l=0}^{L-1}$ after the quadrature mirror relationship is satisfied specified as $g_l = (-1)^{l+1} h_{L-1-l}$ for $l = 0, \dots, L - 1$. The coefficients of wavelet and scaling time series $X(t)$ at the j^{th} level are stated as:

$$w_{j,t} = \sum_{l=0}^{L-1} h_{j,l} X_{2^j(t+1)-l-1 \bmod N}, t = 0, \dots, N-1, \quad (6)$$

$$v_{j,t} = \sum_{l=0}^{L-1} g_{j,l} X_{2^j(t+1)-l-1 \bmod N}, t = 0, \dots, N-1. \quad (7)$$

Daubachies –a constructive category of wavelet filters, supported the wavelet filters of width L and between the extremal phase filters $D(L)$ and the least asymmetric filters $LA(L)$ are differentiated (Daubechies, 1992).

Taking over less support for the number of vanishing moments Daubachies wavelet is one of the constructive property⁶. However, DWT suffers from the issues such as paired requirement of length which involves the sample size divisible by 2^j , and the shift invariant wavelet coefficients due to their sensitivity to circular shifts.

⁵ The scaling filter of support L is stated in order to fulfill few properties, (1) $\sum_{l=0}^{L-1} g_l = \sqrt{2}$, (2) $\sum_{l=0}^{L-1} g_l^2 = 1$

⁶ The number of vanishing moments is half the length of the filter for Daubechies wavelets.

2.5. Wavelet Granger Coherence Analysis

The traditional approaches advocate to granger causality which has considerably contributed to providing perceptive causality perspectives. Yet these approaches by the dint of their implicit perspective in determining the vivid direction and strength of causality vary over different frequencies. In the short and long run, the method of spectral density presents a comprehensive scenario than the only measure applied across all time periodicities. Pierce (1979) devised an explicit approach for disintegrating the granger causality between time series across the spectrum. The granger causality at each frequency was measured by proposing R squared for the time process which was decomposed over the spectrum's frequency p . This granger causality test depends on a modified coherence coefficient for which the distributional properties are derived with a nonparametric estimation. The measure is performed on the ut and vt , univariate innovation series that results from the derivation of X_t and Y_t which are then formed as univariate ARMA model.

$$\theta^x(L)X_t = C^x + \phi^x(L)u_t$$

$$\theta^y(L)Y_t = C^y + \phi^y(L)v_t \quad (8)$$

The potential deterministic components which are autoregressive polynomials are $\theta^x(L)$ and $\theta^y(L)$ respectively, moving average polynomials are represented as $\phi^x(L)$ and $\phi^y(L)$, and C^x and C^y . The ut and vt innovation series is attained with zero mean as a white noise process after the series have been filtered. Possibly they correlate with one another at different lags. Let the spectral density functions be $S_u \lambda$ and $S_v \lambda$ of ut and vt at frequency $\lambda \in]0, \pi[$ delineated as

$$S_u \lambda = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_u(k) e^{-i\lambda k} \text{ and } S_v \lambda = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_v(k) e^{-i\lambda k} \quad (9)$$

Where the auto covariance of ut and vt at k lag is represented as $\gamma_u(k) = \text{cov}(ut, ut-k)$ and $\gamma_v(k) = \text{cov}(vt, vt-k)$. To decompose each series into integral of components is concept of the representation which is uncorrelated, and each one is linked to a specific frequency. Koopmans (1995) presents detailed analysis on spectral time series. In order to assess the stochastic process, the allying ut and vt cross spectrum $S_{uv} \lambda$ is considered.

$$S_{uv} \lambda = C_{uv}(\lambda) + iQ_{uv}(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{-i\lambda k} \quad (10)$$

The parts of cross spectrum are displayed as cospectrum $C_{uv}(\lambda)$ and the quadrature spectrum Q_{uv} . The $\gamma_{uv}(k) = \text{cov}(ut, vt-k)$ is the cross covariance at lag k for ut and vt . The nonparametric modeling of cross spectrum which is said to be the weighted covariance estimator with the cross covariance

$\hat{\gamma}_{uv}(k) = \hat{Cov}(ut, vt - k)$ is shown by

$$\hat{S}_{uv} \lambda = \frac{1}{2\pi} \left\{ \sum_{k=-M}^M W_k \hat{\gamma}_{uv}(k) e^{-i\lambda k} \right\} \quad (11)$$

Koopmans (1995) explains that the cross spectrum permits the computation of coefficient of coherence

$$h_{uv}(\lambda) = \frac{|s_{uv}(\lambda)|}{\sqrt{s_u(\lambda)s_v(\lambda)}} \quad (12)$$

Linear relationship strength by frequency between the two series is explained by the coherence coefficient, although it does not account for the associative direction in the time series. The elaboration of squared coefficient of coherence is in line with the interpretation of R squared regression. The regression R squared of vt on every past and future values of ut is fundamental over frequencies of squared coefficient of coherence. According to Pierce (1979), the cross spectrum (10) performs the decomposition into following parts.

- i. $Su \leftrightarrow v$, the instant ut and vt relationship
- ii. $Su \rightarrow v$, the immediate direct relationship of vt and lagged ut
- iii. $Sv \rightarrow u$, the immediate direct relationship of ut and lagged vt

That is,

$$\begin{aligned} S_{uv} \lambda &= [S_{u \leftrightarrow v} + S_{u \rightarrow v} + S_{v \rightarrow u}] \\ &= \frac{1}{2\pi} [\gamma_{uv}(0) + \sum_{k=-\infty}^{-1} \gamma_{uv}(k) e^{-i\lambda k} + \sum_{k=1}^{\infty} \gamma_{uv}(k) e^{-i\lambda k}] \end{aligned} \quad (13)$$

The suggested measures of spectral GC support the property that X_t does not granger cause Y_t if $\gamma_{uv}(k) = 0$ for all $k < 0$. As a result, respective to Y_t one's interest would be in second part of equation 13, if the objective is to determine the predictive ability of X_t . Thus, granger coefficient coherence is specified as

$$h_{u \leftrightarrow v}(\lambda) = \frac{|s_{u \leftrightarrow v}(\lambda)|}{\sqrt{s_u(\lambda)s_v(\lambda)}} \quad (14)$$

3. RESULTS AND DISCUSSION

3.1. Preliminary Statistics

The analysis is based on changes in consumer confidence and returns. The return calculation is based on continuous compounding for log of first difference. The Table 1 displays the descriptive statistics for the CCI and all sector returns. The coefficients of skewness demonstrate that Consumer confidence index, Oil and gas and Health care are negatively skewed, while other variables show positive skewness. The kurtosis values indicate that most of the distribution has leptokurtic properties while few sectors also exhibit platykurtic properties in the series. Further, the Jarque Bera statistics of the series show evidence for normality rejection. The Ljung Box Q test indicates the presence of autocorrelation except Basic resources. Moreover, the unit root tests for all the return variables reject the unit root hypothesis at level as shown in table 2. The unit root results suggest -as expected- that all variables are found to be significant at 1% level of significance.

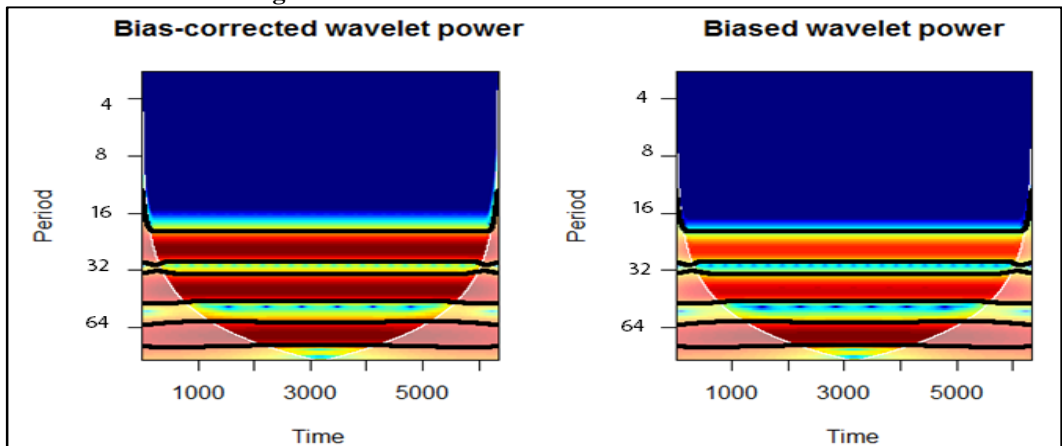
Table 1: Descriptive Statistics and Unit Root Testing

Variables	Skewness	Kurtosis	Jarque-Bera	Q(1) (ARCH)	Unit Root Test ADF Statistics
Consumer Confidence	-0.2196	2.9954	78.6174***	177.859(0.000)	-4.1917
Oil and Gas	-0.2587	1.0764	821.774***	164.745(0.000)	-10.7861
Basic Material	1.8424	2.2377	41.6263***	121.615(0.000)	-3.4852
Chemical	1.02211	3.3387	144.110***	40.796 (0.000)	-5.2387
Basic Resources	1.9311	7.5708	98.4353***	10.7307(0.585)	-4.2826
Industrial and Mining	0.8475	3.0257	42134.84***	17.4213(0.008)	-7.9877
Construction	1.2698	5.3031	378.18***	21.2109(0.000)	-6.2675
Aerospace and Defense	1.0997	4.4126	69.3426***	211.426(0.000)	-4.0772
Financial	0.37954	3.1862	1796.4***	6.9218 (0.009)	-9.0759
Food and Beverages	0.4473	2.6658	928.19***	9.5781 (0.002)	-8.8572
Health Care	-0.5088	138.636	486.17***	66.305 (0.000)	-7.7839
Retails	0.8613	4.6218	7824.15***	50.815 (0.000)	-10.5428
Personal and Households	0.6793	3.7170	7824.15***	50.815(0.000)	-9.4537
Technology	1.3539	6.2863	236.88***	51.815(0.000)	-11.5468
Travel and Leisure	1.4634	4.9447	69.273***	19.834 (0.002)	-7.1178
Utilities	0.5981	4.0943	271.47***	56.284 (0.000)	-9.6197

Notes: The table reports the summary statistics of Consumer confidence and Sector index returns. LM test is Breush Godfrey test in order to check serial correlation in the series with 12 lags. The statistics of Unit root test is significant at 1% level of significance.

3.2. Biased and Bias-Corrected Wavelet Power

We begin our analysis by correcting potential bias in the local wavelet power. The problem of biasness which occurs to the lower frequency vibrations in the cross spectrum⁷ is resolved using Bias correction following Ng and Chan (2012) as shown in Figure -1. Wavelet coefficients are used to generate the bias-corrected power that shows each frequency or period contribution in the time series.

Figure 1: Biased and Bias-Corrected Wavelet Powers

⁷Liu et al. 2007, Veleda et al. 2012

3.3. Cross Wavelet Power Spectrum

We then conduct cross- wavelet power spectrum to examine coherency between consumer confidence and sectoral stock returns. Figure 2-16 shows the plotted cross wavelet power spectrum of each series. The dimensions include the period on vertical axes, time on the horizontal axis and wavelet power where the color codes indicate the extent of similarity that is blue represents lower and red represents higher similarity. The prominent white line separates the regions of statistically significant squared coherences. The blue color is visibly governed in all series particularly at lower frequencies until the mid of the sample period implying stability over the time spans. It is noticeable that the period 64 is significant for all the variables across entire horizon during which the joint importance in the middle is deduced as per the series construction. This implies that changes in consumer confidence and sector returns synchronize at higher frequencies in China. Further, a common red vortex pattern is observed for Oil and gas, Aerospace and defense, Health care, Technology, Retail, Personal and households. However, these vortices are disintegrated which suggests the existence of short-lived shifts. However, the co movement analysis using the cross wavelet power spectrum is not preferred due to the shortcomings regarding phase information, therefore we use Wavelet coherence tool for analyzing the phase movements and differences among the series.

Figure 2: Cross Wavelet Power Levels: CCI -oil gas series

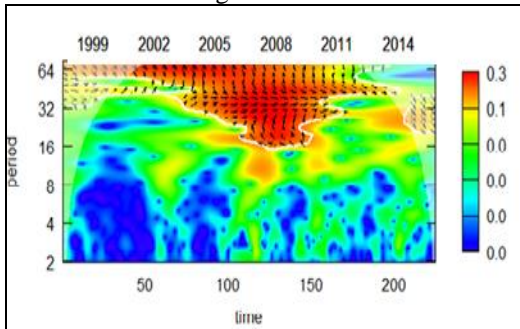


Figure 3: Cross Wavelet Power Levels: CCI- Basic material series

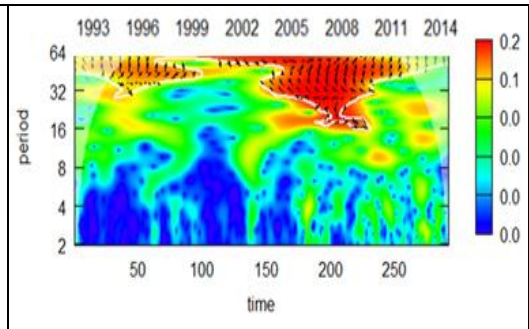


Figure 4: Cross Wavelet Power Levels: CCI - Chemical series

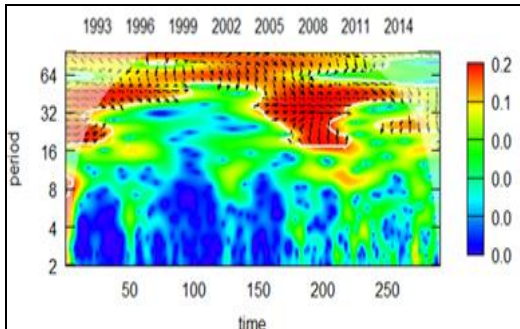


Figure 5: Cross Wavelet Power Levels: CCI- Basic resources series

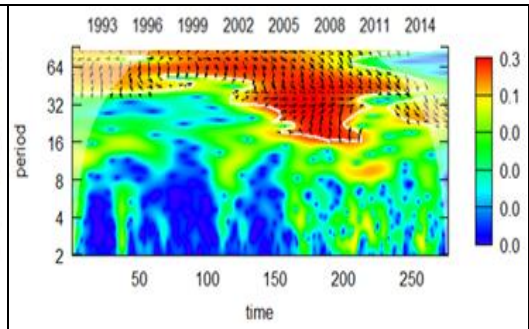


Figure 6: Cross Wavelet Power Levels: CCI - Industrial and mining series

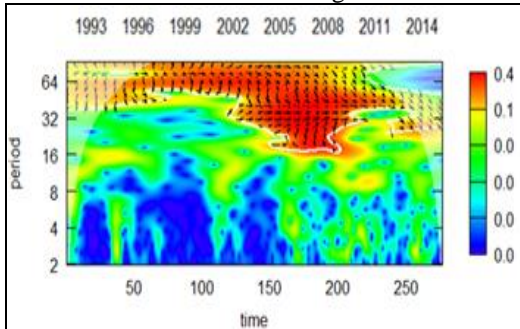


Figure 7: Cross Wavelet Power Levels: CCI - construction series

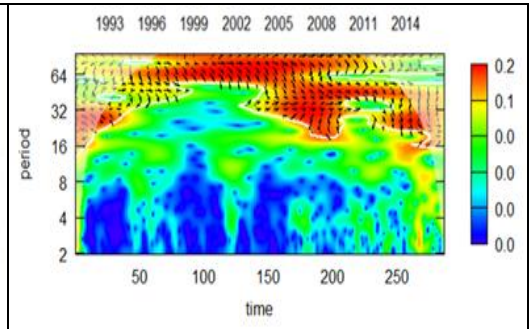


Figure 8: Cross Wavelet Power Levels: CCI - Aerospace and defense series

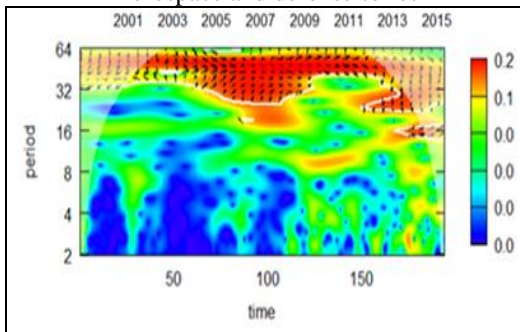


Figure 9: Cross Wavelet Power Levels: CCI - Financial series

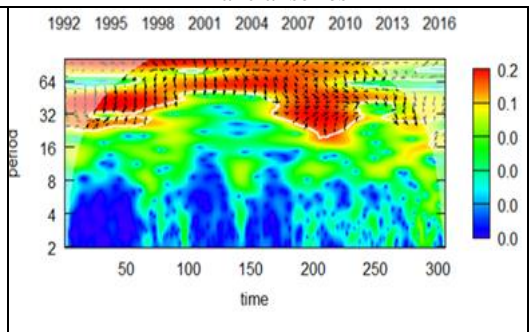


Figure 10: Cross Wavelet Power Levels: CCI - Food and beverages

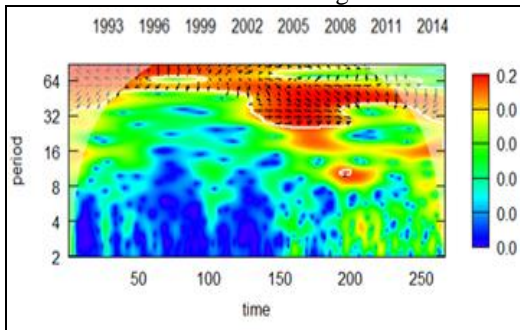


Figure 11: Cross Wavelet Power Levels: CCI - Health care

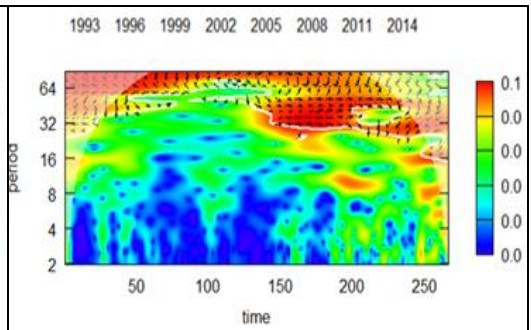


Figure 12: Cross Wavelet Power Levels: CCI- Retails

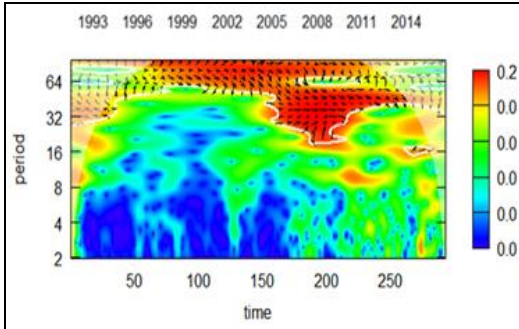


Figure 13: Cross Wavelet Power Levels: CCI - Personal and households

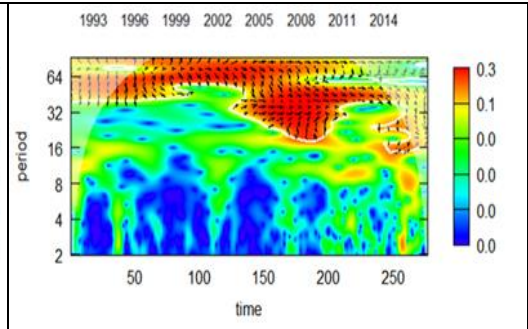


Figure 14: Cross Wavelet Power Levels: CCI - Technology

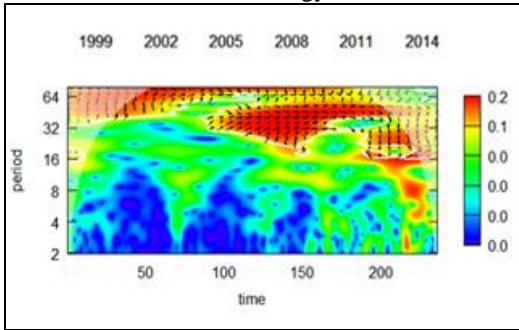


Figure 15: Cross Wavelet Power Levels: CCI - Travel and leisure

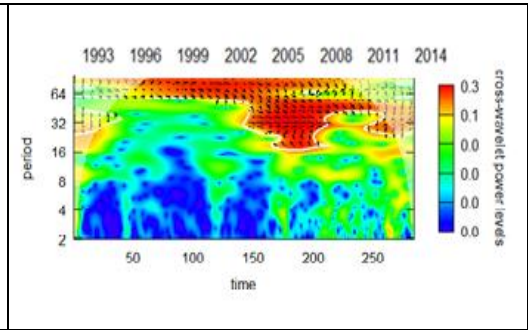
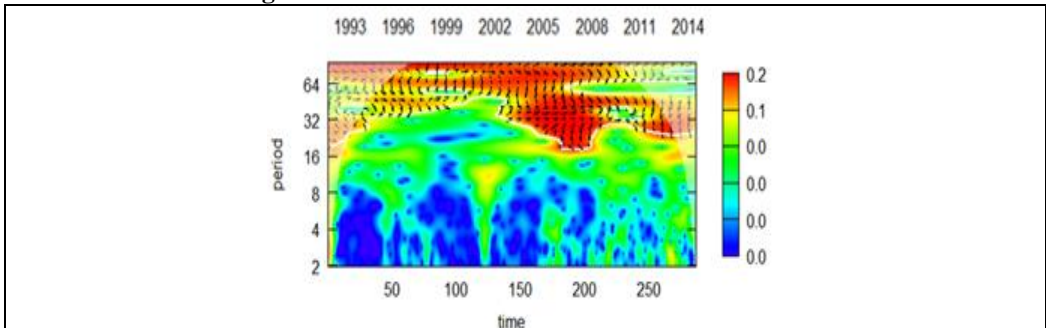


Figure 16: Cross Wavelet Power Levels: CCI-Utilities



3.4. Wavelet Coherence Analysis

The results of Wavelet coherence analysis are reported in the Figures 17-31. The Figure 17-31 show the wavelet relations among the series across various time horizons. From Figure 17, wavelet coherency of the CCI and Oil and gas reveal that there is interrelation between variables in the 4th month in different periods whereas the interrelation is strong in higher period frequency for the overall period. The arrows are in-phase in that period, signifying that oil and gas returns are leading the

consumer confidence in the long run. The Figure 20 shows n-phase movements for CCI and Basic resource mostly through 2003-2016. From the information of monthly long term frequencies, the arrows point towards right down, indicating that CCI is controlled to Basic resource returns suggesting that high sector returns stimulates consumer confidence. These results support study of Otoo (1999). Furthermore, the Figures 19 and 22 exhibit the CCI-Chemical and Construction returns respectively. The coherence for Chemical reveals mixed movements of both in phase and anti-phase for the period of 2004-2013 at different scales. Similarly, coherence for construction shows anti-phase movements during beginning of the sample period and in phase for the rest of the period that is 1997 and onwards.

Figure 17: Wavelet Coherence: CCI versus Oil **Figure 18:** Wavelet Coherence: CCI versus Basic material and gas

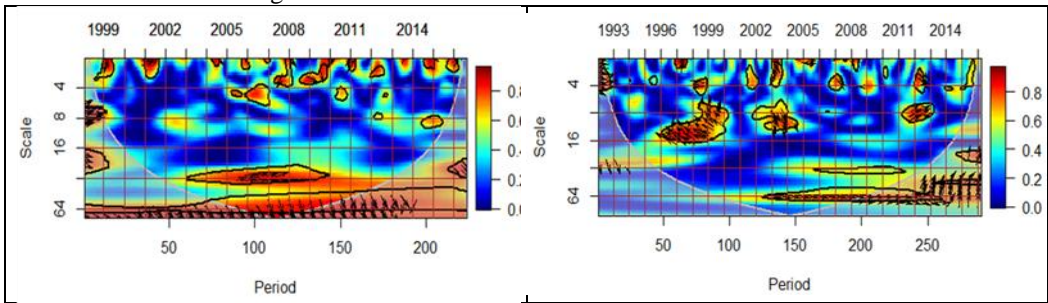


Figure 19: Wavelet Coherence: CCI versus Chemical **Figure 20:** Wavelet Coherence: CCI versus Basic resources

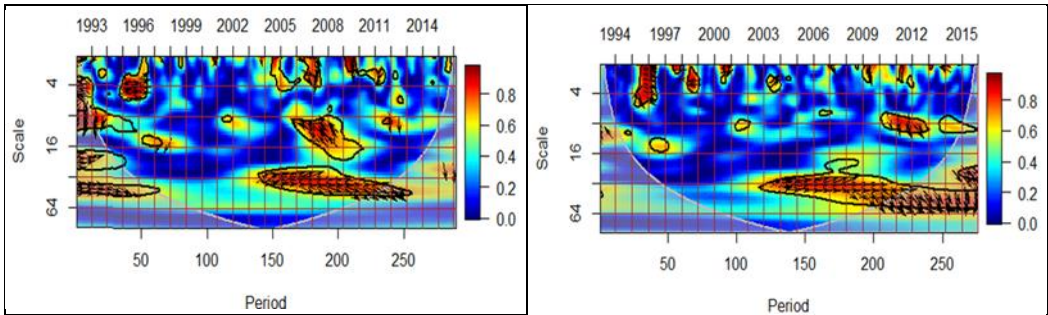


Figure 21: Wavelet Coherence: CCI versus Industrial and mining **Figure 22:** Wavelet Coherence: CCI versus Construction

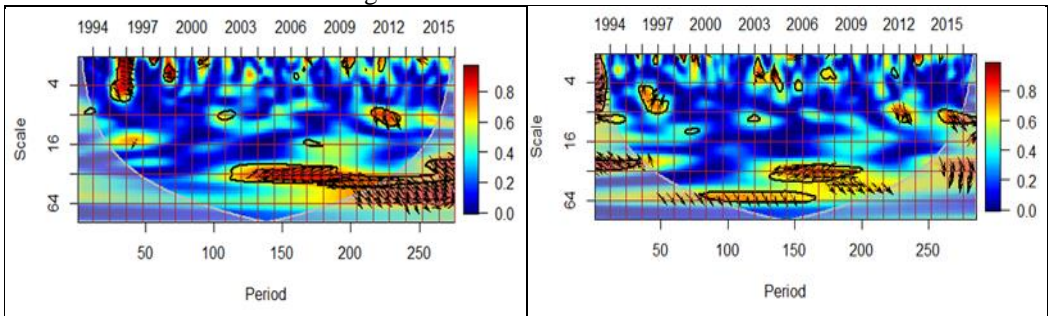


Figure 23: Wavelet Coherence: CCI versus Aerospace and defense

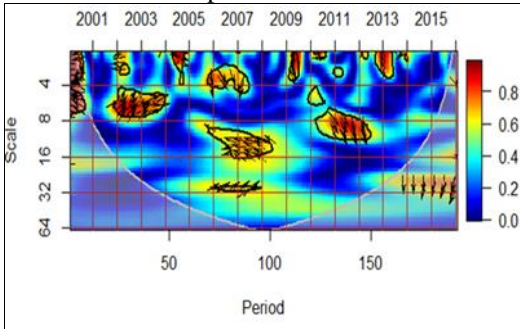


Figure 24: Wavelet Coherence: CCI versus Financial

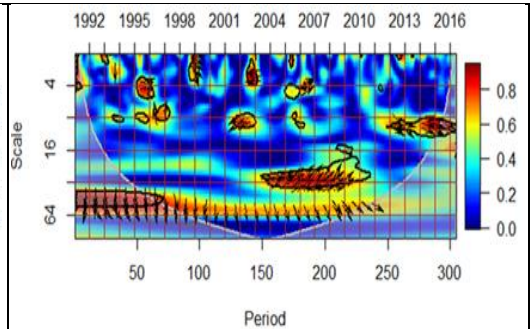


Figure 25: Wavelet Coherence: CCI versus Food and beverages

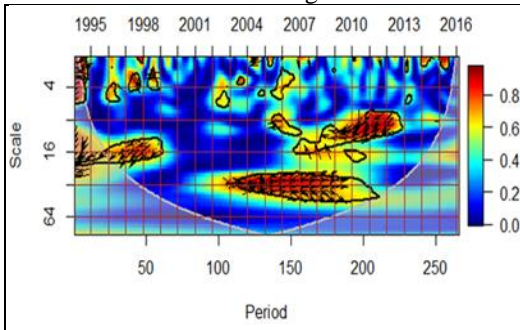


Figure 26: Wavelet Coherence: CCI versus Health care

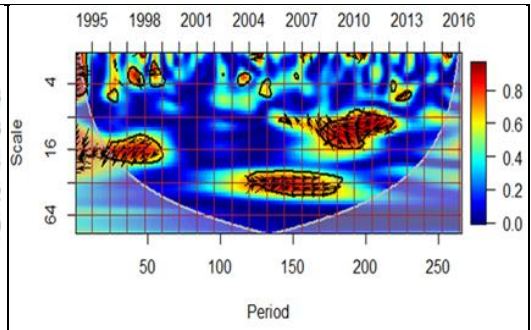


Figure 27: Wavelet Coherence: CCI versus Retails

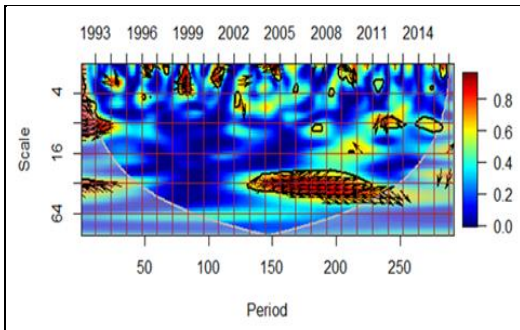


Figure 28: Wavelet Coherence: CCI versus Personal and households

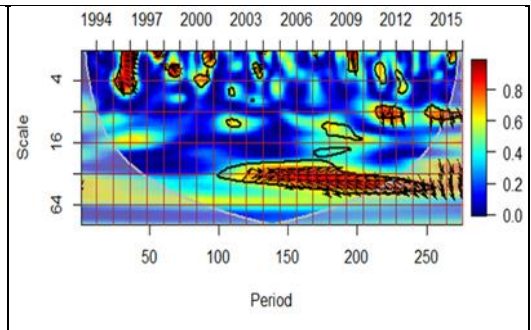
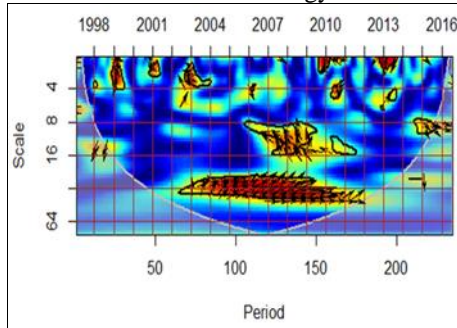
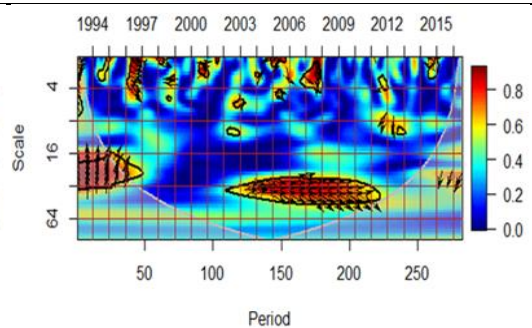
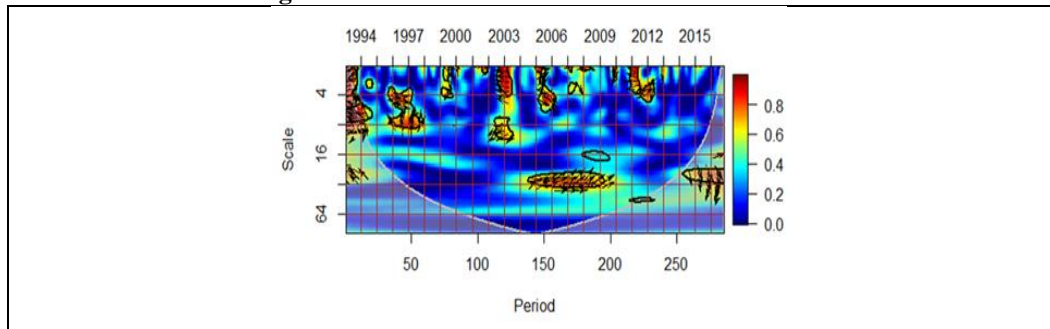


Figure 29: Wavelet Coherence: CCI versus Technology**Figure 30:** Wavelet Coherence: CCI versus Travel and leisure**Figure 31:** Wavelet Coherence: CCI versus Utilities

The Industrial and Mining and Personal and household coherences are observed in Figure 21 and 28 respectively whereby the predominant movements of both the sectors are in phase between 2003 and 2016. The right down direction of arrows confirms that CCI is controlled against fluctuations of Industrial and Mining and Personal and household returns. According to Figure 23, the coherence of the Aerospace and defense with CCI lies in the colder region in general, however the two variables interestingly switch movements to in-phase and anti-phase throughout the period. The findings reveal that significant relation is hardly observed at lower term frequencies for all the variables. Figure 24 displays the CCI and Financial coherency are mostly in-phase for the entire period between 1992 to 2011 and 2013 to 2016. The pointing of arrows indicates that Financials is leading the CCI. There is slight change in the direction of arrows from up to down over the period of 2005 – 2010.

The coherence of CCI and Health care in Figure 26 exhibits that the variables are typically anti-phase between 1994-1998 and 2008-2012. These results imply that the increase in consumer confidence would bring the returns down, hence corresponding to the findings of Fisher and Statman (2002). Further, from 1994 to 1998, the scale inter linkage fell in the 4th and 8th-32nd month scale. On the other hand, from 2004 to 2011 this significant relation was noticed in frequencies at different levels. Finally, figure 31 represents the Utilities-CCI whereby the insignificant interrelations are clear since the variables are observed to be surrounded by blue regions. During 2005-2010, the movement was in phase. Due to weak significance, a plain finding concerning the influence of the variables cannot be formed. The strength of the relation across all time periods is summarized in Table 3 which has been divided into main categories of lead and lag variables. The empirical evidence confirms that

Sector returns affect consumer confidence. On the other hand, there is less evidence of consumer confidence influence on return indices

Table 3: Wavelet Coherence Summary: CCI versus Sector returns

Return Indices	High Coherency (Period)	High Coherency (Scale)	Phase-Difference	Return Indices (Lead/ Lag)
Oil and Gas	2003-2010	32-64	In-phase	Leading
Basic Material	1996-1999	4-16	Anti-phase	Lagging
	2003-2012	64	In phase	Leading
Chemical	1992-1997	4-16	In-phase	Leading
	2005-2013	16-32	Anti-phase	Leading
Basic Resources	2003-2016	32-64	In-phase	Leading
Industrial and Mining	2003-2016	32-64	In-phase	Leading
Construction	2000-2009	32-64	Anti-phase	Leading
			In-phase	Leading
Aerospace and Defense	No any	No any	Anti-phase	Leading
			In-phase	Leading
Financial Services	2004-2009	16-64	In-phase	Both
	2012-2016			
Food and beverages	1994-1998	8-32	Anti-phase	Lagging
	2003-2011		In-phase	Leading
Health Care	1994-1999	8-16	Anti-phase	Both
	2004-2012		In-phase	Leading
Retails	2003-2011	16-64	Anti-phase	Leading
			In-phase	Leading
Personal and households	2004-2014	32-64	In-phase	Leading
Technology	2003-2010	16-64	Anti-phase	Leading
			In-phase	Lagging
Travel and Leisure	1993-1997	16-64	In-phase	Leading
	2002-2011			
Utilities	No any	No any	In-phase	Both

3.5. Granger Coherence Analysis

The study further investigates the causal relation of the changes in consumer confidence and sector returns using the Granger coherence technique. The Pierce framework⁸ based granger coefficients of coherence analyze the extent of the causalities at different frequencies. The 5% level of critical bound significance is represented by the baseline as depicted in Figures 32-46. We observe a consistent pattern across most of the series specifically Travel and leisure, Utilities, Health care, Personal and households, Construction, Food and beverages and Basic resources whereby the Granger causalities at lower frequencies correspond to the short run constituents and the causalities at higher frequencies coincide with long run constituents. However, this increasing trend is nonlinear and continuously sways until the highest frequency. This finding suggests that the granger causality remains pronounced at higher frequency periods. While there is less causality evidence over all the frequency levels for Industrial and Mining and Oil and gas. The composition of coefficients of coherence for Basic material, Chemical, Financial, Aerospace and defense, Retails and Technology confirms that the magnitude of returns significantly causes the consumer confidence which is notable in the very

⁸ See for example, Pierce (1979)

long run reaching nearly 80%. In addition, the causality swings cannot be ignored as reflected by the coefficients of coherence in Tables shown in appendix⁹.

Figure 32: Granger Coefficient of Coherence: CCI rate versus Oil and gas

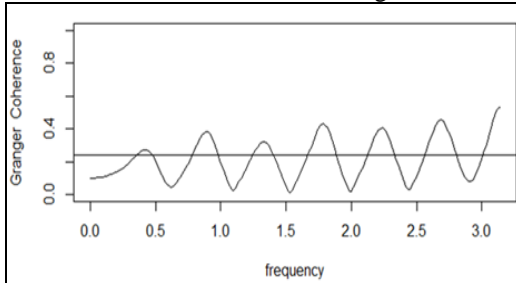


Figure 33: Granger Coefficient of Coherence: CCI rate versus Basic material

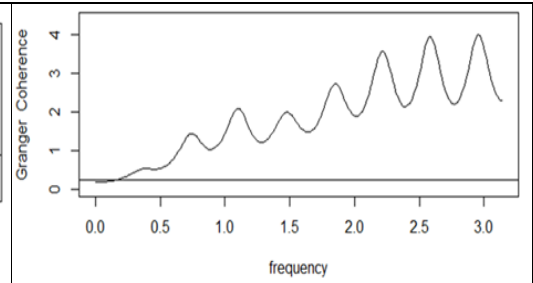


Figure 34: Granger Coefficient of Coherence: CCI rate versus Chemical

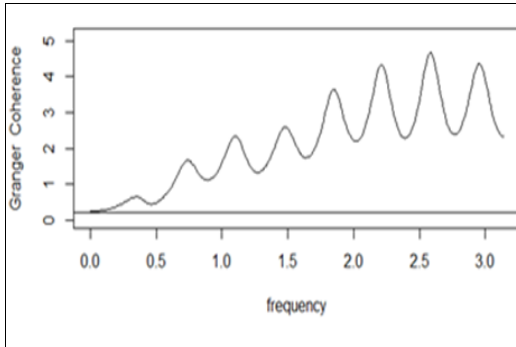


Figure 35: Granger Coefficient of Coherence: CCI rate versus Basic resources

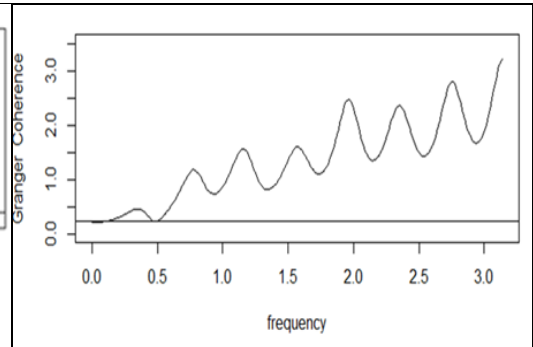


Figure 36: Granger Coefficient of Coherence: CCI rate versus Industrial and mining

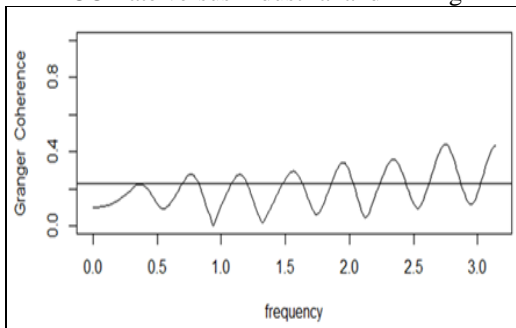
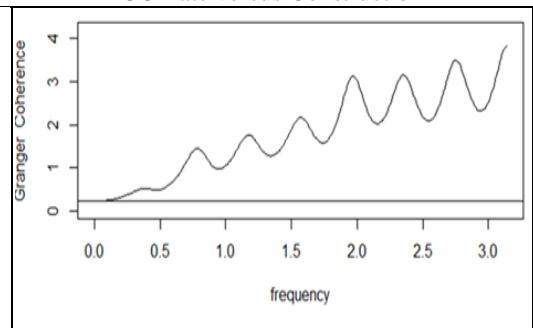


Figure 37: Granger Coefficient of Coherence: CCI rate versus Construction



⁹ Results of coefficients of coherence for rest of the sectors are available upon request

Figure 38: Granger Coefficient of Coherence: CCI rate versus Aerospace and defense

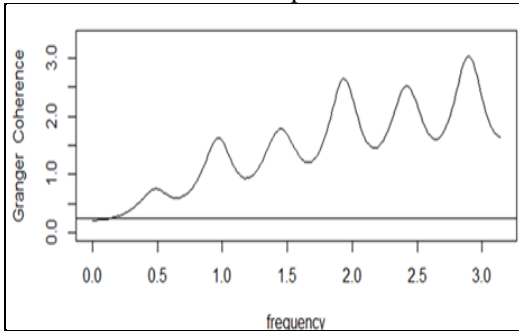


Figure 39: Granger Coefficient of Coherence: CCI rate versus Financial

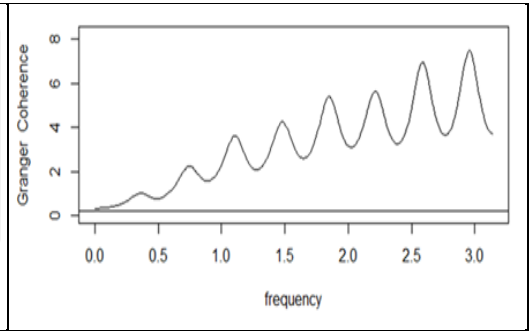


Figure 40: Granger Coefficient of Coherence: CCI rate versus Food and beverages

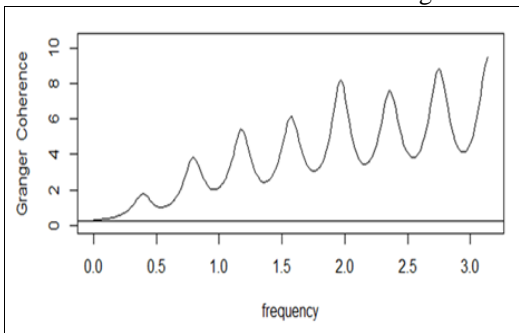


Figure 41: Granger Coefficient of Coherence: CCI rate versus Health care

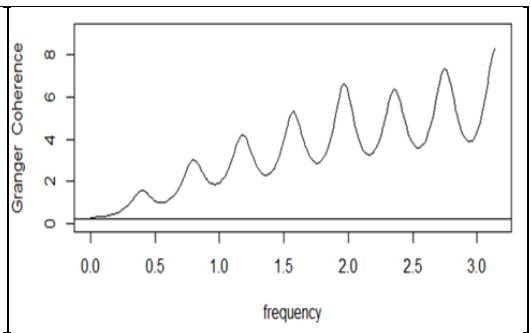


Figure 42: Granger Coefficient of Coherence: CCI rate versus Retails

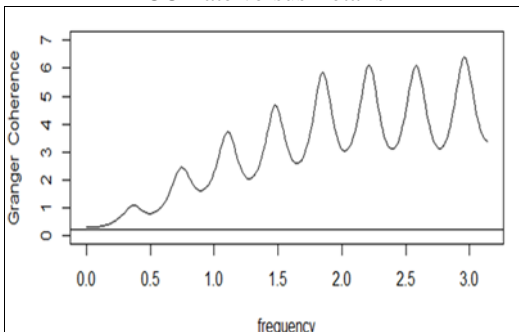


Figure 43: Granger Coefficient of Coherence: CCI rate versus Personal and households

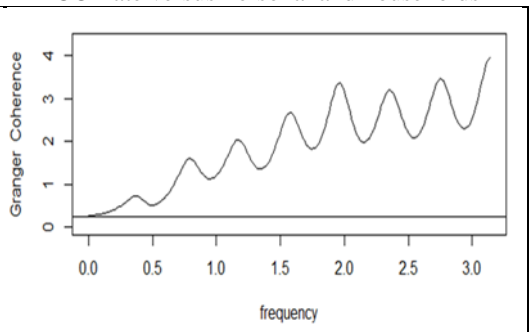
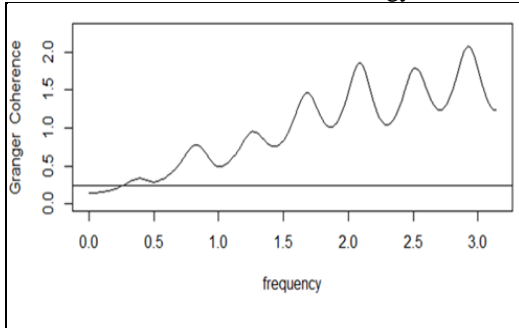
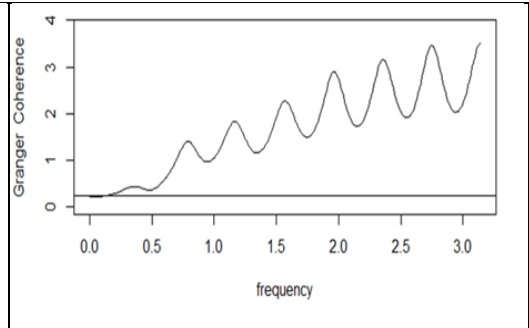
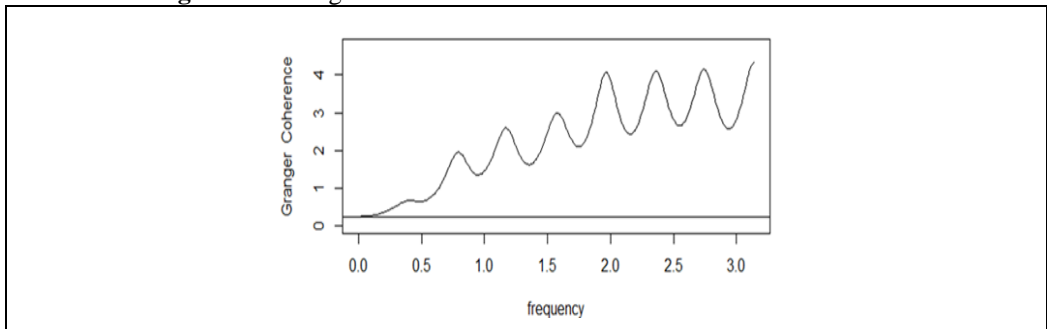


Figure 44: Granger Coefficient of Coherence: CCI rate versus Technology**Figure 45:** Granger Coefficient of Coherence: CCI rate versus Travel and leisure**Figure 46:** Granger Coefficient of Coherence: CCI rate versus Utilities

4. CONCLUSIONS AND IMPLICATIONS

While previous studies extensively analyze consumer confidence and sector returns linkage and causality for the overall time period, this paper investigates the consumer confidence changes and sectoral returns relationship using Wavelet and granger coherence methodologies which provides useful insights at various frequency domains. We find that the consumer confidence sector return indices association differs across sectors. The results are thus mainly categorized as Sector returns lead consumer confidence and the direction of association keeps shifting. Most of the sectors predict changes in consumer confidence and the coherency is stronger for medium and long run frequencies. These findings have implications for institutional investors who trade for a longer horizon cycle. It may also assist heterogeneous decisions of market participants to counterpart the investment heterogeneity. Further, by decomposing the causalities over various time periods, we identify that sector returns significantly predict consumer confidence. The causalities are momentous at the highest frequencies implying strength in the long run however this strength is illustrious by unswerving causality swings. The speculators and portfolio managers therefore may assess the forecasting ability for future economic changes.

REFERENCES

- Aftab, M., Rehman, I. U., & Anifowose, A. D. (2016). Disposition Effect and Asset Pricing in an Emerging Stock Market. *International Journal of Economics and Empirical Research*, 4(6), 320-332.
- Aguiar-Conraria, L., & Soares, M. J. (2011). Oil and the macroeconomy: using wavelets to analyze old issues. *Empirical Economics*, 40(3), 645-655.
- Akoun, I., Graham, M., Kivihaho, J., Nikkinen, J., & Omran, M. (2012). Co-movement of oil and stock prices in the GCC region: A wavelet analysis. *The Quarterly Review of Economics and Finance*, 52(4), 385-394.
- Barnett, S. A., & Sakellaris, P. (1998). Non-Linear Response of Firm Investment to Q: Testing a Model of Convex and Non-Convex Adjustment Costs. *Journal of Monetary Economics*, 42(2), 261-288.
- Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1(Part C), 1341-1393.
- Blanchard, O. (1993). Consumption and the Recession of 1990-1991. *The American Economic Review*, 83(2), 270-274.
- Chen, S. S. (2011). Lack of consumer confidence and stock returns. *Journal of Empirical Finance*, 18(2), 225-236.
- Chui, C. K. (1992). *Wavelet analysis and its applications*. USA: Academic press.
- Daubechies, I. (1992). *Ten lectures on wavelets*. Philadelphia, USA: Society for industrial and applied mathematics (SIAM).
- Ferrer, E., Salaber, J., & Zalewska, A. (2016). Consumer confidence indices and stock markets' meltdowns. *The European Journal of Finance*, 22(3), 195-220.
- Fisher, K. L., & Statman, M. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management*, 30(1), 115-127.
- Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear processes in geophysics*, 11(5/6), 561-566.
- Hau, L. C. (2011). Stock Market and Consumption: Evidence from China. *Berkeley Undergraduate Journal*, 24(3), 35-49.
- Jansen, W. J., & Nahuis, N. J. (2003). The stock market and consumer confidence: European evidence. *Economics Letters*, 79(1), 89-98.
- Koopmans, L. H. (1995). *The spectral analysis of time series*. San Diego: Academic press.
- Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, 19(4), 1499-1529.
- Liu, Y., Liang X. S., & Weisberg R. H. (2007). Rectification of the Bias in the Wavelet Power Spectrum. *Journal of Atmospheric and Oceanic Technology*, 24, 2093-2102.
- Ludvigson, S. C. (2004). Consumer confidence and consumer spending. *The Journal of Economic Perspectives*, 18(2), 29-50.
- Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock market liquidity and the business cycle. *The Journal of Finance*, 66(1), 139-176.
- Ng, E. K., & Chan, J. C. (2012). Geophysical applications of partial wavelet coherence and multiple wavelet coherence. *Journal of Atmospheric and Oceanic Technology*, 29(12), 1845-1853.
- Otoo, M. W. (1999). *Consumer Sentiment and the Stock Market*. Finance and Economics Discussion Series No 1999-60.
- Pierce, D. A. (1979). R-squared measures for time series. *Journal of the American Statistical Association*, 74, 901-910.

- Poterba, J. M. (2000). Stock market wealth and consumption. *The Journal of Economic Perspectives*, 14(2), 99-118.
- Rehman, I. U., Mahdzan, N. S., & Zainudin, R. (2016). Is the relationship between macroeconomy and stock market liquidity mutually reinforcing? Evidence from an emerging market. *International Journal of Monetary Economics and Finance*, 9(3), 294-316
- Sajjad, S., Jan, S. U., Saddat, M., & Rehman I. U. (2012). Exploring the Nexus; Stock Market, T. Bills, Inflation, Interest Rate and Exchange Rate. *Journal of Economics and Behavioral Studies*, 4(7), 384-389
- Schleicher, C. (2002). *An introduction to wavelets for economists*. Bank of Canada Working Paper 2002-3.
- Shahbaz, M., Islam, F., & Rehman, I. U. (2016a). Stocks as hedge against inflation in Pakistan: Evidence from ARDL approach. *Global Business Review*, 17(6), 1280-1295.
- Shahbaz, M., Rehman, I. U., & Afza, T. (2016b). Macroeconomic determinants of stock market capitalization in an emerging market: fresh evidence from cointegration with unknown structural breaks. *Macroeconomics and Finance in Emerging Market Economies*, 9(1), 75-99.
- Strang, G., & Nguyen, T. (1996). *Wavelet and Filter Banks*. Wellesley, MA: Wellesley-Cambridge Press.
- Sum, V. (2014). Effects of business and consumer confidence on stock market returns: Cross-sectional evidence. *Economics, Management, and Financial Markets*, 9(1), 21-25.
- Veleda, D., Montagne, R., & Araujo, M. (2012). Cross-wavelet bias corrected by normalizing scales. *Journal of Atmospheric and Oceanic Technology*, 29(9), 1401-1408.
- Yacob, N., & Mahdzan, N. S. (2014). The predictive ability of consumer sentiment's volatility to the Malaysian stock market's volatility. *Afro-Asian Journal of Finance and Accounting*, 4(4), 460-476.

APPENDICES

Appendix 1: Granger Coefficients of Coherence for CCI and oil and gas

[1,]	[2,]	[3,]	[4,]	[5,]	[6,]	[7,]	[8,]	[9,]	[10,]
0.1003	0.1005	0.1010	0.1017	0.1028	0.10426468	0.10601850	0.1081	0.1106	0.1135
[11,]	[12,]	[13,]	[14,]	[15,]	[16,]	[17,]	[18,]	[19,]	[20,]
0.1168	0.1206	0.12492064	0.1297	0.1351	0.1411	0.1478	0.1552	0.1634	0.1723
[21,]	[22,]	[23,]	[24,]	[25,]	[26,]	[27,]	[28,]	[29,]	[30,]
0.1819	0.1923	0.20337713	0.2148	0.2266	0.2382	0.2491	0.2588	0.2665	0.2714
[31,]	[32,]	[33,]	[34,]	[35,]	[36,]	[37,]	[38,]	[39,]	[40,]
0.2727	0.2698	0.26245500	0.2504	0.2342	0.2145	0.1923	0.1685	0.1441	0.1201
[41,]	[42,]	[43,]	[44,]	[45,]	[46,]	[47,]	[48,]	[49,]	[50,]
0.0974	0.0767	0.05933657	0.0474	0.0439	0.0494	0.0608	0.0752	0.0910	0.1079
[51,]	[52,]	[53,]	[54,]	[55,]	[56,]	[57,]	[58,]	[59,]	[60,]
0.1255	0.1440	0.16354267	0.1840	0.2056	0.2282	0.2518	0.2760	0.3002	0.3236
[61,]	[62,]	[63,]	[64,]	[65,]	[66,]	[67,]	[68,]	[69,]	[70,]
0.3449	0.3628	0.37552211	0.3815	0.3796	0.3693	0.3511	0.3261	0.2959	0.2626
[71,]	[72,]	[73,]	[74,]	[75,]	[76,]	[77,]	[78,]	[79,]	[80,]
0.2279	0.1932	0.15975233	0.1279	0.0984	0.0712	0.0471	0.0288	0.0258	0.0394
[81,]	[82,]	[83,]	[84,]	[85,]	[86,]	[87,]	[88,]	[89,]	[90,]
0.0583	0.0783	0.09891914	0.1197	0.1410	0.1627	0.1847	0.2070	0.2293	0.2512
[91,]	[92,]	[93,]	[94,]	[95,]	[96,]	[97,]	[98,]	[99,]	[100,]
0.2718	0.2905	0.30608987	0.3173	0.3232	0.3229	0.3160	0.3026	0.2837	0.2602
[101,]	[102,]	[103,]	[104,]	[105,]	[106,]	[107,]	[108,]	[109,]	[110,]
0.2335	0.2050	0.17585183	0.1467	0.1184	0.0911	0.0652	0.0408	0.0193	0.0152
[111,]	[112,]	[113,]	[114,]	[115,]	[116,]	[117,]	[118,]	[119,]	[120,]
0.0339	0.0555	0.07779064	0.1004	0.1238	0.1480	0.1733	0.1998	0.2276	0.2566

Appendix 1: Granger Coefficients of Coherence for CCI and oil and gas (cont.)

[121,]	[122,]	[123,]	[124,]	[125,]	[126,]	[127,]	[128,]	[129,]	[130,]
0.2865	0.3167	0.34626502	0.3738	0.3978	0.4162	0.4272	0.4292	0.4217	0.4047
[131,]	[132,]	[133,]	[134,]	[135,]	[136,]	[137,]	[138,]	[139,]	[140,]
0.3796	0.3483	0.31280754	0.2752	0.2372	0.2001	0.1645	0.1310	0.0996	0.0704
[141,]	[142,]	[143,]	[144,]	[145,]	[146,]	[147,]	[148,]	[149,]	[150,]
0.0435	0.0214	0.02066078	0.0406	0.0638	0.0877	0.1121	0.1371	0.1628	0.1894
[151,]	[152,]	[153,]	[154,]	[155,]	[156,]	[157,]	[158,]	[159,]	[160,]
0.2169	0.2452	0.27394110	0.3025	0.3301	0.3556	0.3774	0.3939	0.4035	0.4049
[161,]	[162,]	[163,]	[164,]	[165,]	[166,]	[167,]	[168,]	[169,]	[170,]
0.3976	0.3819	0.35896559	0.3302	0.2976	0.2631	0.2279	0.1932	0.1598	0.1280
[171,]	[172,]	[173,]	[174,]	[175,]	[176,]	[177,]	[178,]	[179,]	[180,]
0.0980	0.0701	0.04543211	0.0284	0.0318	0.0508	0.0743	0.0995	0.1257	0.1530
[181,]	[182,]	[183,]	[184,]	[185,]	[186,]	[187,]	[188,]	[189,]	[190,]
0.1815	0.2112	0.24224586	0.2742	0.3067	0.3391	0.3703	0.3989	0.4232	0.4416
[191,]	[192,]	[193,]	[194,]	[195,]	[196,]	[197,]	[198,]	[199,]	[200,]
0.4524	0.4546	0.44771288	0.4322	0.4094	0.3809	0.3487	0.3144	0.2796	0.2454
[201,]	[202,]	[203,]	[204,]	[205,]	[206,]	[207,]	[208,]	[209,]	[210,]
0.2126	0.1817	0.1531	0.1273	0.1051	0.0879	0.07812197	0.07794826	0.0875	0.1046
[211,]	[212,]	[213,]	[214,]	[215,]	[216,]	[217,]	[218,]	[219,]	[220,]
0.1270	0.1532	0.1826	0.21497222	0.2500	0.2876	0.32734218	0.36823012	0.4090	0.4477

Appendix 2: Granger Coefficients of Coherence for CCI and Basic resources

[1,]	[2,]	[3,]	[4,]	[5,]	[6,]	[7,]	[8,]	[9,]	[10,]
0.217	0.2179	0.2186	0.2199	0.2216	0.2238	0.2266	0.2299	0.2338	0.2383
[11,]	[12,]	[13,]	[14,]	[15,]	[16,]	[17,]	[18,]	[19,]	[20,]
0.2434	0.2491	0.2555	0.2626	0.2705	0.2792	0.2887	0.2990	0.3102	0.3223
[21,]	[22,]	[23,]	[24,]	[25,]	[26,]	[27,]	[28,]	[29,]	[30,]
0.3352	0.3489	0.3633	0.3782	0.3934	0.4086	0.4233	0.4370	0.4488	0.4579
[31,]	[32,]	[33,]	[34,]	[35,]	[36,]	[37,]	[38,]	[39,]	[40,]
0.4635	0.4645	0.4602	0.4500	0.4339	0.4121	0.3856	0.3558	0.3248	0.2947
[41,]	[42,]	[43,]	[44,]	[45,]	[46,]	[47,]	[48,]	[49,]	[50,]
0.2683	0.2483	0.2369	0.2356	0.2439	0.2604	0.2832	0.3103	0.3406	0.3732
[51,]	[52,]	[53,]	[54,]	[55,]	[56,]	[57,]	[58,]	[59,]	[60,]
0.4078	0.4440	0.4821	0.5219	0.5638	0.6079	0.6543	0.7032	0.7544	0.8078
[61,]	[62,]	[63,]	[64,]	[65,]	[66,]	[67,]	[68,]	[69,]	[70,]
0.8629	0.9189	0.9747	1.0286	1.0786	1.1222	1.1569	1.1801	1.1898	1.1849
[71,]	[72,]	[73,]	[74,]	[75,]	[76,]	[77,]	[78,]	[79,]	[80,]
1.1655	1.1328	1.0895	1.0390	0.9851	0.9314	0.8812	0.8369	0.8004	0.7727
[81,]	[82,]	[83,]	[84,]	[85,]	[86,]	[87,]	[88,]	[89,]	[90,]
0.7543	0.7451	0.7447	0.7526	0.7681	0.7907	0.8198	0.8550	0.8960	0.9425
[91,]	[92,]	[93,]	[94,]	[95,]	[96,]	[97,]	[98,]	[99,]	[100,]
0.9941	1.0505	1.1112	1.1753	1.2418	1.3089	1.3746	1.4361	1.4903	1.5336
[101,]	[102,]	[103,]	[104,]	[105,]	[106,]	[107,]	[108,]	[109,]	[110,]
1.5628	1.5750	1.5687	1.5436	1.5010	1.4439	1.3761	1.3020	1.2259	1.1513
[111,]	[112,]	[113,]	[114,]	[115,]	[116,]	[117,]	[118,]	[119,]	[120,]
1.0814	1.0183	0.9635	0.9178	0.8816	0.8547	0.8369	0.8278	0.8268	0.8334
[121,]	[122,]	[123,]	[124,]	[125,]	[126,]	[127,]	[128,]	[129,]	[130,]
0.8471	0.8673	0.8938	0.9262	0.9641	1.0072	1.0552	1.1077	1.1640	1.2233
[131,]	[132,]	[133,]	[134,]	[135,]	[136,]	[137,]	[138,]	[139,]	[140,]
1.2846	1.3462	1.4065	1.4631	1.5137	1.5557	1.5865	1.6042	1.6075	1.5962
[141,]	[142,]	[143,]	[144,]	[145,]	[146,]	[147,]	[148,]	[149,]	[150,]
1.5711	1.5343	1.4882	1.4361	1.3812	1.3266	1.2749	1.2283	1.1885	1.1565
[151,]	[152,]	[153,]	[154,]	[155,]	[156,]	[157,]	[158,]	[159,]	[160,]
1.1334	1.1195	1.1152	1.1207	1.1359	1.1609	1.1957	1.2404	1.2950	1.3595
[161,]	[162,]	[163,]	[164,]	[165,]	[166,]	[167,]	[168,]	[169,]	[170,]
1.4340	1.5183	1.6120	1.7142	1.8235	1.9377	2.0534	2.1663	2.2707	2.3605

Appendix 2: Granger Coefficients of Coherence for CCI and Basic resources (cont.)

[171,]	[172,]	[173,]	[174,]	[175,]	[176,]	[177,]	[178,]	[179,]	[180,]
2.4292	2.4711	2.4823	2.4618	2.4111	2.3347	2.2388	2.1306	2.0170	1.9039
[181,]	[182,]	[183,]	[184,]	[185,]	[186,]	[187,]	[188,]	[189,]	[190,]
1.7963	1.6975	1.6100	1.5351	1.4736	1.4257	1.3912	1.3698	1.3612	1.3647
[191,]	[192,]	[193,]	[194,]	[195,]	[196,]	[197,]	[198,]	[199,]	[200,]
1.3800	1.4066	1.4440	1.4918	1.5494	1.6162	1.6914	1.7736	1.8612	1.9519
[201,]	[202,]	[203,]	[204,]	[205,]	[206,]	[207,]	[208,]	[209,]	[210,]
2.0428	2.1303	2.2102	2.2780	2.3295	2.3609	2.3698	2.3555	2.3191	2.2631
[211,]	[212,]	[213,]	[214,]	[215,]	[216,]	[217,]	[218,]	[219,]	[220,]
2.1913	2.21085	2.0193	1.9280	1.8386	1.7541	1.6769	1.6089	1.5513	1.5050
[221,]	[222,]	[223,]	[224,]	[225,]	[226,]	[227,]	[228,]	[229,]	[230,]
1.4703	1.4477	1.4372	1.4390	1.4531	1.4794	1.5181	1.5689	1.6318	1.7066
[231,]	[232,]	[233,]	[234,]	[235,]	[236,]	[237,]	[238,]	[239,]	[240,]
1.7930	1.8901	1.9967	2.1111	2.2306	2.3516	2.4693	2.5783	2.6726	2.7460
[241,]	[242,]	[243,]	[244,]	[245,]	[246,]	[247,]	[248,]	[249,]	[250,]
2.7935	2.8116	2.7991	2.7574	2.6901	2.6025	2.5009	2.3915	2.2799	2.1709
[251,]	[252,]	[253,]	[254,]	[255,]	[256,]	[257,]	[258,]	[259,]	[260,]
2.0684	1.9751	1.8930	1.8236	1.7676	1.7256	1.6979	1.6849	1.6865	1.7031
[261,]	[262,]	[263,]	[264,]	[265,]	[266,]	[267,]	[268,]	[269,]	[270,]
1.7347	1.7814	1.8435	1.9207	2.0130	2.1197	2.2397	2.3711	2.5108	2.6544
[271,]	[272,]	[273,]	[274,]	[275,]	[276,]				
2.7963	2.9292	3.0450	3.1353	3.1929	3.2127				

Appendix 3: Granger Coefficients of Coherence for CCI and Chemical

[1,]	[2,]	[3,]	[4,]	[5,]	[6,]	[7,]	[8,]	[9,]	[10,]
0.2555	0.2558	0.2567	0.2583	0.2605	0.2635	0.2671	0.2714	0.2765	0.2823
[11,]	[12,]	[13,]	[14,]	[15,]	[16,]	[17,]	[18,]	[19,]	[20,]
0.2891	0.2967	0.3052	0.3148	0.3254	0.3372	0.3502	0.3645	0.3801	0.3972
[21,]	[22,]	[23,]	[24,]	[25,]	[26,]	[27,]	[28,]	[29,]	[30,]
0.4157	0.4356	0.4570	0.4796	0.5034	0.5278	0.5526	0.5769	0.5999	0.6203
[31,]	[32,]	[33,]	[34,]	[35,]	[36,]	[37,]	[38,]	[39,]	[40,]
0.6371	0.6486	0.6537	0.6512	0.6409	0.6230	0.5988	0.5703	0.5403	0.5117
[41,]	[42,]	[43,]	[44,]	[45,]	[46,]	[47,]	[48,]	[49,]	[50,]
0.4871	0.4688	0.4581	0.4554	0.4604	0.4724	0.4902	0.5131	0.5404	0.5715
[51,]	[52,]	[53,]	[54,]	[55,]	[56,]	[57,]	[58,]	[59,]	[60,]
0.6062	0.6446	0.6867	0.7328	0.7831	0.8380	0.8977	0.9625	1.0322	1.1068
[61,]	[62,]	[63,]	[64,]	[65,]	[66,]	[67,]	[68,]	[69,]	[70,]
1.1855	1.2672	1.3500	1.4310	1.5069	1.5732	1.6256	1.6600	1.6738	1.6660
[71,]	[72,]	[73,]	[74,]	[75,]	[76,]	[77,]	[78,]	[79,]	[80,]
1.6381	1.5934	1.5366	1.4728	1.4069	1.3430	1.2845	1.2335	1.1914	1.1590
[81,]	[82,]	[83,]	[84,]	[85,]	[86,]	[87,]	[88,]	[89,]	[90,]
1.1365	1.1240	1.1213	1.1280	1.1441	1.1692	1.2034	1.2465	1.2986	1.3598
[91,]	[92,]	[93,]	[94,]	[95,]	[96,]	[97,]	[98,]	[99,]	[100,]
1.4299	1.5089	1.5963	1.6912	1.7920	1.8964	2.0008	2.1006	2.1901	2.2631
[101,]	[102,]	[103,]	[104,]	[105,]	[106,]	[107,]	[108,]	[109,]	[110,]
2.3134	2.3362	2.3287	2.2911	2.2269	2.1416	2.0424	1.9363	1.8300	1.7285
[111,]	[112,]	[113,]	[114,]	[115,]	[116,]	[117,]	[118,]	[119,]	[120,]
1.6358	1.5543	1.4853	1.4294	1.3868	1.3570	1.3396	1.3342	1.3402	1.3571
[121,]	[122,]	[123,]	[124,]	[125,]	[126,]	[127,]	[128,]	[129,]	[130,]
1.3846	1.4226	1.4707	1.5289	1.5970	1.6746	1.7615	1.8565	1.9585	2.0652
[131,]	[132,]	[133,]	[134,]	[135,]	[136,]	[137,]	[138,]	[139,]	[140,]
2.1738	2.2802	2.3798	2.4669	2.5358	2.5818	2.6012	2.5927	2.5577	2.4996
[141,]	[142,]	[143,]	[144,]	[145,]	[146,]	[147,]	[148,]	[149,]	[150,]
2.4236	2.3360	2.2427	2.1493	2.0603	1.9790	1.9081	1.8490	1.8029	1.7703
[151,]	[152,]	[153,]	[154,]	[155,]	[156,]	[157,]	[158,]	[159,]	[160,]
1.7515	1.7465	1.7554	1.7782	1.8150	1.8661	1.9315	2.0116	2.1065	2.2163

Appendix 3: Granger Coefficients of Coherence for CCI and Chemical (cont.)

[161,]	[162,]	[163,]	[164,]	[165,]	[166,]	[167,]	[168,]	[169,]	[170,]
2.3408	2.4790	2.6296	2.7897	2.9551	3.1200	3.2765	3.4154	3.5268	3.6016
[171,]	[172,]	[173,]	[174,]	[175,]	[176,]	[177,]	[178,]	[179,]	[180,]
3.6330	3.6182	3.5591	3.4620	3.3362	3.1922	3.0402	2.8891	2.7456	2.6148
[181,]	[182,]	[183,]	[184,]	[185,]	[186,]	[187,]	[188,]	[189,]	[190,]
2.4997	2.4024	2.3237	2.2640	2.2235	2.2018	2.1989	2.2147	2.2492	2.3024
[191,]	[192,]	[193,]	[194,]	[195,]	[196,]	[197,]	[198,]	[199,]	[200,]
2.3747	2.4662	2.5773	2.7079	2.8579	3.0260	3.2102	3.4065	3.6089	3.8086
[201,]	[202,]	[203,]	[204,]	[205,]	[206,]	[207,]	[208,]	[209,]	[210,]
3.9942	4.1516	.2664	4.3259	4.3225	4.2556	4.1323	3.9653	3.7703	3.5623
[211,]	[212,]	[213,]	[214,]	[215,]	[216,]	[217,]	[218,]	[219,]	[220,]
3.3541	.1553	2.9724	2.8093	2.6681	2.5494	2.4533	2.3795	2.3273	2.2963
[221,]	[222,]	[223,]	[224,]	[225,]	[226,]	[227,]	[228,]	[229,]	[230,]
2.2861	.2965	.3275	2.3793	2.4524	2.5473	2.6644	2.8041	2.9664	3.1503
[231,]	[232,]	[233,]	[234,]	[235,]	[236,]	[237,]	[238,]	[239,]	[240,]
3.3537	.5724	3.7999	4.0264	4.2392	4.4230	4.5622	4.6429	4.6566	4.6017
[241,]	[242,]	[243,]	[244,]	[245,]	[246,]	[247,]	[248,]	[249,]	[250,]
4.4844	4.3167	4.1143	3.8929	3.6666	3.4466	3.2408	3.0543	2.8900	2.7492
[251,]	[252,]	[253,]	[254,]	[255,]	[256,]	[257,]	[258,]	[259,]	[260,]
2.6323	2.5390	2.4686	2.4206	2.3942	2.3891	2.4049	2.4415	2.4989	2.5771
[261,]	[262,]	[263,]	[264,]	[265,]	[266,]	[267,]	[268,]	[269,]	[270,]
2.6761	.7957	2.9353	3.0934	3.2676	3.4536	3.6453	3.8345	4.0105	4.1615
[271,]	[272,]	[273,]	[274,]	[275,]	[276,]	[277,]	[278,]	[279,]	[280,]
.2754	4.3420	4.3544	4.3113	4.2167	4.0789	3.9096	3.7211	3.5248	3.3305
[281,]	[282,]	[283,]	[284,]	[285,]	[286,]	[287,]	[288,]	[289,]	[290,]
3.1454	2.9749	2.8221	2.6891	2.5766	2.4850	2.4141	2.3638	2.3337	2.3237

Appendix 4: Granger Coefficients of Coherence for CCI and Basic material

[1,]	[2,]	[3,]	[4,]	[5,]	[6,]	[7,]	[8,]	[9,]	[10,]
0.1880	0.1882	0.1889	0.1901	0.1917	0.1938	0.1963	0.1994	0.2031	0.2073
[11,]	[12,]	[13,]	[14,]	[15,]	[16,]	[17,]	[18,]	[19,]	[20,]
0.2121	0.2176	0.2237	0.2306	0.2382	0.2467	0.2560	0.2663	0.2776	0.2899
[21,]	[22,]	[23,]	[24,]	[25,]	[26,]	[27,]	[28,]	[29,]	[30,]
0.3034	0.3180	0.3338	0.3507	0.3686	0.3875	0.4072	0.4273	0.4474	0.4671
[31,]	[32,]	[33,]	[34,]	[35,]	[36,]	[37,]	[38,]	[39,]	[40,]
0.4857	0.5025	0.5169	0.5283	0.5363	0.5409	0.5422	0.5408	0.5375	0.5332
[41,]	[42,]	[43,]	[44,]	[45,]	[46,]	[47,]	[48,]	[49,]	[50,]
0.5289	0.5255	0.5236	0.5239	0.5268	0.5324	0.5411	0.5528	0.5676	0.5856
[51,]	[52,]	[53,]	[54,]	[55,]	[56,]	[57,]	[58,]	[59,]	[60,]
0.6069	0.6317	0.6600	0.6921	0.7281	0.7683	0.8129	0.8618	0.9151	0.9726
[61,]	[62,]	[63,]	[64,]	[65,]	[66,]	[67,]	[68,]	[69,]	[70,]
1.0337	1.0975	1.1626	1.2271	1.2884	1.3435	1.3894	1.4229	1.4418	1.4449
[71,]	[72,]	[73,]	[74,]	[75,]	[76,]	[77,]	[78,]	[79,]	[80,]
1.4325	1.4062	1.3689	1.3241	1.2755	1.2267	1.1804	1.1388	1.1036	1.0756
[81,]	[82,]	[83,]	[84,]	[85,]	[86,]	[87,]	[88,]	[89,]	[90,]
1.0554	1.0431	1.0388	1.0424	1.0539	1.0732	1.1001	1.1349	1.1774	1.2278
[91,]	[92,]	[93,]	[94,]	[95,]	[96,]	[97,]	[98,]	[99,]	[100,]
1.2861	1.3521	1.4256	1.5059	1.5918	1.6814	1.7720	1.8599	1.9408	2.0095
[101,]	[102,]	[103,]	[104,]	[105,]	[106,]	[107,]	[108,]	[109,]	[110,]
2.0609	2.0905	2.0956	2.0755	2.0318	1.9685	1.8907	1.8043	1.7148	1.6269
[111,]	[112,]	[113,]	[114,]	[115,]	[116,]	[117,]	[118,]	[119,]	[120,]
1.5441	1.4689	1.4030	1.3471	1.3016	1.2663	1.2410	1.2254	1.2189	1.2213
[121,]	[122,]	[123,]	[124,]	[125,]	[126,]	[127,]	[128,]	[129,]	[130,]
1.2320	1.2509	1.2775	1.3115	1.3527	1.4006	1.4545	1.5138	1.5773	1.6437
[131,]	[132,]	[133,]	[134,]	[135,]	[136,]	[137,]	[138,]	[139,]	[140,]
1.7110	1.7770	1.8391	1.8944	1.9400	1.9733	1.9922	1.9958	1.9840	1.9582

