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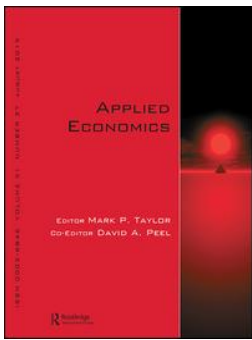
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The Indian inflation–growth relationship revisited: robust evidence from time–frequency analysis

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ABSTRACT

This article re-visits the inflation–growth nexus in India using the tools of wavelet, i.e. wavelet correlation, wavelet cross-correlation and scale by scale Granger causality test. Wavelet cross-correlation analysis shows that at the shortest scales inflation and economic growth were independent; at medium scales, there exists feedback effect; and at higher scales, only economic growth is leading to inflation. Furthermore, we find: (a) high and increasing dependence between inflation and economic growth, particularly after mid-2002; (b) high-frequency components of economic growth Granger-cause low-frequency component of CPI-based inflation and vice-versa, and at all scales economic growth Granger-cause inflation at scales of 4–6 and no evidence of causality was detected from WPI-based inflation to economic growth; (c) results indicate that there is no long-run causal link between inflation and economic growth. This study presents new insights for policymakers to sustain economic development by using inflation as an economic tool in India.

KEYWORDS

Inflation-growth; nexus; time-frequency relationship; wavelet cross-correlation; India

JEL CLASSIFICATION

C40; E31; E32; E64

1. Introduction

Inflation–growth nexus is one of the most widely discussed issues since the resurgence of interest in economic growth. Consequent to the global financial crisis, inflation gained momentum in India in 2008 while the economy gradually recovered with over 8% growth rate. Recently, India experienced two years of high inflation – 2009/2010 and 2010/2011. 2009/2010 inflation was due to a deficiency in the monsoon as food production declined by 11 million tonnes, with resultant increase in food prices and consequently triggered off inflation, likewise in 2010/2011 (Ramachandran and Kumar 2017). This manifested in wholesale price index (WPI), that reached the peak of 11% in April 2010, and as of February 2011, year-on-year basis inflation was 8.3%. The high level of inflation in these two years raised certain questions about the relationship between inflation and growth. Hence, the debate on inflation–growth trade-off and the role of monetary policy has reappeared, taking the centre stage in recent policy debates in India. This, as also noted by Bhaduri (2016) raise a critical question of whether the

monetary policy price stability objective undermines the ability of the economy to sustain high growth. However, there could be situations when the high growth rate contributes to inflationary trend when the growth rate exceeds the potential capacity, thereby ‘over-heating’ the economy. (Laxton, Meredith, and Rose 1995). This was the case for India in 2007 when rising inflation was attending to a high growth rate around 9% (Mohan and Ray 2019). This was transient because of the high investment rate that push output up enough to meet increasing demand. Consistent with this was accompanied monetary aggregates and credit growth, unprecedented net capital inflows of \$108 billion, improved balance sheet position of banks and sustained financial stability (Mohan and Ray 2019). As argued by Tobin (1965), the perfect substitutability nature of money and capital propel investment positively when experienced with inflation which improves the growth potential. This suggested that against the potential inflationary risk to growth, higher inflation tolerance could yield higher growth, which upheld the trade-off between growth and

inflation as expressed by the short run Phillips Curve.

The concerns that inflation surge in many developing countries might eventually retard growth have motivated many researchers focus on the problem and sought to establish a relationship between inflation and growth. Despite these efforts controversies still lingers, and theoretical and empirical consensus is yet to be reached. One possible reason for this is that many studies tried to juxtapose low inflation countries with those with high inflation.

A voluminous body of literature in both developed and developing countries focuses on the empirical verification of this relationship (e.g. Barro 1990; Fischer 1993; Bruno and Easterly 1996; Ambler and Cardia 1997; Ghosh and Phillips 1998; Singh and Kalirajan 2003; Burdekin et al. 2004).¹ Other studies such as Baillie, Chung, and Tieslau (1996), Andres and Hernando (1999), Nguyen and Wang (2010) and Pradhan, Arvin, and Bahmani (2015) have also reported finding suggesting the direction of short-run and long-run causality between inflation and output growth. These studies have used either single country data or multi-country panel data to study the relationship within the time-domain framework. Nevertheless, the dynamic relationship between inflation and growth can vary across different frequencies. Consistent with Bhaduri (2016) the true economic relationships between the variables can be expected to hold at the disaggregated (scale) level rather than at the usual aggregated level (e.g. Gallegati et al. 2011).

The remainder of the article is organized as follows. Section II describes the motivation to the methodology. Section III discuss the methodology used to explore the research question. Section IV gives the data description. The results of empirical estimation are presented and discussed in Section V. Section VI draws conclusion and policy implications.

II. Motivation to the methodology

There are at least two basic reasons to frown on the time-domain analyses of the inflation–growth relationship. Empirically, Lee (1995) and Zhu (2005)

documented that there could be substantial variations in the strength of the relationship between inflation and economic activity. Realizing this, studies such King, Stock, and Watson (1995) and Sbordone and Kuttner (1994) specifically focussed on the identified frequency of interest by applying an HP-filter to separate the long-run and business cycle movements in data before using them. Theoretically, the dichotomy between long-run and short-run Phillips curves has a polarizing effect on the received understanding about the relationship. On one hand, it is surmised that the trade-off between inflation and unemployment reflecting output growth via labour productivity is only a short-run phenomenon (Lee 1995). Consistently, with the natural rate hypothesis, Phelps (1967) and Friedman (1968) argue that the trade-off is consequent on the imperfect anticipation of inflation and that once inflation is perfectly anticipated the pendulum fully shifts to support the long-run Phillips curve. Perhaps, the most virulent expression in the relationship is that Phillips curve is not truly a structural relationship and as such will be subject to the whimsicality of expectations, an argument echoing the celebrated Lucas (1976) critique. If the underlying economic structure is changing so will be the expectations. On the other hand, Blanchard and Summers (1987) suggested there could be a permanent trade-off because of hysteresis in unemployment – the longer individuals stayed unemployed the more difficult for them to find jobs and the less willing they are to seek employment. Stock (1991) opines that hysteresis in unemployment can be interpreted as a time-scale phenomenon. Similar position can be held for inflation, which can be frequency dependent because inflation-expectations formation is equally scale dependent. Inflation expectations of individuals naturally differ depending on economic phase. Indeed, in the absence of explicit inflation target, private agents' inflation expectations cannot be coordinated and anchored centrally, meaning that heterogeneity in individual perceptions will give rise to scale dependence. Given that the time-series of inflation and output growth are amalgams of different frequencies, the short-run or business cycle

¹Another line of research estimating the threshold level of inflation. For example, Samantaraya and Prasad (2001) found the threshold level for India to be around 6.5%. Mubarik (2005) found that inflation rate beyond 9% is detrimental for growth in Pakistan and below is favourable. Pattanaik and Nadhanael (2013) examined why persistent high inflation impedes growth in India and identified the factors causing inflation to appear well above the threshold level.

signals can be overwhelmed by the size and variability of the long-run components thereby confounding the Phillips curve relationship.

The possibility of viewing the time-series, both over time and over frequency should be more appealing in economics than over either time or frequency alone since the time-series is often subject to regime shifts and structural breaks as well as outliers and clustering (Benhmad, 2013). For one, though the Fourier transform offers a perspective on the short, medium and high-frequency fluctuations in time-series, it views time-series solely in frequency domain and assumes stationarity. However, Naccache (2011, 339) pointed out, ‘any abrupt change is not captured by the Fourier transform since its harmonics are globally defined and do not depend on the time variable’. Thus, the Fourier approach is appealing when working with stationary time-series or signals and may not be useful when the time-series is fraught with non-stationarity. For another, in time domain, stationarity of time-series is fundamental to the applications of a wide range of statistical and significance tests and, at the same time, we miss the opportunity of classifying the frequency fluctuations in the time-series. Oftentimes, the stationarity requirement is only satisfied under some very restrictive conditions, and the stationarity test statistics themselves are often not unanimous in giving the results, thus making time-domain analysis very difficult and the results reached dubious. Wavelet analysis relaxes the stationarity requirement by providing the opportunity of viewing the time-series in both time and frequency domains. Wavelet analysis has only recently been used to study economic issues; Crowley (2007), Yogo (2008), Gallegati and Gallegati (2007), Gençay et al. (2001), Fan and Gençay (2010) and Bhaduri (2016) present a few examples.

Following Gallegati et al. (2011) who highlighted some of the issues regarding 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 establish relationships at different frequencies. As such, we are able to unravel some hidden time–

frequency relations and we try to answer the following questions: Are inflation and growth inversely or directly related? Is the empirical inflation growth nexus primarily a long-run, medium-run or short-run relationship and how this relationship varies across different frequencies and over time? What is the direction of causality across different frequencies and over time? Is there evidence of Granger-causality running from the shortest or the longest scale of one variable to the longest or the shortest scale of another variable? Hence, we also tried to provide evidence on whether short-term or long-term movements in one variable Granger-cause long-term or short-term movements in another variable.

III. Methodology

According to Fan and Gençay (2010, 1308), wavelet is ‘a small wave that grows quickly and decays within a limited time period’. In wavelet analysis, the main object is the quantification of the changes in the original time-series on a given scale and at a given point in time. The modelling of undulating movements in wavelets is facilitated by translating and dilating the mother wavelet $\varphi(t)$ satisfying the properties $\int_{-\infty}^{\infty} \varphi(t)dt = 0$ and $\int_{-\infty}^{\infty} |\varphi(t)|^2 dt = 1$. This process of translating and dilating yields

$$\varphi_{(s,\tau)}(t) = \frac{1}{\sqrt{s}} \varphi\left(\frac{t-\tau}{s}\right), \quad (1)$$

where s and τ are the scale and location parameters with $1/\sqrt{s}$ normalizing the expression to unit. The father wavelet $\psi_{(s,\tau)}(t)$ is likewise defined. Therefore, a continuous wavelet transform (CWT) of the original series is constructed through the process of projecting the original series $x(t)$ onto $\varphi_{(s,\tau)}(t)$, yielding the wavelet coefficient $W(s, \tau)$:

$$W(s, \tau) = \int_{-\infty}^{\infty} x(t) \circ \varphi_{(s,\tau)}(t) dt, \quad (2)$$

where $\circ$ is the convolution operator. There are basically two sides to the discrete wavelet transform (DWT). The first involves the analysis or the decomposition of the time-series while the other

involves the reconstruction to recover the original time-series. More practically, at the analysis stage, the DWT involves sampling the CWT at the dyadic points. This dyadic sampling is achieved by letting the scale and location parameters in Equation (1) be set as $s = 2^j$ and $\tau = k2^j$ respectively. By translating and dilating the mother wavelet – involving changing the values of k and j respectively – the daughter wavelets are obtained. Although the father wavelet function can be translated, it is unaffected by the process of dilatation. This property ensures that one can use the father wavelet function to construct the associated father wavelet filter coefficient that measures the long-term trend movements in the series. The daughter wavelet functions are used to construct the associated wavelet filter coefficients, which capture the short-term movements and fluctuations of the time-series around the trend. The daughter wavelet coefficients and father wavelet coefficient are given by

$$\omega_{j,k} = \int x(t) \circ \varphi_{j,k}(t) dt \text{ and } s_{J,k} = \int x(t) \circ \psi_{J,k}(t) dt$$

where $j = 1, 2, \dots, J$ and $J = \log_2(T)$. In DWT, the wavelet coefficients are given by

$$W_{j,t} = 2^{j/2} \tilde{W}_{j,2^j(t+1)+1}, \quad \left[(L-2) \left(1 - \frac{1}{2^j} \right) \right] \leq t \leq \left[\frac{N}{2^j} - 1 \right], \quad (3)$$

where

$$\tilde{W}_{j,t} = \frac{1}{2^{j/2}} \sum_{l=0}^{L_j-1} h_{j,l} x_{t-1}, \quad t = L_j - 1, \dots, N - 1$$

The $\tilde{W}_{j,t}$ coefficients, associated with changes on a scale of length $\tau_j = 2^{j-1}$, are obtained by subsampling every 2^j th of the $\tilde{W}_{j,t}$ coefficients using the Mallat (1989) pyramid algorithm and the multiresolution analysis can be summarized as follows:

To improve on the results, we use the maximal overlap DWT (MODWT), which does not decimate the coefficients hence the number of scaling and wavelet coefficients at every level of the

transform is the same as the number of sample observations and can handle any sample size and translation-invariant since a shift in the signal does not change the pattern of wavelet transform coefficients. For the MODWT wavelet and scaling coefficients, we have

$$\begin{aligned} \tilde{W}_{j,t} &= \sum_{l=0}^{L-1} \tilde{g}_l \tilde{v}_{j-1,t-1 \bmod N} \text{ and} \\ \tilde{v}_{j,t} &= \sum_{l=0}^{L-1} \tilde{h}_l \tilde{v}_{j-1,t-1 \bmod N} \end{aligned} \quad (4)$$

The reconstruction of the original series can be done using the multiresolution analysis (MRA) and this process can be achieved through a recursion on the inverse MODWT given by

$$\begin{aligned} \tilde{v}_{J-1,t \bmod N} &= \sum_{l=0}^{L-1} \tilde{h}_l \tilde{W}_{J-1,t-1 \bmod N} \\ &+ \sum_{l=0}^{L-1} \tilde{g}_l \tilde{v}_{J,t-1 \bmod N} \end{aligned}$$

to obtain the following reconstruction of the original time series,

$$x(t) = \sum_k s_{J,k} \tilde{v}_{J,k}(t) + \sum_{j=1}^J \sum_k \omega_{j,k} \tilde{W}_{j,k}(t) \quad (5)$$

where J is the number of multiresolution levels, and k ranges from 1 to the number of coefficients in each level. Further, to decompose the data we used the Daubechies' least asymmetric wavelet filter LA which is a widely used wavelet because it provides the most accurate time alignment between wavelet coefficients at various scales and the original time series, and is applicable to a wide variety of data types. Our choice of a filter length $L = 8$ is in response to the strategy that suggests using the smallest L that gives reasonable results in empirical studies.² We use reflecting boundary conditions, where each time series beyond its boundaries is assumed to be a symmetric reflection of itself, to lessen the impact of circular filtering (Percival and Walden 2000).

²Shorter widths can introduce undesirable artefacts while wider widths, even if better matching the characteristic feature of the time series, can result in a decrease in the degree of localization of wavelet coefficients.

To study the relative importance of the short, medium and long-term dynamics, we use the energy of both variables' (i.e. inflation and output growths') wavelet decomposition on each scale. The energy is analogous to the variance of each detail level, and it is measured as the percentage of the overall energy. Hence, we examine the percentage of variance that each scale is explaining. For details, readers are invited to read Percival and Walden (2000) and, Percival and Mofjeld (1997). Hence, for time-series $x(t)$,

$$\|x\|^2 = \sum_{t=1}^N x(t)^2 = \sum_{j=1}^J \sum_{t=1}^N \tilde{w}_{j,t}^2 + \sum_{t=1}^N \tilde{v}_{j,t}^2$$

where $\tilde{w}_{j,t}$ and scaling coefficients $\tilde{v}_{j,t}$, the MODWT-based wavelet coefficients at scale j .

The wavelet correlation and cross-correlation

Having decomposed the series into the smooth component and the detail coefficients, we can compute the wavelet variance, covariance and correlation of stochastic process X using the MODWT coefficients for scale $\tau_j = 2^{j-1}$ through:

$$\hat{\sigma}_X^2(\tau_j) = \frac{1}{\hat{N}_j} \sum_{k=L_j-1}^{N-1} (\hat{W}_{j,k})^2 \quad (6)$$

$$\gamma_{XY}(\tau_j) = \text{cov}_{XY}(\tau_j) = \frac{1}{\hat{N}_j} \sum_{k=L_j-1}^{N-1} \hat{W}_{j,k}^x \hat{W}_{j,k}^y \quad (7)$$

$$\hat{\rho}_{XY}(\tau_j) = \frac{\text{cov}_{XY}(\tau_j)}{\hat{\sigma}_X^2(\tau_j) \hat{\sigma}_Y^2(\tau_j)} \quad (8)$$

The wavelet correlation is analogous to its Fourier equivalent, the complex coherency (Genaçay, Selcuk, and Whitcher 2002). Likewise, the wavelet cross-correlation decomposes the cross-correlation between two time-series on a scale-by-scale basis. Thus, it becomes possible to see how the association between two time-series changes with time horizons. Genaçay, Selcuk, and Whitcher (2002) define the wavelet cross-correlation as:

$$\hat{\rho}_{x,k}(\tau_j) = \frac{\gamma_{x,k}(\tau_j)}{\hat{\sigma}_1(\tau_j) \hat{\sigma}_2^2(\tau_j)} \quad (9)$$

where $\sigma_{x,k}^2(\tau_j)$, $\sigma^2(\tau_j)$ are, respectively, the wavelet variances for $x_{1,t}$ and $x_{2,t}$ associated with scale τ_j and $\gamma_{x,k}(\tau_j)$, and the wavelet covariance between $x_{1,t}$ and $x_{2,t-k}$ associated with scale τ_j . The usual cross-correlation is used to determine lead-lag relationships between two time-series; the wavelet cross-correlation gives a lead-lag relationship on a scale-by-scale basis.

The evolutionary co-spectral analysis (ESA)

The relevance of frequency domain concepts as developed by Croux et al. (2001) and Ftiti (2010) shows that the extent and direction of co-movement can differ between frequency bands. Thus, we introduce time concept with frequency domain, and analyse the time-frequency relationship because in the frequency-domain framework time information is lost. Hence, in our contribution, we use the evolutionary co-spectral analysis (ESA), as presented Priestley and Tong (1973) and based on the methodology of Ftiti (2010). The ESA illustrates the evolution of the co-variance of a time-series at the different frequencies and demonstrates the correlation coefficient in the time-frequency space. The information on the delay between the oscillations of two time-series, i.e., lead-lag relationships, is provided by phase-difference.

The idea behind the ESA is simple. Let the observable bivariate time series be (X_t, Y_t) , which are not necessarily stationary. The time-varying magnitude squared coherence is given by

$$K_{XY}^2(w_j, t) = \frac{A_{XY}^2(w_j, t)}{S_X(w_j, t) * S_Y(w_j, t)} \quad (14)$$

where $S_X(w, t)$ and $S_Y(w, t)$ are the time-varying spectra of and the time-varying cross-amplitude between them is $A_{XY}(w_j, t) = |S_{XY}(w_j, t)|$. The cross-spectra $S_{XY}(w_j, t)$ is given by $S_{XY}(w_j, t) = C_{XY}(w_j, t) - iQ_{XY}(w_j, t)$, and can be written in polar coordinate as:

$$S_{XY}(w_j, t) = A_{XY}(w_j, t) \exp\{i\theta_{XY}(w_j, t)\}$$

where the time-varying phase spectrum $\theta_{XY}(w_j, t) = \arctan[-Q_{XY}(w_j, t)/C_{XY}(w_j, t)]$ and $C_{XY}(w_j, t) = \Re\{S_{XY}(w_j, t)\}$ and $Q_{XY}(w_j, t) = -\Im\{S_{XY}(w_j, t)\}$ are the real co-spectrum (the gain) and the

quadrature spectrum (the phase) respectively. $\Re$ and $\Im$ are the real and the imaginary parts of the time-varying cross-spectrum. It is noteworthy that in both evolutionary spectral estimation and time-varying coherence function, we necessarily lose 10 observations at the beginning and 10 at the end. Therefore, we apply a different test to $T = T - 20$.³ Using the (j) and (jj) conditions in Essaadi and Boutahar (2010), we choose $\{t_i\}$ and $\{w_i\}$ as⁴ $\{t_i = 18 + 20i\}_{i=1}^I$ and $\{w_i = \frac{\pi}{20}(1 + 3(j-1))\}_{j=1}^7$ respectively, where $I = \lfloor \frac{T^*}{20} \rfloor$ and T^* is the sample size. $[x]$ denotes the integer part of x . Using (jj) condition, we inspect instability in these frequencies: $\pi/20, 4\pi/20, 7\pi/20, 10\pi/20, 13\pi/20, 16\pi/20$ and $19\pi/20$.

Causality in continuous wavelet transform

As an alternative to the discrete wavelet transform (DWT) for the Granger causality above, we employ the continuous wavelet transform (CWT) for the Granger causality proposed by Olayeni (2015), which in turn is built on CWT-based correlation measure by Rua (2013). It is given by

$$G_{Y \rightarrow X}(s, \tau) = \frac{\zeta\{s^{-1}|\Re(W_{XY}^m(s, \tau))I_{Y \rightarrow X}(s, \tau)|\}}{\zeta\{s^{-1}\sqrt{|W_X^m(s, \tau)|^2}\} \cdot \zeta\{s^{-1}\sqrt{|W_Y^m(s, \tau)|^2}\}}$$

where $W_Y^m(s, \tau)$, $W_X^m(s, \tau)$ and $W_{XY}^m(s, \tau)$ are the wavelet transformations and $I_{Y \rightarrow X}(s, \tau)$ as the indicator function which is defined

$$I_{Y \rightarrow X}(s, \tau) = \begin{cases} 1, & \text{if } \varphi_{XY}(s, \tau) \in (0, \pi/2) \cup (-\pi, -\pi/2) \\ 0, & \text{otherwise} \end{cases}$$

and

$$\varphi_{XY}(s, \tau) = \tan^{-1} \left(\frac{\Im\{W_{XY}^m(s, \tau)\}}{\Re\{W_{XY}^m(s, \tau)\}} \right)$$

Other directional indicator functions are given in Olayeni (2015).

IV. Data description

Given the extreme problems associated with CPI in the Indian context, the wholesale price index (WPI) is also considered (Ramachandran and

Kumar 2017; Mohan and Ray 2019). The base year of agricultural and rural labourers being 1986–1987 provides a very poor account of new entries into the consumption basket for 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. Index of industrial production (IIP) is used to proxy growth because Mazumbar (2005) finds IIP a reliable leading indicator of business cycles in India.⁵ The data set covers the period from January 1992 to December 2015⁶ and sourced from IFS CD-ROM 2017. The growth rates are calculated as the first difference of the logarithmic transformation of the concerned variables.

Descriptive statistics of inflation (DlnWPI) and economic growth (DlnIIP) are reported in Table 1. The sample means of both variables is positive. Skewness and kurtosis measure the shape of the distribution. Economic growth is left-skewed whereas for inflation skewness is positive while the value of kurtosis illustrates that they are leptokurtic. The Jarque–Bera results show that the null can be rejected, and the normality of our series cannot be supported. In Figure 1 we present the time series plot of inflation and economic growth.

V. Results and discussion

Figures 2 and 3 illustrate the multiresolution analysis (MRA) of order $J = 6$ for inflation and economic growth by applying the MODWT based on the Daubechies' least asymmetric (LA) wavelet

Table 1. Descriptive statistics.

	D(LnIIP)	D(LnCPI)	D(LnWPI)
Mean	0.483,445	0.608,924	0.479,042
Median	0.436,698	0.626,967	0.410,439
Maximum	15.40,864	4.473,589	3.107,046
Minimum	−25.13,144	−2.120,221	−1.909,366
Std. Dev.	5.741,178	0.842,184	0.711,383
Skewness	−0.714,229	0.230,706	0.238,813
Kurtosis	5.199,110	4.969,870	3.969,015
Jarque–Bera	86.53,023	51.50,724	14.68,620
Probability	0.000000	0.000000	0.000647

³For both spectral and cross-spectra density estimation we lose 20 observations, 10 observations each.

⁴(j) and (jj) conditions are defined as: (j) $|t_1 - t_2| \geq T$ and (jj) $|w_1 \pm w_2| \geq \pi/h$. For details please refer to Essaadi and Boutahar (2010).

⁵See Sethi (2012) for additional reasons.

⁶We following Nachane and Dubey (2011) for the 1992 starting period (see for reason). Eviews-7 and R (2012) was used to analysis.

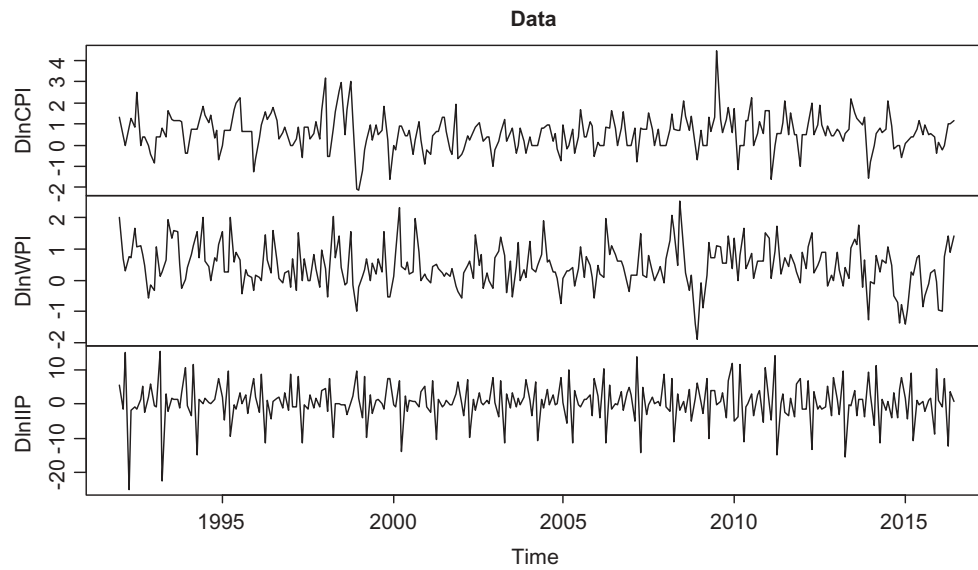


Figure 1. Inflation and output growth.

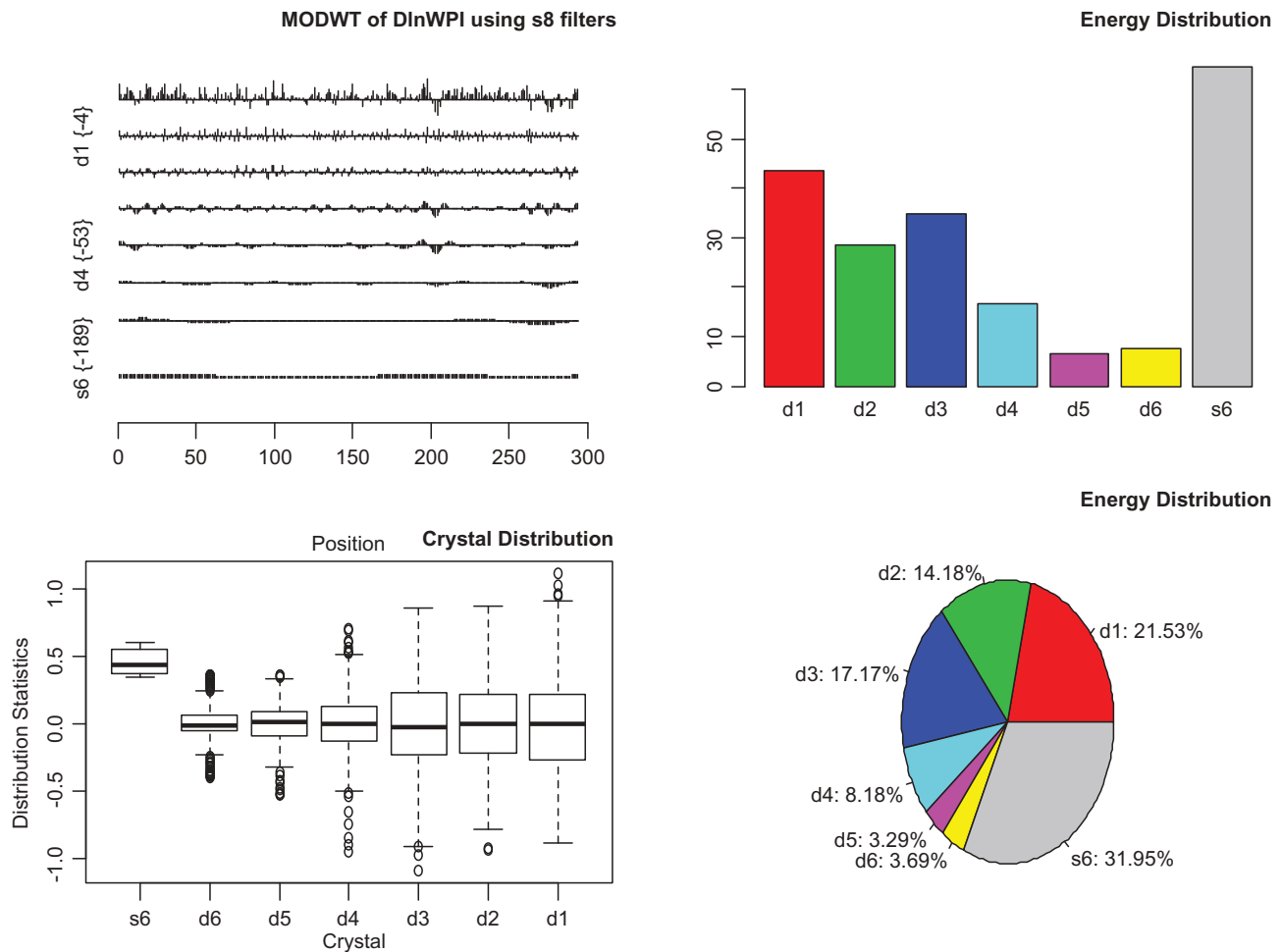


Figure 2. MODWT decomposition of WPI-inflation.

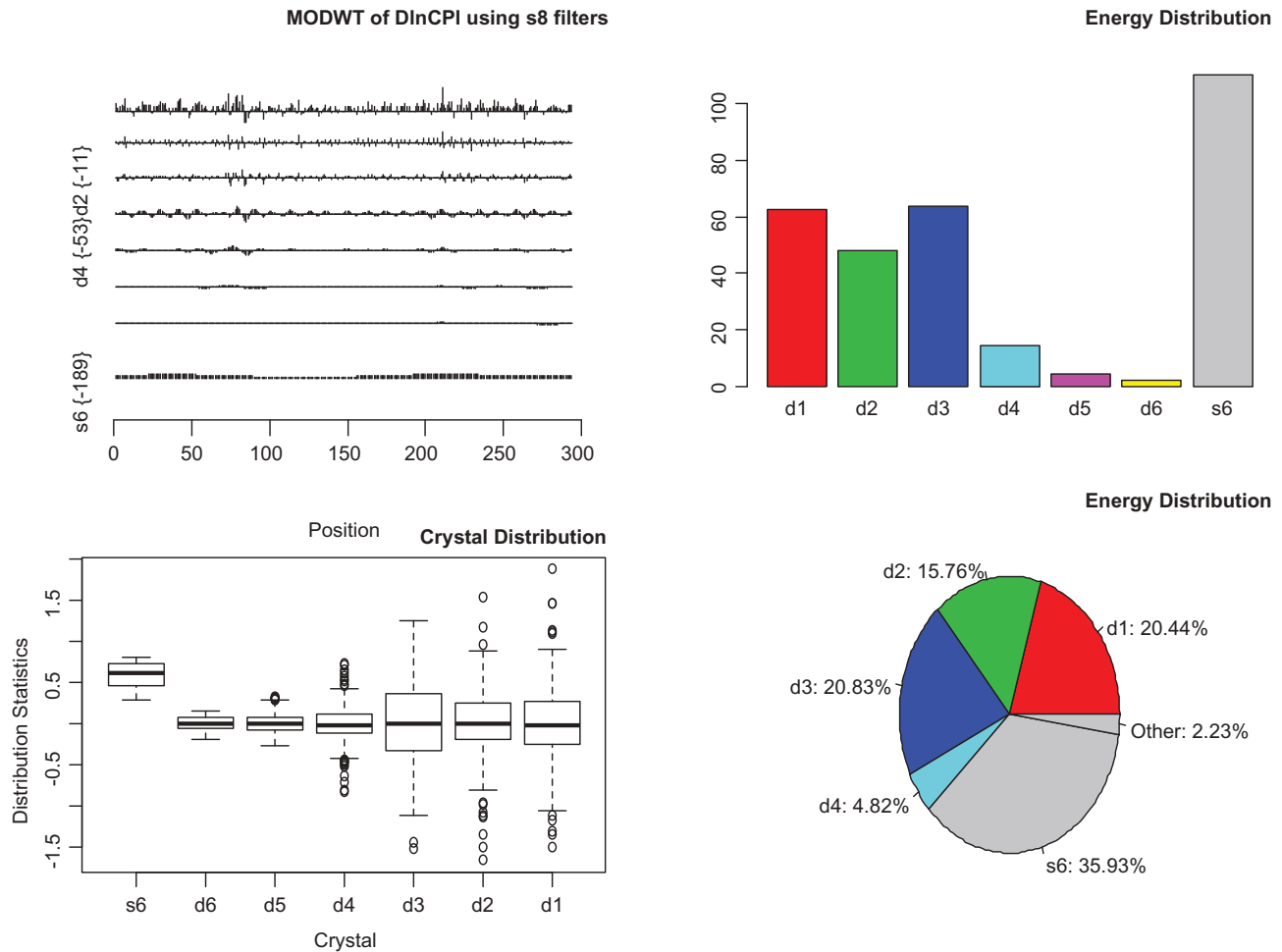


Figure 3. MODWT decomposition of CPI-Inflation.

filter LA(8) (Daubechies 1992). In each figure, the details and the smooth components are plotted, i.e. from the smooth component s6 (in Figure 2 WPI.s6 and in Figure 3 IIP.s6) to the finest detail component d1 (in Figure 2 IIP.d6 and in Figure 3 IIP.d6) in the top row. The MODWT plots for inflation in Figure 2 and output growth Figure 3 show that there is a great pick in the original series, which is captured in D1-D3 component. These shocks get smaller as the timescale increases, meaning that the short-term shocks do not affect the long-run movement of inflation and economic growth, respectively. The transitory shock impacts imply that the Reserve Bank of India (RBI) and the Indian Ministry of Finance need not worry much about the long-term economic growth and inflation. This creates policy space for monetary and fiscal policy coordination to manage the macroeconomic environment. Nevertheless, the trade-off suggested by the

correlated short-run movements in economic activity and inflation cannot be explored in this context. A formalized approach will be employed below to address the Phillips curve relating the economic growth and inflation.

Table 2 presents the energy of each scale (as percentage of the overall energy) for the two variables under consideration. In Table 2, the coefficients affected by the boundaries were not accounted for in order to get an unbiased estimate. Notice that here only six scales were used (the seventh scale is included in the smooth). This is done to disregard as few of the boundary observations as possible not to lose too much information. The Daubechies' least asymmetric wavelet filter, LA, was used given that it is less affected by the boundaries.

In Table 2, the first column presents the wavelet scales, and the second and third columns respectively present the energy distribution of inflation and economic growth corresponding to the wavelet scales.

Table 2. Energy decomposition for inflation and economic growth.

Wavelet scales	CPI- Inflation	WPI- Inflation	Output growth
D1 (2–4-month cycles)	20.438%	21.532%	80.056%
D2 (4–8-month cycles)	15.756%	14.182%	10.519%
D3 (8–16-month cycles)	20.83%	17.174%	7.659%
D4 (16–32-month cycles)	4.816%	8.177%	0.774%
D5 (32–64-month cycles)	1.419%	3.295%	0.176%
D6 (64–128-month cycles)	0.812%	3.693%	0.076%
S6 (above 128-month cycles)	35.928%	31.947%	0.739%

We discuss energy distribution in four major periods, namely, short-run (D1 + D2), medium-run (D3 + D4), long-run (D5 + D6) and very long-run (s6). It is interesting to see that for inflation series, the very long-run dominates all other periods/frequencies, explaining most of the variance (i.e. s6 = 38%) whereas for output growth it is the short-run that explains most of the variance (i.e. D1 + D2 = 90.31%). This highlights the issue that the high-frequency variations and seasonality components are more important for economic growth than for inflation in the very short run. However, this importance declines much faster in economic growth than in inflation over low frequencies. These findings can be rationalized by the sources and nature of shocks in the economy. For instance, if prices adjust contemporaneously to clear the market, then there will of course be more disproportionately high variations in economic growth than inflation in the short run, corresponding to the contemporaneous high frequency in economic growth. In other words, the degree of price stickiness in the economy will justify the relation observed between inflation and economic growth in Table 2. The findings imply that short-run output growth may be much less predictable than the short-run inflation. Furthermore, they suggest that if the government wants to create stability in the short run, it will have to pursue an explicit commitment policy rather than a discretionary policy.

Examining the trend part of inflation, that is, s6 in Figure 2 shows that the trend has traversed the period of low steady-state inflation around 2002 reaching its peak around 2007. Following Ball, Mankiw, and Romer (1988) and Dotsey, King, and Wolman (1999), we can rationalize this transition from low to high inflation steady state as implying

the emergence of high-frequency price adjustments and hence of the vertically tilting Phillips curve for India. Inspecting Table 2, we see that indeed, high variation in inflation, in other terms, high frequency of price adjustment, accompanies the long-term inflation authenticating that India has been experiencing a flattening of the Phillips curve. Figure 4 illustrates the MODWT-based wavelet variance of two series against the wavelet scales. The broken-straight lines indicate the variance and broken-straight lines with name L-L and U-U respectively indicate the lower and upper limits of 95% confidence interval. We find from Figure 4 that there is an approximate linear relationship between the wavelet variance and the wavelet scale. The variances of both inflation and economic growth, decrease as the wavelet scale increases and this decline is relatively steeper for economic growth than inflation. More specifically, a wavelet variance in a particular timescale indicates the contribution to sample variance.

In addition to the examination of variances of the two time-series, a natural question is to consider how the two series are associated with one another. Note that a wavelet covariance in a particular timescale indicates the contribution to the covariance between two series. Although there is an increasing association between inflation and output growth, it is difficult to compare the wavelet scales because of the different variability exhibited by them. In this case, dividing by the variance of each series is a natural way to standardize the covariance, thereby overcoming this influence and making it possible to compare the magnitude of the association across scales. Therefore, the wavelet correlation should be constructed to examine the magnitude of the association of each series. Indeed, correlation gives the first snapshot of the theorized relationship between inflation and economic growth, and the strength of this relationship can serve explore the existence or otherwise of the Phillips curve.

The wavelet correlation between inflation and economic growth is shown in Figure 5. It shows that there is a significant difference between the short-, medium- and long-run, i.e. in the short- and the medium-run

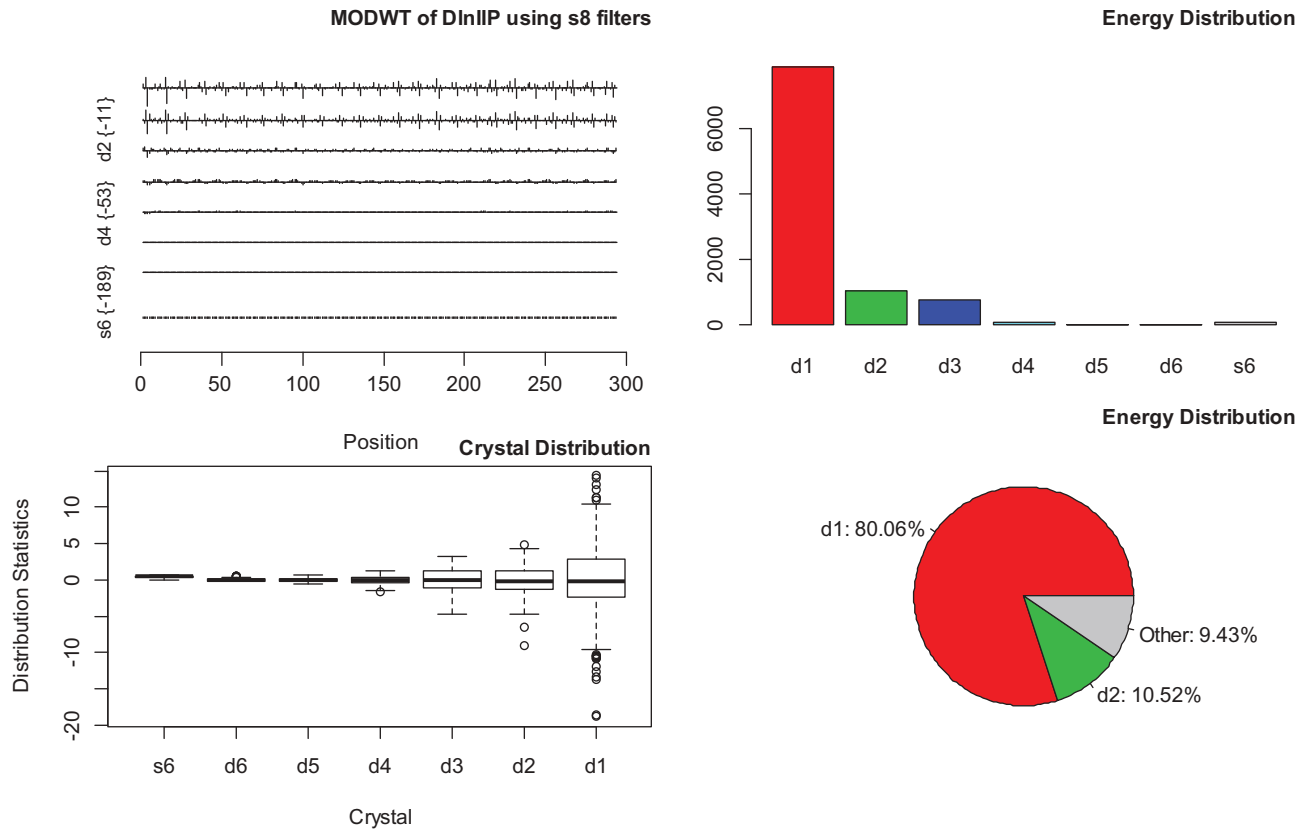


Figure 4. MODWT decomposition of economic growth.

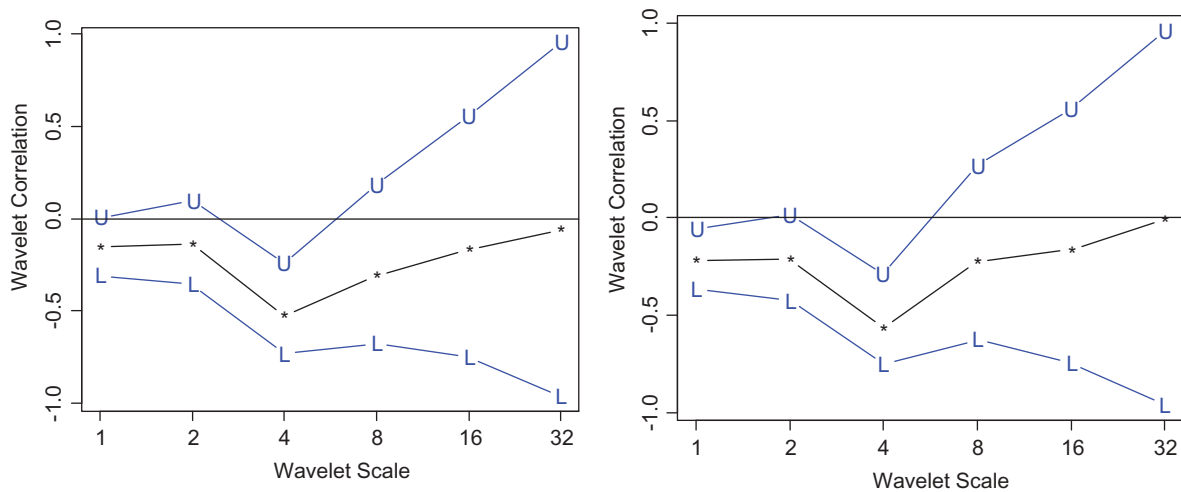


Figure 5. Wavelet correlation between inflation and economic growth.

(during first to fifth scale) we have evidence of negative correlation whereas in the long-run correlation is positive (at the sixth scale). However, there is a general tendency in the correlation coefficients to move upward with scales. Of interest is the uncertainty surrounding the higher scales, contrary to that surrounding the lower scales. Hence, it is reasonable to

assume that Phillips curve in India, although heterogeneous across scales, has negative, indicating steep short-run Phillips curve corroborating the findings of Singh, Kanakaraj, and Sridevi (2011), who employ time-domain analysis.

We further use wavelet cross-correlation, as shown in Figure 6, to test the causal relationship

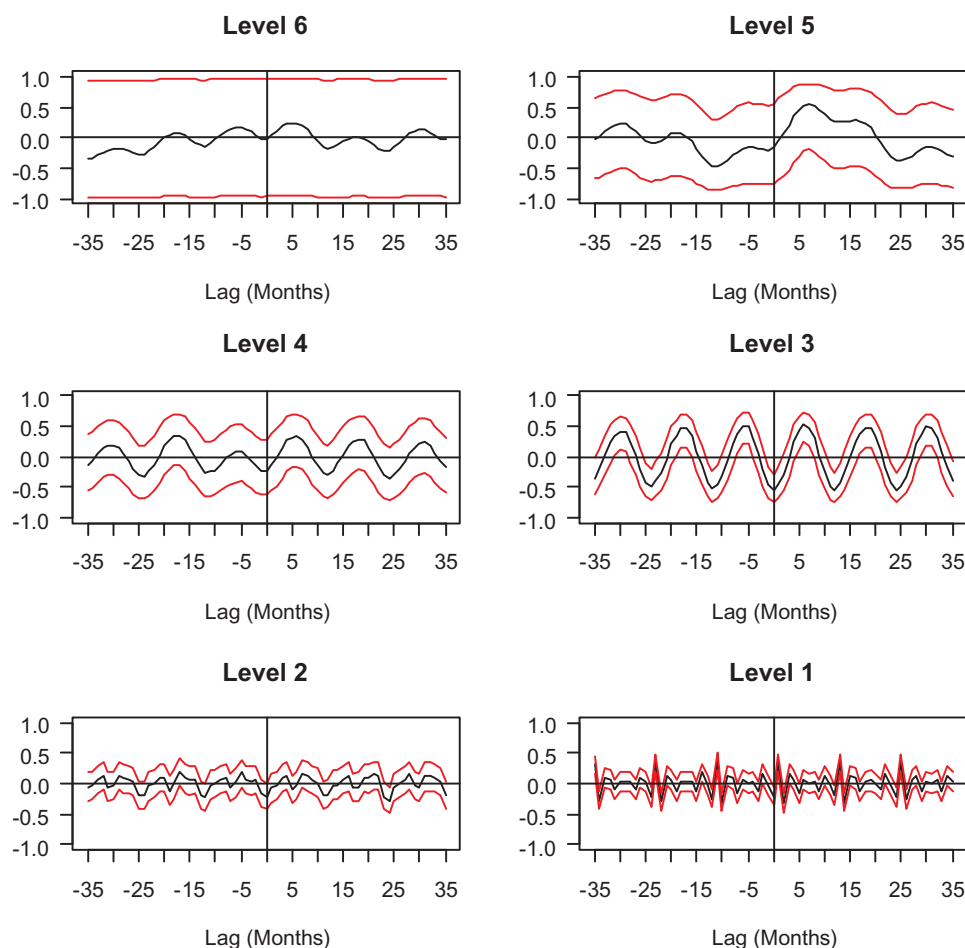


Figure 6. Wavelet cross-correlation between WPI-Inflation and economic growth.

between inflation and output growth. This wavelet cross-correlation examines the lead-lag relationship between inflation and output growth in various timescales. More specifically, Figure 6 illustrates wavelet cross-correlation between inflation at time t and output growth at time $(t-k)$, at the six levels of decomposition. As can be seen, short-term fluctuations of both variables are less correlated than long term, so that the magnitude of the cross-correlation increases by increasing in frequency band. Our findings show that at the shortest scales, i.e. 1–2 scales, the relationship between inflation and economic growth is in general not significantly different from zero at all leads and lags indicating that inflation and economic growth in this period were independent and historical information of inflation was not significantly predictive for economic growth. However, for the third and fourth levels, the relationship between these variables has many significant events, where correlation is either positive or

negative, on both sides of the graph. This means that inflation leads to economic growth, and vice versa, with either a positive or a negative correlation, and probably corresponds to feedback effects between inflation and economic growth. Furthermore, for the fifth, we can observe another feature: inflation is not significantly leading economic growth anymore. However, for the sixth level, we find evidence of a bi-directional causal link, reflected by the peaked correlation on both sides of the graph. Moreover, the correlation of these significant events (from level one to level four) is negative while the correlation of these significant events (from level five to level six) is positive.

In the next step, we examine the evolutionary spectral density and the time-varying coherence function. First, we present the results of evolutionary spectral density analysis in Figure 7.

From Figure 8, we can observe the changes in importance at the low and medium frequency

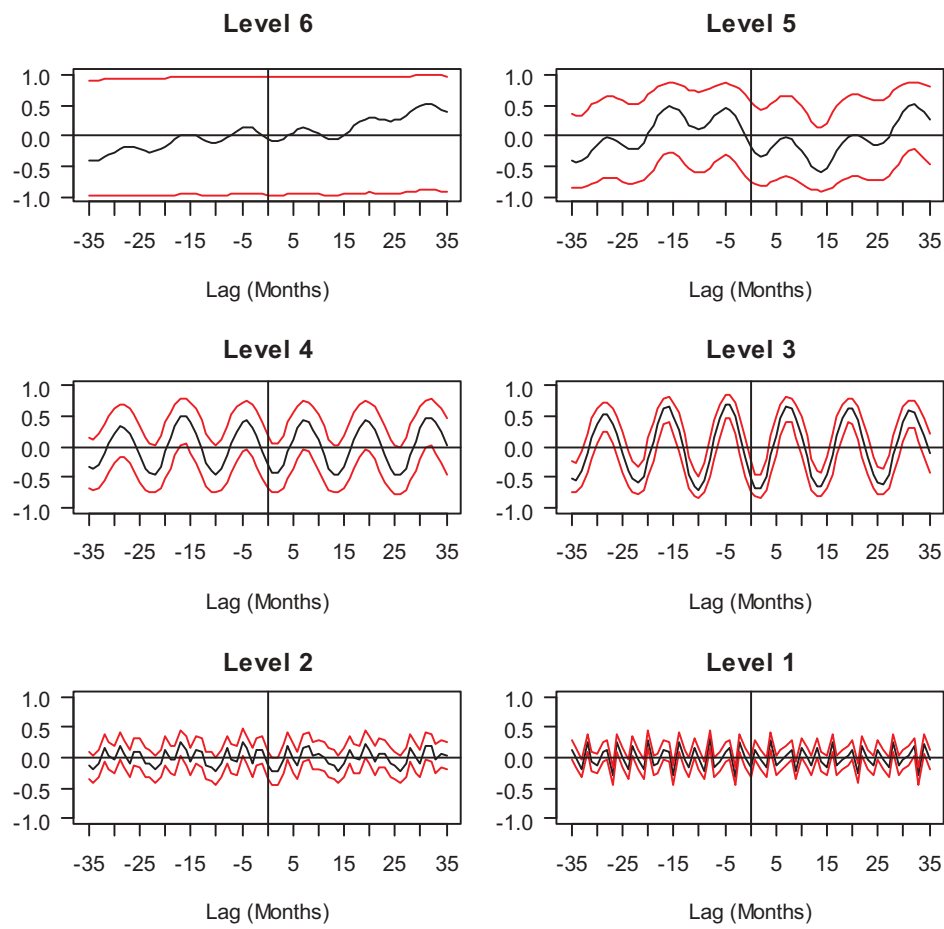


Figure 7. Wavelet cross-correlation between CPI-Inflation and economic growth.

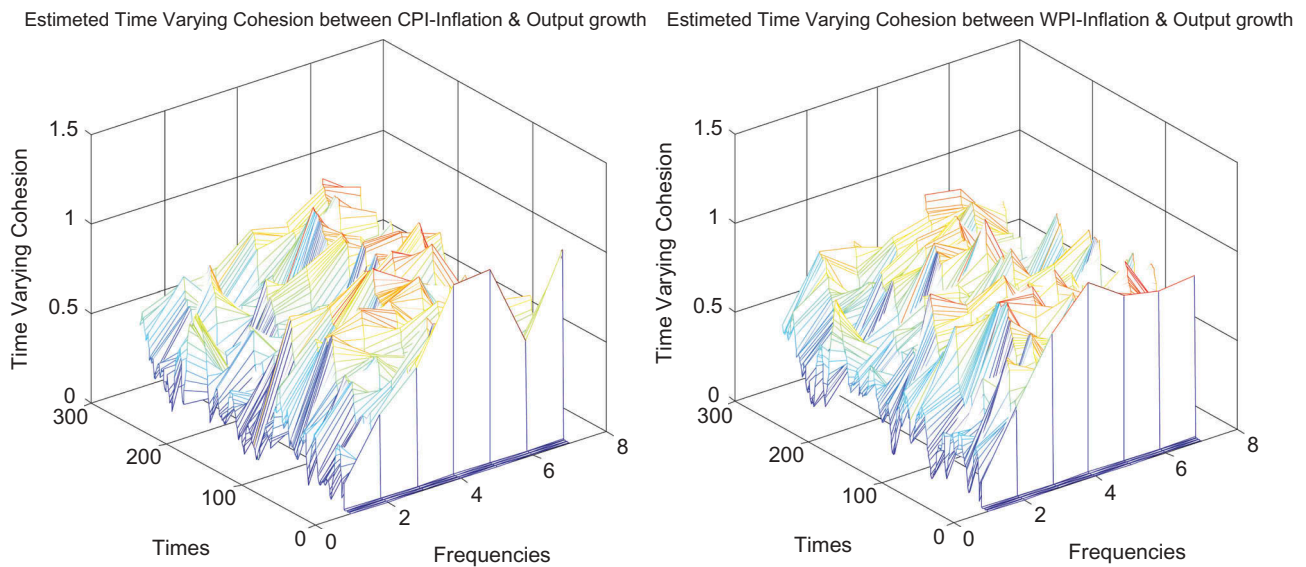


Figure 8. Time-varying coherence function between inflation and economic growth.

cycles for inflation and high and very high-frequency cycles for economic growth. This difference seems to be the source of the difference in

amplitude in the low-frequency components. Though the evolutionary spectrum seems to have a bit difference in the importance of frequencies of

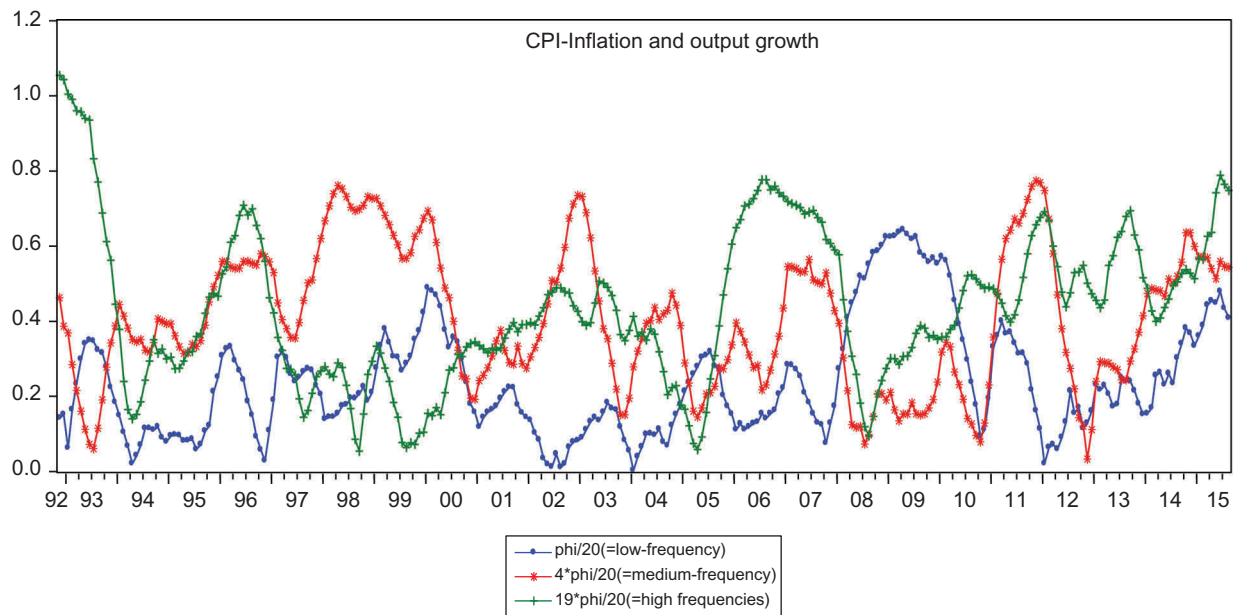


Figure 9. Time-varying coherence function between inflation and economic growth for low, medium and high frequencies.

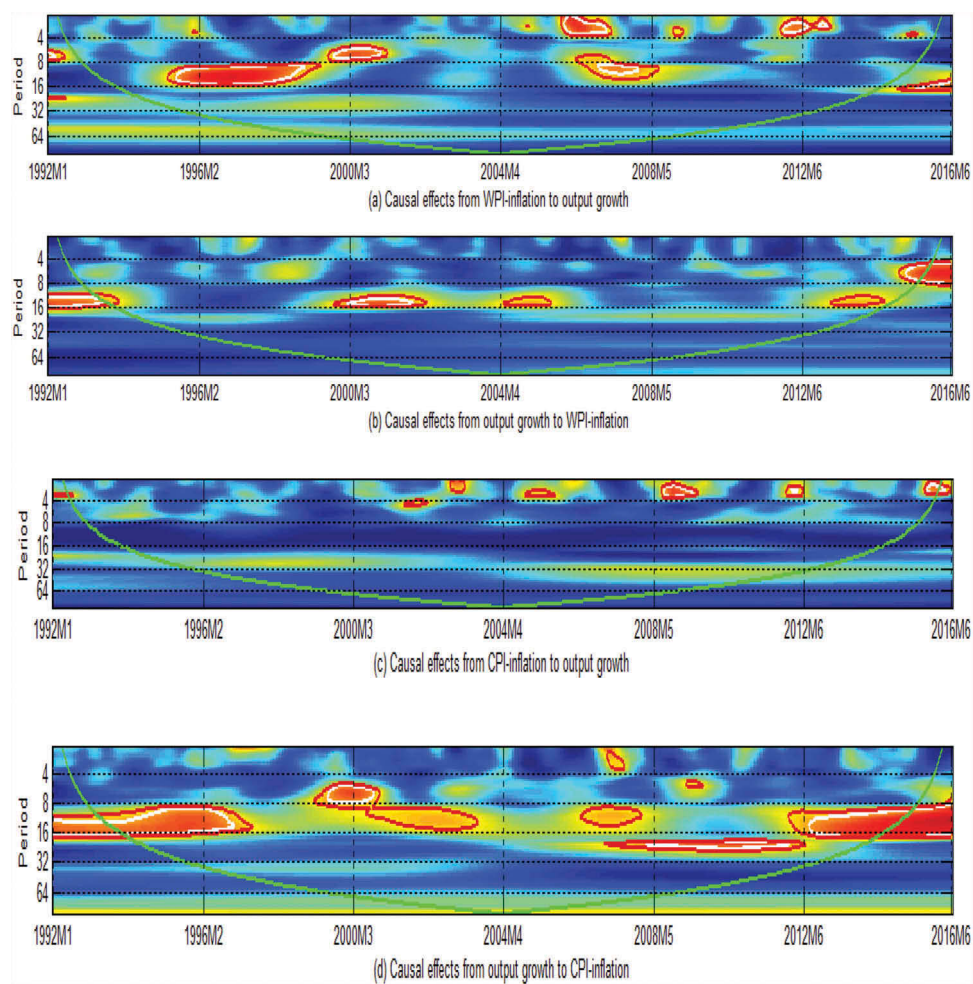


Figure 10. Time-varying coherence function between inflation and economic growth for low, medium and high frequencies.

both series, there is still a mild degree of common behaviour in the evolution of the series. Next, we analyse the time-varying coherence of both the series and present the results in Figures 8 and 9. Figure 8 presents time-varying coherence all seven frequencies and 3D picture and to make it more reader-friendly we put results of just three frequencies (i.e., low, medium and high frequency) in Figure 9 as 2D picture.

In Figure 10, we focus on three frequencies between inflation and economic growth. The first one reflects the long-run (low frequency, $\frac{\pi}{20}$), medium-term (medium-frequency; $\frac{4\pi}{20}$) and short-term (high frequencies; $\frac{19\pi}{20}$). These three frequencies are chosen to assess whether the long-run, medium-run and short-run linkages between inflation and economic growth are different or similar. It is evident from Figure 10 that at the low frequency (i.e. the long run cycles) the co-movement between inflation and economic growth exhibited increasing trend, particularly after mid-2002 when it approximately reached zero level. Moreover, in 2009, it reached its peak. Interestingly, the medium frequency (i.e. medium run cycles) shows that the co-movement attained its peak in mid-2002 and thereafter declined in trend. Lastly, the long cycles show the trough in mid-2002 and peak in 1991–1992, 1997, 1999–2000, 2004–2005, end of 2008 and at the beginning of 2009 and 2010. Thus, our findings really match the observed behaviour between inflation and economic growth. In short, the frequencies offer different informational contents.

While the relationship between inflation and economic growth codified in Phillips curve is essentially a correlation one, the test of Granger causality is necessary because if there is no causal relationship in at least one direction the relationship will be feeble. In fact, it constitutes the test of the long-run Phillips correlation (Zhu 2005). The causal link explored via cross-correlation cannot ideally systematize the flow of information, as it involves inferring information flow; however, by finding whether there exists a peak in the correlation at some non-zero lag. From this, it could be inferred that the leading variable ‘causes’ or transmits information to the lagged variable. However, using such an approach to infer causation,

or even a direction of information flow, can be quite misleading. The cross-correlation, for example, is a symmetric measure and, therefore, may not be suitable for identifying the lag-lead relationships in the systems with feedback. Granger-causality testing provides a much more stringent criterion for causation (or information flow) than simply observing high correlation with some lead-lag relationship. We therefore offer two tests at various scales to unearth the causal links using Granger-causality: the first is based on the discrete wavelet transform (DWT) and the second based on the continuous wavelet transform (CWT). The results presented in Table 3 shed light on the varying nature of Granger-causality over different timescales.

These results affirm that scale-by-scale causal relations can be more dynamic than previously anticipated in the literature that envisions causal relations to manifest on the same scale, while cross-scale causal effects are blatantly relegated. These results, however, convincingly establish that cross-scale causal links are too important to be ignored. With the variables under study, we observe that inflation and economic growth are intricately linked in terms of information flows across scales. While the results are too complex to be encapsulated briefly, some key results stand out obviously. Firstly, at scale one and two economic growth Granger-cause CPI-based inflation at scale 4, at scales 3 and 4 economic growth Granger-causes CPI-based inflation at scale 5 and at all scales economic growth Granger-cause inflation at scale 6. However, CPI-based inflation at scales 4 and 7 Granger-cause economic growth at scale 2. These results confirm the evidence that high-frequency components of economic growth Granger-cause low-frequency component of inflation and vice-versa. Further, when we analysed the Granger-causality relation between economic growth and WPI-based inflation, we find that at all scales economic growth Granger-cause inflation at scales of 4–6 and no evidence of causality was detected from WPI-based inflation to economic growth.

We now present the results of the wavelet Granger causality in CWT between economic growth and inflation in Figure 10. In Panel (a) of Figure 10, we

Table 3. Results of Granger-causality tests.

Causal scale	Caused scale	Model I: IIP and CPI		Model II: IIP and WPI	
		IIP to CPI	CPI to IIP	IIP to WPI	WPI to IIP
Scale 1	Scale 1	42.104	48.410	57.23	19.34
Scale 2	Scale1	58.936	55.571	54.71	38.09
Scale 3	Scale 1	64.213	48.010	55.16	25.57
Scale 4	Scale 1	21.839	43.706	48.95	34.92
Scale 5	Scale 1	20.692	19.503	38.80	34.31
Scale 6	Scale 1	27.496	25.528	34.43	18.88
Scale 7	Scale 1	30.973	43.851	30.12	26.25
Scale 1	Scale 2	73.897	40.330	54.66	31.85
Scale 2	Scale 2	54.828	64.993	66.63	47.32
Scale 3	Scale 2	50.697	59.519	72.17	42.26
Scale 4	Scale 2	28.470	99.84***	46.97	54.14
Scale 5	Scale 2	24.072	27.555	34.42	40.10
Scale 6	Scale 2	44.797	27.967	48.93	20.05
Scale 7	Scale 2	47.431	40.66*	38.14	39.86
Scale 1	Scale 3	49.864	45.218	52.20	47.81
Scale 2	Scale 3	68.063	51.240	52.13	53.86
Scale 3	Scale 3	59.214	74.771	79.00	69.50
Scale 4	Scale 3	42.087	113.62*	55.55	91.26
Scale 5	Scale 3	24.194	28.087	44.13	30.46
Scale 6	Scale 3	60.452	30.575	32.05	32.52
Scale 7	Scale 3	34.372	44.34**	32.73	26.16
Scale 1	Scale 4	61.06**	20.298	85.00**	45.79
Scale 2	Scale 4	90.81**	32.051	92.19***	61.60
Scale 3	Scale 4	67.791	35.304	81.62**	51.21
Scale 4	Scale 4	73.530	69.222	120.72**	77.26
Scale 5	Scale 4	89.622	62.349	66.13*	59.83
Scale 6	Scale 4	52.228	53.930	72.10**	38.05
Scale 7	Scale 4	62.630	38.889	56.06	17.68
Scale 1	Scale 5	20.638	36.904	65.42**	58.65
Scale 2	Scale 5	47.050	50.706	67.31**	34.45
Scale 3	Scale 5	74.43*	40.107	54.35*	48.48
Scale 4	Scale 5	99.95*	58.966	94.60**	50.98
Scale 5	Scale 5	191.264	94.948	141.62***	87.95
Scale 6	Scale 5	61.739	43.674	65.57***	39.81
Scale 7	Scale 5	68.225	49.995	53.42*	26.27
Scale 1	Scale 6	81.45**	25.338	31.16*	24.47
Scale 2	Scale 6	93.53***	30.143	86.04*	31.50
Scale 3	Scale 6	89.00**	39.734	79.76*	54.59
Scale 4	Scale 6	81.67**	38.750	108.22**	37.29
Scale 5	Scale 6	86.60*	33.625	61.69	86.29
Scale 6	Scale 6	192.557	107.292	282.67	66.52
Scale 7	Scale 6	129.177	44.430	64.05	30.54
Scale 1	Scale 7	28.831	32.524	43.62	38.30
Scale 2	Scale 7	34.004	43.109	45.05	39.57
Scale 3	Scale 7	44.765	38.812	39.28	50.26
Scale 4	Scale 7	48.289	54.960	66.52	55.50
Scale 5	Scale 7	50.398	45.333	97.17	122.57
Scale 6	Scale 7	28.789	44.940	48.43	62.99
Scale 7	Scale 7	128.296	132.132	170.70*	137.44

***, ** and * refer to 1%, 5% and 10% levels of significance based on the bootstrap p-values on 100 re-drawings. Toda-Yamamoto causality test has been implemented for the two models at the respective scales.

present the causal effects from inflation to economic growth, while in Panel (b) we present the causal effects from economic growth to inflation. As the results are presented in level curves, the colour code indicates the height and refers to the strength of causal effects between inflation and economic growth, which runs from 0 (that is, no causal effect) to 1 (that is, full causal effect). The vertical axis reports the frequency in the months while the horizontal axis reports the time.

We observe that Granger-causality is predominantly unidirectional over some specified periods,

although there is an instance of bidirectional causality as well between inflation and economic growth. Also, most of these effects are generally confined to the business cycle period, that is, a period of about 1–5 quarters. For instance, in Panel (b), economic growth was found to Granger-cause inflation on a business cycle of 8 ~16-month frequency, occurring between January 1991 and January 1995. In the same business cycle of 8 ~16-month frequency, as shown in Panel (a), the causal role was swapped between the two variables with inflation Granger-causing economic

growth between January 1995 and March 1999. This unidirectional causal link probably lends credence to the theoretical justification as advanced by Gillman and Kajek (2011). They argued that in an inflationary environment lower interest rates will encourage the repression, which will in turn discourage savings rate and reduce capital-labor ratio. Consequently, economic growth will be reduced. Beginning from March 1999 to sometime in 2001, however, causal effects are bidirectional between inflation and economic growth. These bidirectional causal effects are short-lived as the era of unidirectional causal effects soon resurfaces between 2005 and 2008. Since 2008, the causal effects seemed to have become nil, indicating a breakdown of the tie. The weakening tie can be associated with how significance the transitory effects of income in the Indian economy, particularly at the beginning of 2008 global economy. At that time, as elsewhere, any economic gains were seen more as transitory gains and were thus severed from impacting on demand. This result not only shows the nature of the factors (that is, whether or not those factors are long-run factors) responsible for the causal link but also the historical development of such a link. Also clear from the figure is that there is no long-run causal link between inflation and economic growth.

VI. Conclusions

The study analysed the time-varying dependence through time-varying coherence function and time-frequency causal relationship between inflation and economic growth for India by using monthly data covering January 1992 to December 2015. To analyse the issue in depth, we examined the time-frequency relationship between inflation and economic growth by utilizing a multi-scale wavelet approach based on a MODWT as well as continuous wavelet. In particular, the relationship is analysed using: (1) correlation and (2) the lead-lag relationship. To highlight the importance of wavelet scales, we further analysed the energy distribution of both series at all scales. The wavelet correlation is estimated by testing the correlation between inflation and economic growth in the various timescales. To examine the lead-lag relationship between the two markets, we employ wavelet

cross-correlation and the Granger-causality test for various timescales.

Our results from spectral density estimates highlighted the importance of evolutions in the short frequency components for inflation and high-frequency components of economic growth. The long-run cycles show very high and increasing dependence between inflation and economic growth, particularly after mid-2002 whereas medium run shows the reverse. Note that though coherency only shows the dependency, we are able to provide answers to the lead-lag relationship between inflation and economic growth through Granger-causality analysis at scale by scale basis. Overall from the Granger causality analysis, we find that high-frequency components of economic growth Granger-cause low-frequency components of CPI-based inflation and vice-versa, and at all scale's economic growth Granger-cause inflation at scales of 4–6 and no evidence of causality was detected from WPI-based inflation to economic growth.

The continuous wavelet-based analysis provided the evidence of uni- as well as bi-directional causal relationship at different timescales. However, continuous wavelet-based Granger-causality results not only show the nature of the factors (that is, whether or not those factors are long-run factors) responsible for the causal link but also the historical development of such a link. Finally, results indicate that there is no long-run causal link between inflation and economic growth. The insightful information as provided by these findings support some divergence in short-, medium- and long-run relationship between inflation and economic growth in terms of the leadership, causality and effects. Thus, policy focus should be on the proper management of inflation, which requires well-planned inflation targeting policy on one hand and monetary and exchange rate policies on the other.

The present study can be extended by analysing the wavelet-based relationship between inflation and other macroeconomic variables like monetary aggregates and stock prices since theoretically all these variables are expected to be highly correlated with each other.

Disclosure statement

No potential conflict of interest was reported by the authors.

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