Central Bank Review
Vol. 14 (May 2014), pp.1-11

ISSN 1303-0701 print 1305-8800 online

https://www3.tcmb.gov.tr/cbr/

INFLATION-INDUSTRIAL GROWTH NEXUS IN INDIA – A REVISIT THROUGH CONTINUOUS WAVELET TRANSFORM

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ABSTRACT We study the inflation-industrial growth nexus in India using the methodology of wavelets. More specifically, cross wavelet power spectrum, cross wavelet coherency, and wavelet phase angle, tools of *Continuous Wavelet Transform* are used to unravel time and frequency dependent relationships between industrial growth and inflation. It is shown that inflation and industrial growth are negatively related at low frequencies having time dynamics of eight to sixteen months, with inflation leading industrial growth for almost whole of the time period considered.
JEL C40, E31, E32, E64
Keywords Inflation-industrial growth nexus, Time-frequency relationship, Continuous Wavelet, India

ÖZ Bu çalışmada Hindistan'daki enflasyon-sanayi üretim büyümesi arasındaki ilişki, dalgacıklar yöntemi kullanılarak incelenmektedir. Daha ayrıntılı olarak, enflasyon ve sanayi üretim büyümesi arasındaki zaman ve frekans bağımlı ilişkiyi açığa çıkarmak için, çapraz dalgacık güç spektrumu, çapraz dalgacık tutarlılığı ve dalgacık faz açısı, *Sürekli Dalgacık Dönüşümü* araçları kullanılmıştır. Enflasyon ve sanayi üretim büyümesi arasındaki negatif ilişkinin düşük frekanslarda özellikle sekizden onaltı aya kadar olan frekans aralığında belirgin olduğu, incelenen zaman aralığının neredeyse tümünde enflasyonun sanayi üretimini öncülediği gösterilmiştir.
HİNDİSTAN'DA ENFLASYON SANAYİ ÜRETİMİ İLİŞKİSİ – SÜREKLİ DALGACIK DÖNÜŞÜMÜ ÜZERİNDEN BİR YENİDEN ZİYARET
JEL C40, E31, E32, E64
Anahtar Kelimeler Enflasyon–sanayi üretimi ilişkisi, Zaman frekansı ilişkisi, Sürekli dalgacık, Hindistan

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1. Introduction

The inflation-industrial growth nexus debate has now become one of the most widely discussed issues since the resurgence of interest in economic growth. Motivated by the concern that in many developing countries the surge in inflation might eventually retard growth of economy, many researchers have focussed on the problem and sought to establish a relationship between inflation and growth of the economy. Despite these efforts the issue still remains controversial and there is no consensus regarding the theory and empirical findings. The structuralists and monetarists, for example, hold contrast opinion regarding the inflation-growth nexus. While structuralists believe that inflation is vital for economic growth, monetarists perceive inflation as deleterious to growth. Theoretical evidence therefore hovers around the possibilities of inflation with and without development and no inflation with and without development.

A voluminous body of literature in both developed and developing countries focuses on the empirical verification of this relationship.[1] These studies however, have used either single country data or multi-country panel data to study the relationship within time domain framework. Nevertheless, the dynamic relationship between inflation and growth can vary across different frequencies and true economic relationships among variables can be expected to hold at the disaggregated (scale) level rather than at the usual aggregation level (Gallegati et al., 2011). The recent work by Gallegati et al. (2011) highlights some of the issues related to the estimation of inflation-growth relationship within time domain framework. They use wavelet time scale decomposition based on *Maximal Overlap Discrete Wavelet Transform* (MODWT) to decompose the time series into different frequencies and subsequently use conventional econometric techniques to study the relationships at different frequencies. Recent applications of MODWT in analyzing time-frequency relationships can be found in Dar et al. (2013) and Tiwari et al. (2013a, 2013b).

The *Continuous Wavelet Transform* (CWT) can, however, be used with much more ease for same type of analysis without relying on conventional econometric techniques. Moreover, it can offer new insights regarding the variation of relationship across different frequencies and over time. Further,

[1] See for example: Barro (1990), Fischer (1993), Bruno and Easterly (1996), Ambler and Cardia (1997), Ghosh and Phillips (1998), Singh and Kalirajan (2003), and Burdekin et al. (2004).

it can also be used to unravel the causal relationship between two variables over different time scales.

We therefore revisit the relationship between inflation and industrial growth using the methodology of CWT. Given this methodology, we try to answer the following questions: Is the empirical inflation growth nexus primarily a long-run, medium-run, or short-run relationship and how does this relationship vary across different frequencies and over time? What is the direction of causality across different frequencies and over time? Is the lead-lag relationship cyclical or counter-cyclical?

Our results based on CWT, using the tools of cross wavelet power spectrum (XWT), cross wavelet coherency (WTC), and wavelet phase angle, unravel some relationships, which could have been difficult to detect using conventional econometric techniques. Our results indicate a consistent relationship over time between inflation and industrial growth at frequencies corresponding to the time dynamics of 8~16 months. It is shown that inflation and industrial growth are negatively related and inflation is leading the industrial growth for most of the time. At other frequencies the two variables are mostly independent with ephemeral relationships emerging at times.

The remainder of the paper is organised as follows. The Section 2 describes motivation and introduction to methodology. The Section 3 gives the data description. In the Section 4, the results of the empirical estimation are presented and discussed; and finally the Section 5 draws the conclusions.

2. Motivation and Introduction to Methodology

Until recent past, the inflation-growth nexus has been estimated using conventional time domain approach and underlying time scales have been ignored. The dynamic relationship between inflation and growth can vary across different frequencies and some appealing relations may exist at different frequencies. In fact, true economic relationships among variables can be expected to hold at disaggregated (scale) level rather than at the usual aggregation level. For example, it is clear that strategies used by both employers and employees differ by time scale; that is, employers, for example, may adjust hours worked in the short-run, redesign the plant in the longer-run, move manufacturing abroad in the longest run (Gallegati et al., 2011). The recent work by Gallegati et al. (2011) tested inflation-growth relationship within time domain and subsequently used MODWT analysis to examine the relationship using conventional econometric techniques at each time scale separately. We nevertheless consider CWT for the same type of analysis without relying on conventional econometric techniques to unravel the frequency based relationship between inflation and industrial growth.

Torrence and Compo (1999) developed approaches of the cross wavelet power, the cross wavelet coherency, and the phase difference. We can directly study the interactions between two time series at different frequencies and how they evolve over time with the help of the cross wavelet tools. Whereas (single) wavelet power spectrum helps us understand the evolution of the variance of a time series at different frequencies, with periods of large variance associated with periods of large power at different scales. In brief, the cross-wavelet power of two time series illustrates the confined covariance between the time series. The wavelet coherency can be interpreted as correlation coefficient in the time-frequency space. The term "phase" implies the position in the pseudo-cycle of the series as a function of frequency. Consequently, the phase difference gives us information "on the delay, or synchronization, between oscillations of the two time series" (Aguiar-Conraria et al., 2008, p. 2867).

2.1. The Continuous Wavelet Transform (CWT)[2]

A wavelet, which is basically a function with zero mean and localization in both frequency and time, can be characterized by how localized it is in time (Δt) and frequency ($\Delta\omega$ or the bandwidth). Given the Δt and $\Delta\omega$, there is a limit to the size of the uncertainty of the product $\Delta t \cdot \Delta\omega$ can be. A special character wavelet, the Morlet, is given as

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2} \tag{1}$$

where η and ω_0 are dimensionless time and frequency, respectively.

Application of the CWT, in essence, is same as the application of band pass filter to the time series.[3] The CWT of a function defined over time ($x_n, n = 1,..., N$) with uniform time steps δt, is defined as the convolution of x_n and given as

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi_0 \left[\left(n' - n\right) \frac{\delta t}{s} \right] \tag{2}$$

We define the wavelet power as $\left|W_n^X(s)\right|^2$ and $W_n^X(s)$, which is interpreted as local phase. Since wavelet is not completely localized in time,

[2] The description of CWT, XWT, and WTC is heavily drawn from Grinsted et al. (2004). We are grateful to Grinsted and co-authors for making codes available at: http://www.pol.ac.uk/home/research/waveletcoherence/, which was utilized in the study.

[3] Since, Morlet wavelet (with ω_0 =6) is a good choice for feature extraction, we restrict to this wavelet type only.

Cone of Influence (COI) is introduced to show that below cone the observations are affected due to edge effects. The statistical significance of wavelet power can be assessed relative to the null hypotheses that the signal is generated by a stationary process with a given background power spectrum (P_k). However for general processes one has to rely on Monte-Carlo simulations.

2.2. The Cross Wavelet power

Given the wavelet transforms W^X and W^Y of x and y, the cross wavelet transform (XWT) is given as $W^{XY} = W^X W^{Y*}$. Here the cross wavelet power is defined as $\left|W^{XY}\right|$. For the cross wavelet power spectra of two time series with background power spectra P_k^X and P_k^Y, the theoretical distribution as shown by Torrence and Compo (1998) is given as

$$D\left(\frac{\left|W_n^X(s)W_n^{Y*}(s)\right|}{\sigma_X\sigma_Y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_k^X P_k^Y} \tag{3}$$

where $Z_v(p)$ indicates the confidence level with probability p for a pdf, which is synonymous with the square root of the product of two χ^2 distributions.

2.3. Wavelet Coherence (WTC)

Aguiar-Conraria et al. (2008, p. 2872) defines wavelet coherency as “the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series”. The wavelet coherence is defined as

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right)\cdot S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{4}$$

where S is a smoothing operator.

2.4. Cross Wavelet Phase Angle

In order to calculate the phase difference between two time series the mean and the confidence interval of the phase difference need to be estimated. For calculating the mean phase and quantifying the phase relationship, circular mean of the phase over regions with higher than 5% statistical significance that are outside the COI is used.

The lead lag relationship is given by wavelet phase is given by:

$$\phi_{x,y} = \tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \phi_{x,y} \in [-\pi, \pi] \tag{5}$$

R and I depict real and imaginary components of smooth power spectrum receptively. The phase relationship between two time series is given by phase difference. Time series X and Y are said to be in phase with Y leading X if $\phi_{x,y} \in [0, \pi/2]$ and X leading if $\phi_{x,y} \in [-\pi/2, 0]$. Contrary holds for anti-phase relationship.

3. Data Description

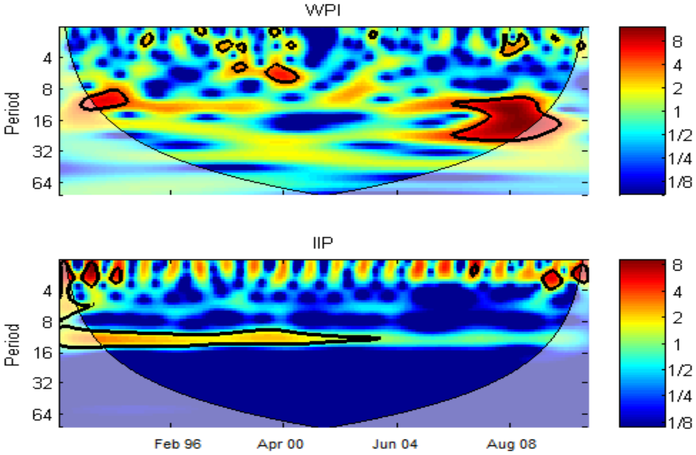
We use the Whole Sale Price Index (WPI) and Index of Industrial Production (IIP) covering the period from January 1992 to June 2011, to construct inflation and industrial growth series for India, respectively. The WPI rather than CPI is considered to derive the inflation rate, because in the Indian context, the CPI is subject to extreme problems. The base year of agricultural and rural labourers is still 1986–1987; therefore it provides a very poor account of new entries into the consumption basket for the two income groups. Given that the structure of the Indian economy has been changing rapidly, such a strong assumption underlying the consumption basket for the last two decades raises serious questions about the reliability of the CPI. Hence we use WPI to construct the inflation data. All the variables are collected from *IFS CD ROM 2012* and growth rates are calculated as the first difference of the logarithmic transformation of the concerned variables.

4. Results and Discussion

The wavelet power spectra of both inflation and industrial growth is shown in Figure 1. The wavelet power spectrum indicates the scale specific variance associated with any macroeconomic time series. The wavelet power spectra of inflation and industrial growth are plotted in Figure 1. The wavelet power varies from deep red (highest) to deep blue (lowest). The significance of the power is indicated by the area within black lines. It can be seen from the Figure 1 that wavelet power is high and significant at 0~4 month time scales for industrial growth. This high power could arise due to the seasonality in the industrial production. Similarly, significant higher power for 8~16 month time scales could be due to the active cycle with time dynamics of 8~16 months. For inflation, we find that there is a homogeneous power distribution except for few occasions during early 90s, late 90s and post 2005. This homogeneous power distribution or stable inflation can be attributed to the fact that we have considered WPI inflation which does not include volatile food and fuel components. Nevertheless, the volatile inflation during post 2005 period could be because of the unusual combination of rise in domestic demand, uncertain monsoons, and global financial crisis. During early 90s the volatility in inflation is evident. This could probably be the crisis and reforms induced volatility in inflation.

We then proceed to test the relationship between inflation and industrial growth by estimating the cross wavelet transform (XWT) of the two series. The cross wavelet transform is synonymous with the covariance and gives the measure of comovement between two variables. The results are presented in Figure 2. It is very interesting to see that based on cross wavelet transform in Figure 2 the relationship at different frequency bands is not same. For example, it is found that the relationship is significant at frequencies corresponding to the time scales of 8~16 months.

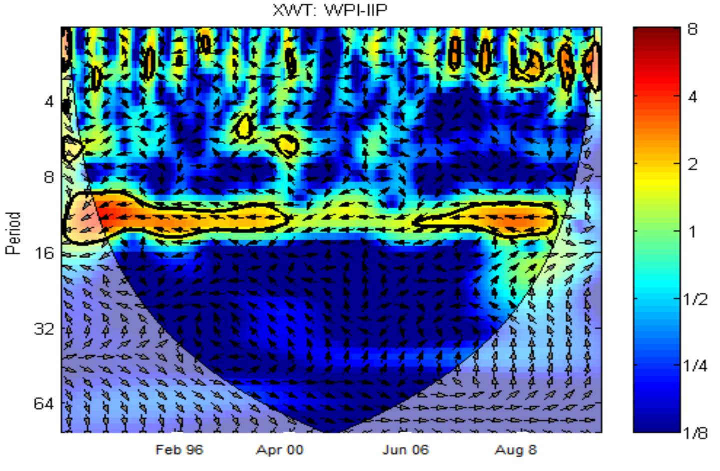
Figure 1. The Continuous Wavelet Power Spectrum of Both Inflation (top) and Industrial Growth (bottom)



Note: The continuous wavelet power spectrum of both inflation (top) and industrial growth (in the bottom) series are shown here. The thick black contour designates the 5% significance level estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is shown with a lighter shade black line. The color code for power ranges from blue (low power) to red (high power). Y-axis measures frequencies or scale and X-axis represent the time period studied.

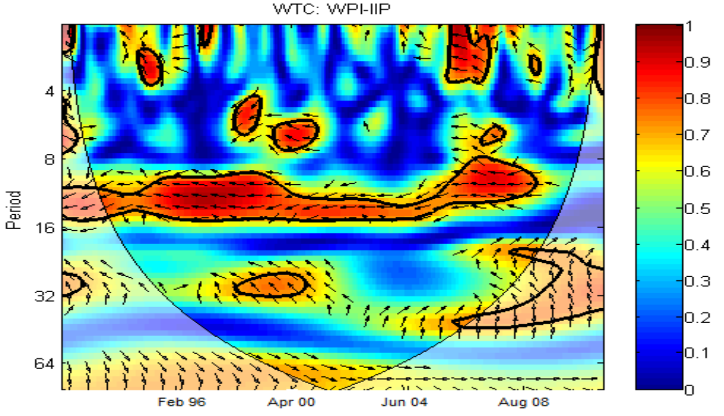
Nevertheless, the relationship breaks during 2000 to 2004. The phase angle indicated by arrows shows that, however, at other frequencies growth and inflation seems to be independent of each other. Further, the wavelet phase angle indicates that the two variables are out of phase (negatively related) with arrows pointing slightly upwards. This indicates that inflation leads growth negatively. Some ephemeral relations do exist at shorter time scales. However, they are too short and perhaps may be contaminated by the seasonal effects. Hence the interpretation of these results is avoided. The use of XWT in testing the relationship has however been criticized for describing the power of two processes without normalization to the single wavelet power spectrum. It has been argued that XWT produces misleading results especially when one of the spectra is locally and the other shows peaks.

Figure 2. Cross Wavelet Power Spectrum of the Inflation and Industrial Growth



Note: The thick black contour designates the 5% significance level estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is shown with a lighter shade black line. The color code for power ranges from blue (low power) to red (high power). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, with inflation is lagging. To the right and down, with Inflation is leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up, with inflation is leading. To the left and down, with inflation is lagging. In phase indicate that variables will be having cyclical effect on each other and out of phase or anti-phase shows that variable will be having anti-cyclical effect on each other.

Figure 3. Cross-Wavelet Coherency or Squared Wavelet Coherence of the Inflation and Industrial Growth



Note: The thick black contour designates the 5% significance level estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, which indicates the region affected by edge effects, is also shown with a light black line. The color code for coherency ranges from blue (low coherency-close to zero) to red (high coherency-close to one). The phase difference between the two series is indicated by arrows. Arrows pointing to the right mean that the variables are in phase. To the right and up, with inflation is lagging. To the right and down, with inflation is leading. Arrows pointing to the left mean that the variables are out of phase. To the left and up, with inflation is leading. To the left and down, with inflation is lagging. In phase indicate that variables will be having cyclical effect on each other and out of phase or anti-phase shows that variable will be having anti-cyclical effect on each other.

These peaks in the cross spectrum therefore produce spurious correlation though actually they are not correlated. Cross wavelet power spectrum therefore fails to be qualified as a suitable tool for testing the relationship between two time series.

We instead use wavelet coherency to detect true relationship between the two variables. The wavelet coherency is used to identify both frequency bands and time interval within which two variables are correlated. Finally, we present the results of cross wavelet coherency in Figure 3. Our results based on cross wavelet coherency show that there is a significant relationship between industrial growth and inflation in the short-run with approximately the time dynamics of 8~16 months.[4] The relationship is out of phase (negative) and almost continuous over time with inflation leading growth for most of the time. Nevertheless, for rest of the frequencies, we do not find any consistent relationship. Some short lived relationships, though exist at higher and lower frequencies, have hardly any policy significance. We therefore provide answer to some of the questions posed earlier. The

[4] We define short-run as the frequencies above business cycle frequency band.

inflation-industrial growth nexus holds at shorter time scales with approximately the time dynamics of 8~16 months. Our results further support the monetarist's view that inflation is detrimental to growth, albeit, at time dynamics of higher frequencies with 8~16 months. With this methodology we therefore unravel time dependent and frequency dependent anti-cyclical relationship between inflation and industrial growth, which could have been impossible to detect with conventional econometric techniques.

5. Conclusions

This study analyzed the nexus between inflation and industrial-growth for India by using monthly data covering the period of January 1992 to June 2011. To analyze the issue in depth, the time-frequency relationship between inflation and industrial growth was decomposed by using continuous wavelet approach. We found from the continuous wavelet power spectrum figure that wavelet power is high and significant at 0~4 months' scales for industrial growth. Further, it was found that power is also high at 8~16 months' scales. We attributed the high power at different time scales to the seasonal fluctuations and active cycle at 8~16 months' scales respectively. For inflation, nevertheless, we found relatively homogeneous power distribution except for the few instances of early 90s, late 90s and post 2005. This homogeneous power distribution or stable inflation was attributed to the use of WPI inflation which does not include volatile food and fuel components. The volatile inflation during early 90s and post 2005 was attributed to the probable causes of 1991 crisis and unusual combination of rise in domestic demand, uncertain monsoons, and global financial crisis respectively. The relationship between inflation and industrial growth was tested by estimating the XWT of two variables. It was shown that the relationship at different frequency bands is not the same. The results, especially, at high frequencies showed that there is a significant relationship between the two variables. Some very short term relationships were also found at lowest time scales. Nevertheless, given the limitations of XWT, the wavelet coherency was relied upon to test the relationship between two variables. The results showed that industrial growth and inflation share an anti-cyclical relationship corresponding to the frequencies of 8~16 months. Further, it was found that the inflation leads the industrial growth. For other frequencies no significant policy relevant relationship was found. From the overall analysis, we could find that inflation-industrial growth nexus exists, though at lower than business cycle frequencies. We interpreted this frequency as the short-run. Our results therefore supported the monetarist's view that inflation is detrimental to growth, albeit, in the short-run.

These results are the unique contribution of the present study, which would have not been drawn if one would have utilized conventional econometric or any other frequency domain based approach. Our results hence showed that, for the Indian economy, the relation between inflation and industrial growth is negative with inflation leading growth in the short-run. The present study can be extended by analyzing the wavelet based relationship between inflation and other macroeconomic variables like monetary aggregates and stock prices since, theoretically all the three variables are expected to be highly correlated with each other.

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