The Vanishing Role of Money in the Macroeconomy:
An Empirical Investigation Based On Spectral and Wavelet Analysis

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Abstract

The recent de-emphasizing of the role of "money" in both theoretical macroeconomics as well as in the practical conduct of monetary policy sits uneasily with the idea that inflation is a monetary phenomenon. Empirical evidence has, however, been accumulating, pointing to an important leading indicator role for money and credit aggregates with respect to long term inflationary trends. Such a role could arise from monetary aggregates furnishing a nominal anchor for inflationary expectations, from their influence on the term structure of interest rates and from their affecting transactions costs in markets. Our paper attempts to assess the informational content role of money in the Indian economy by a separation of these effects across time scales and frequency bands, using the techniques of wavelet analysis and band spectral analysis respectively. Our results indicate variability of causal relations across frequency ranges and time scales, as also occasional causal reversals.

Key words: money, inflation, cointegration, causality, decomposition, band spectra, wavelets

JEL Code(s): C32, E51, E52

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1. Introduction

Recent years have witnessed a considerable downgrading of the status of "money" in both theoretical macroeconomics as well as in the practical conduct of monetary policy. If Milton Friedman's (1963) dictum that "inflation is always and everywhere a monetary phenomenon" was a fairly accurate reflection of macroeconomic thinking in the 1970s, the prevailing mood today is best summarized by the statement a few years ago by Lawrence Meyer (FRB) (2001) to the effect that "money plays no explicit role in today's consensus macro model, and it plays virtually no role in the conduct of monetary policy." The factors contributing to this development are by now too well known to merit a detailed discussion. Briefly, the shift of attitude reflects partly the disillusionment with the monetary targeting experience of the 1970s and partly the dip in the secular inflation trend which has been widely attributed to the increased central bank credibility, associated with inflation targeting and the switchover to interest rate (Taylor type) rules.

The theoretical basis for de-emphasizing the role of money comes from two main sources. Some of the earlier literature had suggested that money should have a limited role for predicting output in equilibrium models where business cycle fluctuations have real rather than monetary origins (King & Plosser (1984), Bernanke (1986), Eichenbaum & Singleton (1986) etc.) Recent literature (e.g. Rotemberg & Woodford (1999)) basing itself on variants of New Keynesian economics, tries to demonstrate that a Taylor interest rate rule, set independently of monetary growth, is near optimal in such a framework. Several empirical studies (Estrella & Mishkin (1997), Stock & Watson (1999), Gerlach & Svensson (2003) etc.) also are in general agreement with this reduced role for "money" in monetary policy. This strand of academic thinking has also heavily influenced central bank thinking on policy. The European Central Bank's (ECB) decision to review its two-pillar concept of policy-making in 1999, furnishes a prime example of the shift in thinking. Earlier the First Pillar (*monetary analysis*) gave a very prominent role to the growth of money and credit aggregates, and even provided reference values for the growth of the broad money aggregate M3. The Second Pillar (*economic analysis)* was envisaged as supplementing the First Pillar by providing a wide range of real and financial indicators. Bowing to the criticism frequently aired by several influential academic

economists[2], the ECB reversed the role of presentation of the two pillars , de-emphasizing its stance on monetary aggregates by explicitly stating that "monetary analysis mainly serves as a means of cross-checking from a medium to long-term perspective, the short to medium-term indications coming from economic analysis" (ECB 2003).

There is thus, an apparent paradox between the idea that inflation is a monetary phenomenon (which is widely agreed) and the declining role of monetary aggregates in monetary policy.

The older vintage of models employed to assess the impact of monetary policy on the macro-economy, typically comprised four components viz., an aggregate demand function (the IS curve relating total demand to interest rates and expected inflation), an aggregate supply curve (the Phillips-Lucas supply curve), a demand for money function (LM curve) and finally, a money supply equation relating the supply of a monetary aggregate to changes in the base money (money multiplier relationship). The more recent models replace the money multiplier equation by an explicit feedback rule for nominal interest rates, and additionally posit a passive adjustment of the money supply to the demand (at any given interest rate), thus easing monetary aggregates totally out of the picture.

If these newer models were accurate descriptions of reality, one would reasonably expect monetary aggregates to be devoid of any "informational content" for future inflation, beyond that contained in nominal interest rates. Several recent studies, most notably Nicoletti-Altimari (2001), Trecroci & Vega (2002), Gerlach & Svensson (2003), Jansen (2004) etc. have, however, found a useful leading indicator role for monetary and credit aggregates with respect to low-frequency trends in inflation.[3]

There could be several explanations for such a leading indicator role for monetary aggregates vis-à-vis inflation. Firstly, as noted by Trecroci & Vega (2002), monetary aggregates may play a nominal anchor role, whereby the announcement of a reference trajectory for future monetary growth, helps agents form expectations about future prices (this role is strongly conditioned by the credibility of the central bank).

Secondly, monetary aggregates could influence macroeconomic developments through changes in the term structure of interest rates. This transmission mechanism has two causal

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[2]For example, Begg et al (2002) pointedly comment "Sensibly, the second pillar is the real deal. So why not say so?"

[3] Most of these studies are for the ECB area.

links –the effects of debt management policy on yield structure[4] (Agell *et al* (1992)) and the importance of "funding policy" in the determination of broad money supply (Goodhart (1999)).

Thirdly, the quantity of money can affect the size of transaction costs in the markets for goods and services as well in financial markets. Recognition of the role of money in reducing frictions in financial markets can provide a potentially more significant role for monetary and credit aggregates in the transmission mechanism (Aiyagari *et al* (1998)).

There is thus a convincing theoretical case for paying attention to the role of the money stock in the transmission of monetary policy. It would be generally agreed that this is largely conditioned by the institutional settings in any particular economy, though (as mentioned above) there is in marked evidence a tendency for central bankers the world over to increasingly relegate money supply to a secondary status as one of several monetary policy *indicators*. At least a part of the reason for this apathy towards monetary aggregates stems from a conviction of their *vanishing* role in influencing the macroeconomy. However the evidence for such a conviction derives from studies which neglect the possibility of monetary aggregates being related to other macroeconomic variables across varying time horizons[5]. The realization of this neglect has revived attempts to assess the role of money in monetary policy making, by examining the "information content" of monetary aggregates for predicting inflation (as well as interest rates and output) over alternate time horizons (Masuch et al (2003), Bruggeman et al (2005) etc.). [6]

Much of the recent literature on this aspect has been for OECD countries where financial liberalization is fairly advanced, where central banks are near full autonomy and government ownership and control of financial institutions is virtually absent. In many emerging market economies (henceforth EMEs), these features do not necessarily obtain, and hence the role of money in the macroeconomy is still open to question. In India, for example, there has been some tendency to look at the role of money somewhat disparagingly. This drift in emphasis on money is partly a simple reflection of a similar drift (remarked on above) for the advanced economies untempered by any realization that India is not a fully liberalized

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[4] Traditional finance theory maintains that equilibrium asset yields are independent of the supplies of different assets, thus denying any role to debt management policy in influencing the shape of the yield curve. The failure of "Operation Twist" in the USA is an oft cited example in support of this position.

[5] There have been notable exceptions to this statement even in the earlier literature (see e.g. Engle (1974), Thoma (1994), Cochrane (1989), Artis et al (1991), Ramsey & Lampart (1998) etc.)

[6] One particularly interesting (but tentative) conclusion to emerge from these studies is that the link between broad money aggregates and inflation seems to be stronger at long horizons but less apparent at shorter horizons.

economy but rather a *liberalizing* one. Neither is this de-emphasis supported by any noteworthy empirical evidence based on rigorous statistical testing. Our study is an attempt to fill in this lacuna, and hopefully contribute to improved understanding of the process of financial liberalization and financial innovation under way (in India) and their impact on operating procedures and monetary policy efficacy[7].

As mentioned above, a correct assessment of the role of money in the macroeconomy needs some attention to a decomposition over different time horizons. Such decomposition can be attempted via either of two avenues viz. traditional band-spectrum analysis (Engle (1974), Harvey (1978) etc.) and the recently arrived literature on wavelets (Ramsey & Lampart (1998), Kim & In (2003), Crowley (2007) etc.). The two approaches are conceptually distinct though not unrelated and throw light on different aspects of any relationship. There is thus some merit in using both and noting points of consonance and dissimilarity, so that any emerging evidence can be presented with a greater degree of confidence for analytic and policy purposes.

The plan of our paper is as follows. Section 1 has laid out the context for the study. Section 2 briefly discusses how various relationships of interest can be decomposed either by frequency (band-spectrum analysis) or by timescales (wavelet analysis). It also offers the major points of distinction between the two approaches. Section 3 discusses the salient institutional features of the Indian economy in its current liberalizing context, sets out the variables and their data base, and presents the benchmark causality results connecting money, output and inflation in three model variants. Section 4 examines the behaviour of the causal relations across various frequency bands, while the decomposition across timescales (using wavelets) is attempted in Section 5. Conclusions are gathered in Section 6.

2. Decomposing Relations by Frequency and by Scale

The idea that the nature of economic relationships can vary according to the time horizon considered, is hardly new. Economists like Marshall, Edgeworth, Keynes and others recognized that behaviour of economic agents could vary over different decision making horizons. However, partly from a reluctance to get too deeply involved in mathematical technicalities (which many of them believed detracted from the economic essence of a theory) and partly from the underdevelopment of the techniques themselves, their analyses rarely transcended broad time classifications such as the *short, medium* and *long* runs. Taking the

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[7] The Reserve Bank of India abandoned monetary targeting and switched to a more eclectic multiple indicator approach towards the end of the 1990s. This shift has often been viewed as a de-emphasizing of the role of money and monetary aggregates in monetary policy. However, in the recent period, whenever there have been signs of inflation resurgence, the need to focus more closely on the quantum channel for money has resurfaced.

lead from natural scientists, several modern economists have not hesitated to look in greater depth at the possibility that economic relations could vary across a cascade of time scales. The two basic approaches here are band spectrum analysis (decomposition across frequency bands) and the more recent wavelet analysis (decomposition across time scales). As the first is now well entrenched in the literature, we provide only a thumbnail sketch of the same. The second being of a more recent vintage, merits somewhat greater attention. We also try to pinpoint some essential differences in   the two approaches, which need to be borne in mind in interpreting and comparing their results.

A. Band-Spectrum Regression:

The essence of this approach lies in defining conceptually interesting components of the data by their frequency ranges[8]. Recall that in spectral analysis each series is viewed as being composed of a superposition of trigonometric cycles of different frequencies. Thus long-term movements in the data series may be identified with the low frequency components of the series (as captured by passing the data through a low-pass filter) while the short term movements can be assigned to the high frequency components (captured similarly by a high pass filter). The long or short term can then be appropriately defined as per the investigator's requirements by deciding on the appropriate cut-off frequency for the filter. Similarly by using band pass filters (i.e. filters which only allow frequencies within particular bands to pass through) we can obtain approximations to movements of the series corresponding to cycles within specified time spans.

Suppose we are given the observed series X_t ; $t = 1, 2 ..... (T-1)$ (monthly observations) and wish to focus on cycles within a specific set of frequencies. We define (see Engle (1974), Thoma (1994) etc.) a row vector w_k as

$$w_k = \{1, \exp(i\theta_k), \exp(2i\theta_k) ..... \exp((T-1)i\theta_k)\} \tag{1}$$

with

$$\theta_k = \left(\frac{2\pi k}{T}\right);$$

Define

$$W = \begin{bmatrix} w_0 \\ w_1 \\ ... \\ w_{T-1} \end{bmatrix} \qquad X = \begin{bmatrix} X_0 \\ X_1 \\ ... \\ X_{T-1} \end{bmatrix}$$

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[8] The approach is usually attributed to Engle (1974) but has precursors in the work of Hannan (1967), Wahba (1968), etc.

Suppose now that interest centers on frequencies corresponding to integral values of k in the range $[k_1, k_2]$. We then construct a $(T \times T)$ matrix A with 1's on the diagonal corresponding to values of k in the range $[k_1, k_2]$ and zeros everywhere else.

Define $X^* = AWX$ and let $X^\oplus = IFT\ [X]$ be the inverse Fourier transform of X^*. Then the entity $X^\oplus$ represents the cyclical component of the original series X with cycles corresponding to integral values of k in the range $[k_1, k_2]$.[9]

B. Wavelets : A Quick Overview

The basic aim of wavelet analysis is to represent a function of time X(t) as a linear superposition of *wavelets* , which are essentially functions with *narrow support* i.e. rapidly converging to zero as t becomes large.[10] Wavelets possess the attractive feature of *rescaling* i.e. they can be represented in the form

$$g(t) = \left(\frac{1}{\sqrt{s}}\right) g\left(\frac{t-u}{s}\right)$$

(2)

so that g(.) may be viewed as being centered at u, with a scale of s. The effect of s is to increase the support of g(.) - a process which is referred to as *integral dilation* in the time domain (see Ramsey (1998)). A number of standard wavelets are now available in the literature e.g. Haar, Daubechies (often called Daublets), Symmlets, Coiflets, Morlet, wavelets $'a\ trous$ etc. Within each family, there are two types of wavelets :

Father Wavelets: $\quad \Phi_{j,k} = 2^{-j/2} \Phi\left(\frac{t - 2^j k}{2^j}\right)$ (3)

With $\int \Phi(t)\,dt\ = 1$

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[9] As an illustration suppose we wish to focus on cycles ranging in duration from 6 to 12 months. These correspond to angular frequencies in the range $(2\pi\ /\ 6)\ to\ (2\pi\ /12)$ i.e. values of k between 30 and 60 (if T=360 say). Thus the matrix A will have 1's on the diagonal for these values of k and zeros elsewhere.

[10] The mathematical properties of wavelets are investigated by Daubechies (1992), Brillinger (1994), Mallat (1998) etc. and an excellent advanced text is Percival & Walden (2000).

Mother Wavelets: $\quad \Psi_{j,k} = 2^{-j/2} \Psi\left(\dfrac{t - 2^j k}{2^j}\right)$ (4)

With $\int \Psi(t)\,dt = 0$

The essence of wavelet analysis consists in projecting the time series of interest $\{X(t)\}$, onto a sequence of *father* and *mother* wavelets from a specific family (e.g. Haar, Morlet etc.), indexed both by the number of translations $k = \{0,1,2\ldots\ldots\}$ and the scale factor $s = 2^j \{j = 1,2,3\ldots\}$. The coefficients of this projection may be approximated by

$$s_{J,k} \approx \int X(t)\,\Phi_{J,k}(t)\,dt$$

$$d_{j,k} \approx \int X(t)\,\Psi_{j,k}(t)\,dt \; ; j = 1,2,\ldots\ldots J$$

In actual data analysis, involving finite discretely sampled data the above coefficients will have to be computed over a lattice. It is convenient to assume the series $\{X(t)\}$ to be of *dyadic* length N (i.e. $N=2^J$, where J is a positive integer).

The multi-resolution representation of the signal X(t) is now given by

$$X(t) = \sum_k s_{J,k}\Phi_{J,k}(t) + \sum_k d_{J,k}\Psi_{J,k}(t) + \ldots$$
$$+ \ldots \sum_k d_{J-1,k}\Psi_{J-1,k}(t) + \ldots \sum_k d_{1,k}\Psi_{1,k}(t)$$
(5)

where the basis functions $\Phi_{J,k}(t)$ and $\Psi_{j,k}(t)$ are assumed to be orthogonal (see Crowley (2007))

$$\int \Phi_{J,k}(t)\Phi_{J,k'}(t) = \delta_{k,k'}$$

$$\int \Psi_{J,k}(t)\Phi_{J,k'}(t) = 0$$

$$\int \Psi_{j,k}(t)\Psi_{j',k'}(t) = \delta_{k,k'}\delta_{j,j'}$$

where $\delta_{k,k'} = 0,\ if\ k \neq k'$ and $\delta_{k,k} = 1,$

In (5), the term $\sum_k d_{j,k}\Psi_{j,k}(t)$ represents the variation of X(t) at time scale $2^j ; j = 1,2\ldots J$, whereas $\sum_k s_{J,k}\Phi_{J,k}(t)$ is a scalar representing the averages on a scale of length 2^J (see Gencay et al (2002) p.117-125). Higher scales correspond to longer term movements in the given series X(t), with the scale 2^J identified with the secular (smooth) movement of the

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series. The number of coefficients $\{d_{j,k}\}$ at scale j are $\left(\dfrac{N}{2^j}\right)$. These coefficients may be called "atoms" following Ramsey & Lampart (1998). Define the "crystals"

$$D_j = \left\{d_{j,k}\right\}_{k=1}^{2^j} \; ; j = 1,2...J \text{ and } S_J = \left\{s_{J,k}\right\}_{k=1}^{2^J}$$

The actual derivation of the atoms and crystals may be done via the so-called discrete wavelet transform (DWT), which can be computed in several alternative ways. The intuitively most appealing procedure is the *pyramid algorithm,* suggested in Mallat (1989) (and fully explained in Percival & Walden (2000)).

The crystals $D_1, D_2 \ldots\ldots D_J, S_J$ represent a convenient way of decomposing a given series $\{X(t)\}$ into changes attributable at different scales. Such a decomposition is referred to as a Multi-resolution analysis (MRA) and is defined by the relationship

$$X(t) = \sum_{j=1}^{J} D_j(t) + S_J(t) \tag{6}$$

The discrete wavelet transform (DWT) introduced above is often referred to as the *decimated* transform as the pyramid algorithm arises from a successive *down-sampling* process, in which only alternate observations are picked up at each sub sampling stage (see Gencay et al (2002), p.121-124) However as indicated by Kim & In (2003) for many economic and financial applications, an *undecimated* DWT is more appropriate, and this is furnished by the so-called *maximum overlap discrete wavelet transform* or MODWT, described in Coifman & Donoho (1995), Percival & Walden (2000) etc. The MODWT coefficients can be obtained via a pyramid algorithm, as in the case of the decimated DWT, except that no down-sampling is involved (so that the wavelet coefficients at each level j comprise N elements). The MODWT provides all basic functions of the DWT, but possesses several advantages over the latter.

a) It does not require the series length N to be dyadic. As a matter of fact, N can be arbitrary (Percival & Walden (2000) p.159).

b) The MODWT coefficients $\left\{d_{j,k}\right\}$ at scale $k = 2^j$ of the signal $(X(1), X(2),......X(m))$, m < N, are strictly the same as the first m coefficients at the same scale of the signal $(X(1), X(2),......X(N))$.

c) In contrast to the DWT, the MODWT details and smooth are associated with *zero-phase filters*, thus making it straightforward to match features in the MRA with those in the original series. (The application of any filter to a series results in a shift in the *phase* of the original series (Gencay et al (2002), p. 35). A *zero-phase* filter is a special type of filter, which leaves the phase of the original series unchanged). Unlike the MODWT, the DWT *detail* and *smooth* filters are not *zero phase filters* (Gencay et al (2002), p. 138).

C. *Spectral Analysis & Wavelets : A Comparison*

The basic and obvious analogy between Fourier analysis (and spectral analysis, which is closely based on it) and wavelets is that both approaches involve representing a function as a linear superposition of certain *basis* functions. These *basis* functions are the complex exponentials $\{\exp(i\omega t)\}$ in the case of Fourier analysis and the *mother and father wavelet* pair $\{\Psi_{j,k}(t), \Phi_{j,k}(t)\}$ in the case of wavelet analysis. Further as pointed out by Strang (1993) and Priestley (1996), a somewhat *tenuous* connection between wavelets and spectral analysis can be established. Certain types of wavelet families such as the *Mexican hat* family[11], have what are called "oscillatory characteristics" (see Priestley (1988), p. 147) and then low values of the parameter j (in $\{\Psi_{j,k}(t)\}$) indicate compression in the time domain and may be interpreted as corresponding to high frequency cycles. Similarly high values of j correspond to time dilation, and may be interpreted as low frequency cycles. We may thus identify the parameters j and k as loosely corresponding to the concepts of *frequency* and *time* respectively in Fourier analysis.

It cannot be overstressed that the above interpretation is only valid for wavelet families possessing the "oscillatory property". In general, there are important differences between wavelets and Fourier analysis. Firstly, whereas Fourier coefficients are indexed by a single parameter ω, wavelets are indexed by two parameters j and k, (with j corresponding to the *width* of the wavelet and k to the *time location*). Put differently the wavelet coefficients are *localized*, being time varying and dependent only on the local properties of X(t) in the vicinity of any time point (see Priestley (1996). By contrast Fourier coefficients depend on the global properties[12] of X(t).

A second difference stressed by Priestley (1996) is that in Fourier and spectral analysis both high and low frequency components are evaluated over the same time interval (the width of the spectral window does not vary with frequency), whereas in wavelet analysis high frequency components (or noise) are evaluated over short time intervals, whereas the low frequency components (or the smooth) are evaluated over longer time intervals. This enables wavelet analysis to highlight short duration transitory features of the data.

Priestley (1996) has also shown that for a restricted class of mother wavelets[13] the DWT (discrete wavelet transform) could be viewed as a *discrete* approximation (in both the

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[11] The Mexican hat family has a mother wavelet (see (4)) described by

$$\Psi(t) = \frac{1}{\sqrt{2\pi}\sigma^3}\left[1 - \frac{t^2}{\sigma^2}\right]\exp\left(\frac{-t^2}{2\sigma^2}\right) \text{ where } \sigma^2 \text{ is a constant}$$

[12] This confers one advantage on wavelets viz. that they are relatively less affected by irregular or discontinuous behaviour (spikes) of X(t) at a particular point.

[13] One type of mother wavelet belonging to this restricted class is defined by $\Psi(t) = \sqrt{2}\sin(2\pi t)\,;\,t\,\varepsilon\,[0,1]$ with $\Psi(t)$ vanishing elsewhere

time and frequency domain) to the *evolutionary spectral* representation of an *oscillatory process*[14]. However, it cannot be over-emphasized that this analogy is sustainable only for this special class of mother wavelets and breaks down, for example, with Haar wavelets.

Further points of analogy between Fourier and wavelet approaches to time series analysis are explored in Hogan & Lakey (2003), Chapter 3.
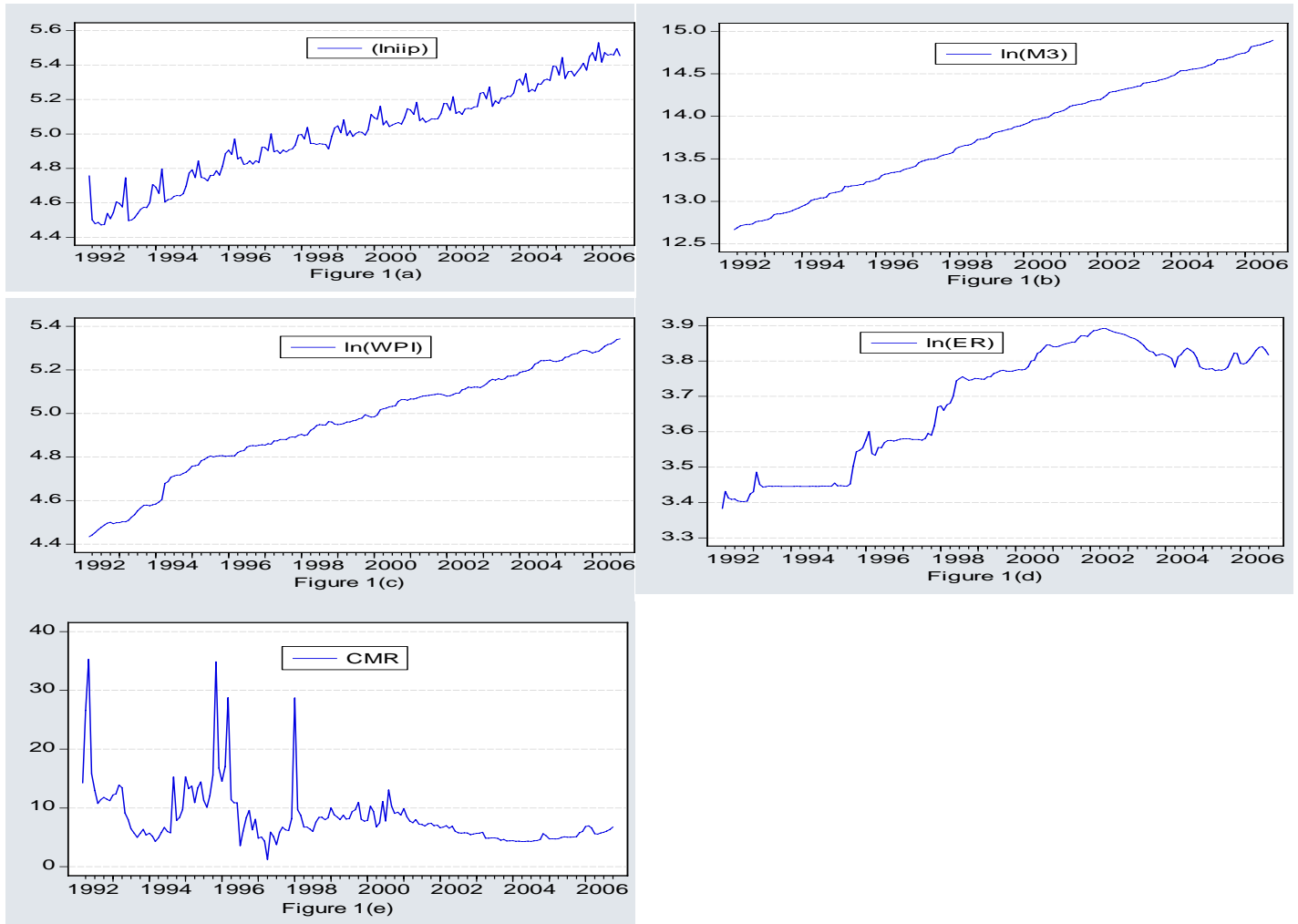
3. Benchmark Results

The main purpose of this paper is to examine whether money has a useful role to play in explaining variations in macroeconomic activity, mainly output and inflation. The rationale and importance of such an inquiry has been set out in Section 1. The techniques discussed in Section 2 can provide deeper insights into several aspects of this problem by decomposing this influence across frequency bands and time scales.

Our earlier discussion makes out the case for a serious re-examination of the role of money in an EME such as India, where the institutional features obtaining may be markedly different from those in OECD countries, which constitute the context for most of the current studies on this subject. Our data set is composed of 176 monthly observations from March 1992 to October 2006 on 5 basic macroeconomic aggregates : index of industrial production (IIP), wholesale price index (WPI), interbank call money rate (CMR), broad monetary aggregate (M3) and the bilateral US\$-INR (Indian rupee) exchange rate (EXR)[15]. Plots of Ln(IIP), Ln(M3), Ln(WPI), Ln(EXR) and CMR are shown in Figure 1(a) –(e) .

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[14] These concepts have been introduced into the literature by Priestley (1965, 1966)

[15] Since prior to 1992, the Indian financial system was a highly regulated one, financial prices were a poor indicator of monetary policy impulses and the *interest rate transmission channel* of monetary policy was virtually non-existent. This together with a pegged exchange rate implies a totally different regime for monetary policy in the pre-reforms period as opposed to the post-reforms period. Hence we decided on 1992 as the starting date for our analysis. Our excuse for the choice of IIP (on which data is available monthly) as a proxy for national output [15] is that the methods we propose to use are heavy consumers of degrees of freedom, though we are fully aware of the limitations of this choice in an era when an increasing proportion of national income is being accounted for by the services sector. An identical argument applies for the choice of the bilateral US\$-INR exchange rate over the conceptually more satisfying NEER (nominal effective exchange rate) The choice of the WPI over the CPI is mainly because the former has been traditionally used by official agencies (including the Reserve Bank of India) to measure "headline inflation". There are tricky problems associated with the choice of an appropriate short-term interest rate. Of the three possible candidates viz. TB-91(yield on 91-day treasury bills), CP (commercial paper) rate, and the CMR (call money rate), the last seems to best capture the market liquidity sentiment. TB-91 is subject to the vagaries of government short-term borrowing requirements and the CP market is a fragmented as well as a narrow one. Finally of the six measure of money supply in current usage in India, M3 is the one most frequently used as a reference point by analysts and policymakers alike.

Figure 1(a)

Figure 1(b)

Figure 1(c)

Figure 1(d)

Figure 1(e)

Unit root tests (Phillips-Perron) (not presented here in the interest of brevity) point to Ln(WPI), Ln(M3) and Ln(EXR) being I(1) processes, with Ln (IIP) and CMR being I(0) (around a linear trend).

The sensitivity of the Granger causality results to issues such as the period of analysis chosen, the number of variables included, the treatment of unit roots and cointegration etc. has been well documented in the earlier literature (see in particular Eichenbaum & Singleton (1986), Stock & Watson (1989), Friedman & Kuttner (1993) etc.). Our preliminary analysis confirmed that this is so for the Indian case too, with results changing somewhat significantly depending on the choice of the period of analysis[16]. We also found that results using a three variable model (Ln(IIP), LN(WPI) and Ln(M3)) or a four variable model (including

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[16]This is particularly noticeable if we restrict our period of analysis to March 1992 to April 2004, as compared to our current choice of March 1992 to October 2006.One possible explanation could be of the Indian economy entering a high growth phase subsequent to 2004.

additionally the interest rate variable CMR) varied in several details from the full model (based on the five variables Ln(IIP), LN(WPI), Ln(EXR) , CMR and Ln(M3)). To avoid too much cluttering of results, we will henceforth concentrate on the full 5-variable model, occasionally drawing attention to the sensitivity of some of our conclusions to this particular version of our model by comparing conclusions with the lower order models.

For the 5 variable model, we tested for cointegration between the three I(1) variables Ln(WPI), Ln(EXR), Ln(M3), treating the I(0) variables CMR and Ln(IIP) as exogenous to the system. We tested jointly for the appropriate model specification and the number of cointegarting vectors using the MacKinnon-Haug-Michelis (1999) approach, based on the AIC. As shown by the results in Table 1, the appropriate model is one in which the co-integration equation has both an intercept and a linear trend and the indicated number of cointegrating vectors is one. This cointegrating vector (normalized on Ln(M3)) is given by

$$Ln(M3) = 11.1550 + 0.010639 \ (T) + 0.287769 Ln(EXR) + 0.129135 Ln(WPI) \quad (7)$$
$$\underset{[-36.3078]}{} \qquad \underset{[-9.45381]}{} \qquad \underset{[-2.30302]}{}$$

(Figures in square parentheses denote t-values of the corresponding coefficients)

TABLE 1: AIC for Different Types of Models

Type of Trend in Data →	*None*	*None*	*Linear*	*Linear*	*Quadratic*
Nature of Cointegrating Vector →	*No Intercept* *No Trend*	*Intercept* *No Trend*	*Intercept* *No Trend*	*Intercept* *Trend*	*Intercept* *Trend*
Number of Cointegrating Vectors ↓					
0	-18.9829	-18.9829	-19.0338	-19.0338	-19.0707
1	-19.0513	-19.0553	-19.0726	*-19.1325*	-19.1314
2	-19.0296	-19.0443	-19.0567	-19.1065	-19.0984
3	-18.9597	-19.0066	-19.0066	-19.0477	-19.0477

Notes: The underlined entry denotes the minimum AIC, corresponding to a single cointegrating vector which has both an intercept and a trend.

We now conduct benchmark causality tests for exploring the relation between (i) money and output and (ii) money and inflation. To place the discussion in a general context, let $\overline{Z}(t) = [Z_1(t), Z_2(t) \dots \dots Z_m(t)]$ be an m-dimensional vector of I(1) processes, which are cointegrated with a single cointegrating relationship. Further let $\overline{W}(t) = [W_1(t), W_2(t) \dots \dots W_p(t)]$ be a p-dimensional vector of I(0) processes. Then the null hypothesis that "$Z_2(t)$ does not cause $Z_1(t)$" may be tested via the equation

$$\Delta Z_1(t) = \alpha + \sum_{i=1}^{m} \sum_{j=1}^{L} \beta_{i,j} \Delta Z_i(t-j) + \sum_{i=1}^{p} \sum_{j=1}^{L} \delta_{i,j} W_i(t-j) + \lambda(EC) + u(t) \qquad (8)$$

where EC denotes the error correction term.

The null hypothesis corresponds to a joint test for

$$\gamma = \beta_{2,1} = \ldots \beta_{2,p} = 0 \qquad\qquad (9)$$

which is tested by the usual F-statistic.

Using the procedure outlined above we conducted benchmark causality tests for our hypotheses of interest, with this variation that since our I(0) variables CMR and Ln(IIP) are stationary around linear trends, we also introduce a trend term in (8). The benchmark results are presented in Table 2, Column (2) along with the results for the lower order models for the sake of facilitating comparison.

TABLE 2: Benchmark Granger Causality Results for All Three Model Variants

Null Hypothesis ↓	F-statistic & P-value (in parenthesis) (5-Variable Model)	F-statistic & P-value (in parenthesis) (4-Variable Model)	F-statistic & P-value (in parenthesis) (3-Variable Model)
ΔLn(M3) does not cause ΔLn(IIP)	2.096891* (0.0479)	2.955241** (0.0095)	4.461017** (0.0002)
ΔLn(M3) does not cause ΔLn(WPI)	1.962003 (0.0646)	2.203893** (0.0459)	1.839677 (0.0837)
ΔLn(IIP) does not cause ΔLn(M3)	6.795166** (0.0001)	6.625299** (0.0000)	6.046809** (0.0001)
ΔLn(WPI) does not cause ΔLn(M3)	2.493396** (0.0193)	1.073550 (0.3811)	1.443194 (0.1922)

Notes: (*) and (**) denote significance at 5% and 1% respectively

The main features to emerge from the causality tests are the following:

a) Money supply growth continues to play a useful role in anticipating growth in real output (as proxied by industrial production). This conclusion is sustained in all the three model variants we have used. Interestingly, we note that the inclusion of an interest rate variable in our model reduces the causal significance of money growth for output growth (compare the results for the 3-varaible model with those in the 4-variable model). This conclusion supports the existence of the *puzzle* first noted by Sims (1980) for the US economy, that the money-output relationship is weakened in the presence of the interest rate. Our study additionally also brings out a further reduction in the causal significance of money (for output) when the exchange rate is allowed to enter the picture. Following Friedman & Kuttner (1993), this could be taken as evidence of the interest rate and exchange rate carrying important information about future output behaviour, beyond that conveyed by money supply.

b) There is at best weak evidence for money stock growth as a predictor of future inflation (at 10% level of significance rather than at the conventional 5% level).

c) A strong feedback seems to prevail from output growth to money stock growth but evidence of feedback from inflation to monetary growth obtains only in the full (5-variable) model.

The strong relationship between money supply growth and output growth is in keeping with several other studies (such as Spence (1989), Feldstein & Stock (1993), Abate & Boldin (1993) etc.). Our results also conform to another pattern uncovered in such studies viz. that the relationship displays a tendency to weaken as more financial variables are added to the model.[17] The disconnect that we observe between monetary growth and inflation, in a sense, is the obverse reflection of the strong relation between money and output. The traditional theoretical justification for this observed *non-neutrality* of money runs in terms of sticky prices and wages stemming from features such as implicit contracts, customer markets, efficiency wages, countercyclical mark-ups etc. (see e.g. Bils (1987), Rotemberg & Saloner (1986), Ball & Romer (1990) etc.). In recent years following from the seminal works of Mankiw (1985), Calvo (1983), Blanchard & Kiyotaki (1987) among others, a new generation of theoretical models (the so-called *neomonetarist* models) has sprung up which attempts to explain non-neutrality of money via *state-dependent pricing*.[18]

The theoretical literature clearly points to the relationship between money and output (and inflation) still being largely unsettled. Part of the ambiguity could be attributable to the possibility that this relationship could vary across time scales and the empirical evidence for such variation has so far been sparse (except for stray attempts such as Ramsey & Lampart (1998), Artis et al (1992), Thoma (1994) etc.). Decomposing empirically the relationship across timescales and/or frequency bands could thus usefully supply further stimulus to theoretical research aimed at shedding light on this conundrum.[19]

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[17] However the weakening evidenced in our model is much less sharp than that noticed in some of these models (see e.g. Friedman & Kuttner (1993))

[18] This refers simply to the phenomenon of individual firms' price responses depending on the state of the economy. The aggregate price level then depends on the fraction of firms that adjust and the degree of price adjustment (see Dotsey et al (1999), Kimball (1995), Christiano et al (2005) etc.).

[19] As two important instances we could mention (i) the possibility of identifying the short-term component of the money-income relationship as a money supply relationship with the long-term component as a money demand relation and (ii) the theoretical possibility raised in Caplin & Leahy (1991) and Dotsey et al (1999) that permanent (low frequency) changes in money stock will only affect output temporarily but will in the long run only affect prices (see also Nicoletti-Altimari (2001), , Gerlach & Svensson (2003), Jansen (2004) etc.).

4. Decomposition Across Frequency (Band-Spectral Analysis)

As mentioned in Section 1, our attempt is to study whether the direction of causality between money growth on the one hand and output growth and inflation on the other could be sensitive to the time horizon of interest. We first approach the issue from the band-spectral perspective which decomposes relationships across spectral frequency bands in the manner indicated in Section 2A.

Causality testing across specific frequency bands proceeds as follows. Suppose the null hypothesis of interest to be that "$Z_2(t)$ does not cause $Z_1(t)$ in the frequency band (ω_1, ω_2)", then letting $\Delta Z_1^\oplus(t)$ and $\Delta Z_2^\oplus(t)$ denote $\Delta Z_1(t)$ and $\Delta Z_2(t)$ with only the frequencies in the band (ω_1, ω_2) retained (and all other frequencies set to zero), we once again use the prototype of equation (8) with $\Delta Z_1^\oplus(t)$ and $\Delta Z_2^\oplus(t)$ replacing $\Delta Z_1(t)$ and $\Delta Z_2(t)$ respectively. As before the null hypothesis corresponds to an F-test (where λ as before is the coefficient of the error correction term but $\beta_{2,1}$ etc. correspond to the coefficients of $\Delta Z_2^\oplus(t)$

$$\lambda = \beta_{2,1} = ...\beta_{2,p} = 0$$

To maintain some comparability with the wavelet results to be discussed in the next section, we zero-pad the original series of 176 observations to a total of 380 observations (i.e. by approximately a factor of 2).[20] We then isolate the following 6 frequency bands for study:

B_1:(0.2500, 0.5000) *corresponding to cycles between* 2 *to* 4 *months*

B_2:(0.1250, 0.2500) *corresponding to cycles between* 4 *to* 8 *months*

B_3:(0.0625, 0.1250) *corresponding to cycles between* 8 *to* 16 *months*

B_4:(0.0313, 0.0625) *corresponding to cycles between* 16 *to* 32 *months*

B_5:(0.01563, 0.0313) *corresponding to cycles between* 32 *to* 64 *months*

S_5':(0.0000, 0.01563) *corresponding to cycles longer than* 64 *months* (*trend*)

The frequency band corresponding to the trend has been dubbed S_5' to emphasize the comparison with the *wavelet smooth* to be discussed in the next section.

We now present the Granger causality results across each of our 6 frequency bands above in Table 3 for the following 4 relationships (using the model variant with 5 variables):

(i)   ΔLn(M3) causes ΔLn(IIP)

(ii)   ΔLn(M3) causes ΔLn(WPI)

(iii) ΔLn(IIP) causes ΔLn(M3) and

(iv)   ΔLn(WPI) causes ΔLn(M3)

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[20] On the general desirability of zero-padding with a view to minimizing the so-called *picket-fencing* and *scalloping* effects, see Jones (2006). Padding to 380 observations enables us to study cycles of upto 64 months.

The benchmark causality results have already been presented in Table 2.

Table 3: Granger Causality Results Across Spectral Frequency Bands (5 Variable Model)

Null Hypothesis ↓	Band B_1 F-statistic & P-value (in brackets)	Band B_2 F-statistic & P-value (in brackets)	Band B_3 F-statistic & P-value (in brackets)	Band B_4 F-statistic & P-value (in brackets)	Band B_5 F-statistic & P-value (in brackets)	Band S_5' F-statistic & P-value (in brackets)
ΔLn(M3) does not cause ΔLn(IIP)	4.9374** (.0052)	3.9230** (0.0048)	2.7892** (0.0073)	3.0216** (.0095)	1.8653 (0.0090)	4.8681** (0.9143)
ΔLn(M3) does not cause ΔLn(WPI)	1.1834 (0.1757)	1.3694 (0.1453)	1.9658 (0.5941)	0.9902 (0.8355)	1.8356 (0.6704)	3.0409** (0.0087)
ΔLn(IIP) does not cause ΔLn(M3)	2.9638** (.0089)	8.3515** (0.0001)	7.9302** (0.0001)	1.1853 (0.3146)	2.6619* (0.0145)	6.8602** (0.0001)
ΔLn(WPI) does not cause ΔLn(M3)	2.4357* (0.0351)	3.0872** (0.0061)	1.5431 (0.0974)	1.2257 (0.1846)	2.7325** (0.0097)	6.4583** (0.0001)

Notes: (*) and (**) denote significance at 5% and 1% respectively

As the results in table 3 indicate, decomposing the various relationships across spectral frequency bands brings to light the changing dimension of the relationships depending on the horizon over which they are studied. Thus money supply growth is a leading indicator of output growth both for cycles as short as 2 to 4 months, as well as, for medium term cycles of between 32 to 64 months. However the trend monetary growth (sometimes called as core money growth) has little predictive value for the secular growth of output. Obversely, almost as a mirror image of the money stock-output relation, money Granger causes output only in the long run (in our analysis covering oscillations of periodicity greater than 64 months). This last feature may serve to highlight the usefulness of such decomposition. The benchmark result of "no causality from money to inflation" actually masks the fact that secular money growth is a useful indicator of secular inflation. There is feedback from both output and inflation to money stock at the short and long ends of the spectral field but the feedback is absent over the middle range (i.e. the bands covering cycles ranging from 16 to 32 months for the output to money feedback and 8 to 32 months for the inflation to money feedback). The low frequency feedback most likely reflects the long run transactions demand for money. So far as the short-term feedback is concerned, two possible explanations could be in order. Firstly, it could be capturing the fact that the monetary authority responds to any perceived temporary shocks to inflation and output with a short term monetary policy response. Secondly, short-term variations in economic activity lead to an immediate response in bank deposits (especially

demand deposits) and this could also partly account for the observed feedback. The absence of feedback in the middle ranges of frequency is more difficult to explain. No theoretical explanation seems to be available, but a plausible empirical explanation could be that the series involved move *in and out of phase* over the frequency band considered (see Ramsey & Lampart (1998)). We postpone an examination of this issue till after we complete the analysis based on wavelets in the next section.

5. Decomposition by Time Scales (Wavelet Analysis)

We now repeat the *causality testing* exercise conducted in the previous section, but using wavelet analysis. The procedure is very similar to that employed earlier except that the frequency bands are now replaced by wavelet decomposition across timescales.

Suppose once again that the null hypothesis of interest is "$\Delta Z_2(t)$ does not cause $\Delta Z_1(t)$ at the j-th time scale $\varsigma(j) = 2^j$; $j = 1,2...J$" Let $D_j[Z_1(t)]$ and $D_j[\Delta Z_2(t)]$ denote the respective *crystals* of $\Delta Z_1(t)$ and $\Delta Z_2(t)$ at the j-th scale. Re-invoking equation (8) with $D_j[Z_1(t)]$ and $D_j[\Delta Z_2(t)]$ replacing $\Delta Z_1(t)$ and $\Delta Z_2(t)$ respectively, the null hypothesis corresponds to the following F-test (where λ as before is the coefficient of the error correction term but $\beta_{2,1}$ etc. correspond to the coefficients of $D_j[\Delta Z_2(t)]$

$$\lambda = \beta_{2,1} = ...\beta_{2,p} = 0$$

However, care has to be taken in the choice of the type of wavelet, the length of the wavelet filter and the highest time scale. As in other areas of econometrics, no hard and fast rules apply here, though some indicative guidelines are available. On the choice of wavelet, the *symmlet* is often recommended for economic applications, as it is nearly symmetric and fairly smooth (being twice differentiable), and has a reasonably narrow compact support (see Strang & Nguyen (1996)).[21] The highest scale of decomposition (i.e scale J in the notation of Section 2) is determined by the number of observations and in our case is taken to be five.[22] We thus get the following crystals for each of our series

D_1 *corresponding to a time scale of* $2 - 4$ *months*
D_2 *corresponding to a time scale of* $4 - 8$ *months*
D_3 *correspond ing to a time scale of* $8 - 16$ *months*
D_4 *corresponding to a time scale of* $16 - 32$ *months*

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[21] Of course it needs hardly be stressed that the choice of the wavelet is guided by the characteristics of the signal on analyzing. Given that our series of interest are relatively smooth over the period of analysis, a symmlet was thought appropriate. For a discontinuous signal, the Haar wavelet, for example, could be a better choice.

[22] For 176 observations, the maximum number of scales could be seven, but the two highest scales will have poor resolution, and hence we restrict attention to only five scales (see Crowley (2007)).

D_5 *correspond ing to a time scale of* $32 - 64 months$

S_5 *correspond ing to* sec *ular or trend movemnets* (*exceeding* 64 *months*)

The length of the wavelet filter (or the width of its support) depends both on the frequency of the data and the number of observations[23]. As a rough rule (see Bruce & Gao (1996), p.69) the length of the filter may be taken as around or slightly less than twice $\left(\frac{N}{2^J}\right)$ where N is the number of observations and J the highest scale of decomposition. Our choice of the wavelet is thus a Symmlet (8).

We note that the choice of the time scales ensures that the crystals $D_1, D_2 ..... D_5$ closely corresponds to the cycles in the spectral bands $B_1, B_2 ..... B_5$, whereas the wavelet smooth S_5 corresponds to the low frequency cycles in band S'_5. This imparts a measure of comparability to the results obtained via wavelet and band spectral analysis, subject of course to the general caveats discussed in Section 2C. Our wavelet based Granger-causality results are presented in Table 4 for the four basic relationships (see Section 3A) which constitute the focus of this study (with the underlying model being the variant with 5 variables).

TABLE 4: Granger Causality Results for Varying Time Scale Crystals (5-Variable Model)

Null Hypothesis ↓	D_1 F-statistic & P-value (in brackets)	D_2 F-statistic & P-value (in brackets)	D_3 F-statistic & P-value (in brackets)	D_4 F-statistic & P-value (in brackets)	D_5 F-statistic & P-value (in brackets)	S_5 F-statistic & P-value (in brackets)
ΔLn(M3) does not cause ΔLn(IIP)	7.637938** (0.0001)	9.411278** (0.0001)	7.42056** (0.0001)	1.299128 (0.2553)	5.158549** (0.0001)	0.580294 (0.7710)
ΔLn(M3) does not cause ΔLn(WPI)	0.950730 (0.4699)	1.194923 (0.3098)	3.530709** (0.0016)	0.265281 (0.9663)	1.549067 (0.1559)	6.081876** (0.0001)
ΔLn(IIP) does not cause ΔLn(M3)	3.433105** (0.0021)	17.84190** (0.0001)	9.189834** (0.0001)	1.053112 (0.3974)	2.558939* (0.0166)	4.482722** (0.0002)
ΔLn(WPI) does not cause ΔLn(M3)	2.237738* (0.0348)	2.931290** (0.0069)	1.890190 (0.0756)	0.379729 (0.9129)	2.217092* (0.0364)	7.534296** (0.0001)

Notes: (*) and (**) denote significance at 5% and 1% respectively

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[23] As the length increases the mother wavelet becomes wider and smoother

TABLE 5: Crystal-wise Examination of Sims' Puzzle

Crystal ↓	F-values for the Null Hypothesis $\Delta Ln(M3)$ does not cause $\Delta Ln(IIP)$		
	3-Variable Model	4-Variable Model	5-Varaible Model
D_1	7.5729**	7.5178**	7.6379**
D_2	12.6816**	14.7431**	9.4113**
D_3	6.1522**	7.9207**	7.4200**
D_4	1.5951	1.4574	1.2991
D_5	4.0487**	5.1804**	5.1585**
S_5	2.4587*	0.7616	0.5803

Notes: 1. (*) and (**) denote significance at 5% and 1% respectively. 2. Figures in parentheses indicate P values.

The results in Table 4 once again point to how the nuances of the various relationships studied vary across different time scales. To illustrate further the usefulness of wavelet analysis, let us probe a little further into the so-called Sims *puzzle* (noted above in our discussion of the benchmark causality results in Section 3) about the causal significance of money for output declining successively with the inclusion of the interest rate and exchange rate into our model. Table 5 therefore presents the causality results for the relationship "money growth causes output growth" for the wavelet crystals in each of our models. We find that the puzzle really arises only at the crystal S_5, which refers to the long-term (more than 64 months) movements of the variables in our model, and is absent at lower scales (i.e. for short-term movements). Thus essentially the extra information contained in the interest rate and exchange rate (beyond that contained in the money supply) about future output growth really is essentially confined to the long-term.

We have utilized two alternative decompositions for our relationships viz. by frequency and by time scales. We now turn to an examination of how sensitive our results are to the choice of the decomposition method. A comparison of Tables 3 and 4 shows that disagreement among the two methods is limited viz. (i) For the money growth-inflation feedback relationship at the crystal D_3 (or frequency band B_3) and (ii) For the "money growth Granger-causes output growth" at crystal D_4 (or frequency band B_4).

The ambiguity at crystals D_3 (money growth-inflation) and D_4 (money growth-output growth) can be probed further. One possible reason could be that at these crystals, the concerned series move continuously *in* and *out of phase* and this fact could be responsible for the observed ambiguity. In Figures 2(a) & 2(b) we present the spectra for the crystal D_3 for $\Delta Ln(M3)$ and $\Delta Ln(WPI)$ as also for the crystal D_4 for $\Delta Ln(M3)$ and $\Delta Ln(IIP)$. Further

Figures 3(a) & 3(b) overlay the graphs for $\Delta Ln(M3)$ and $\Delta Ln(WPI)$ at the crystal D_3 and of $\Delta Ln(M3)$ and $\Delta Ln(IIP)$ as at the crystal D_4.
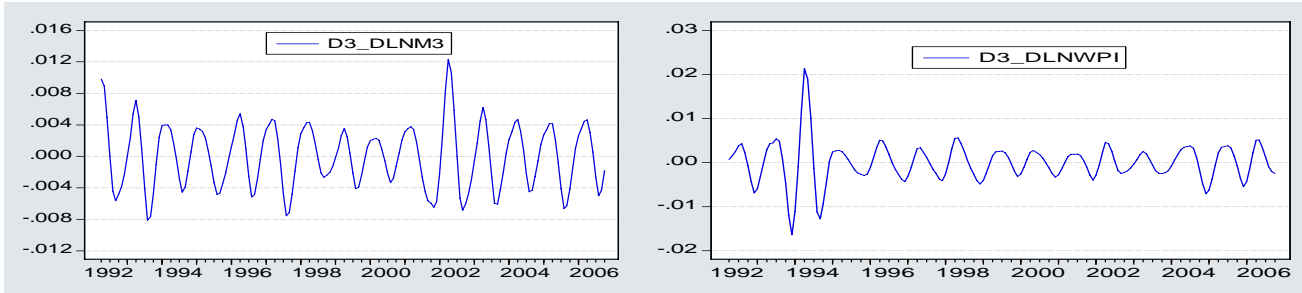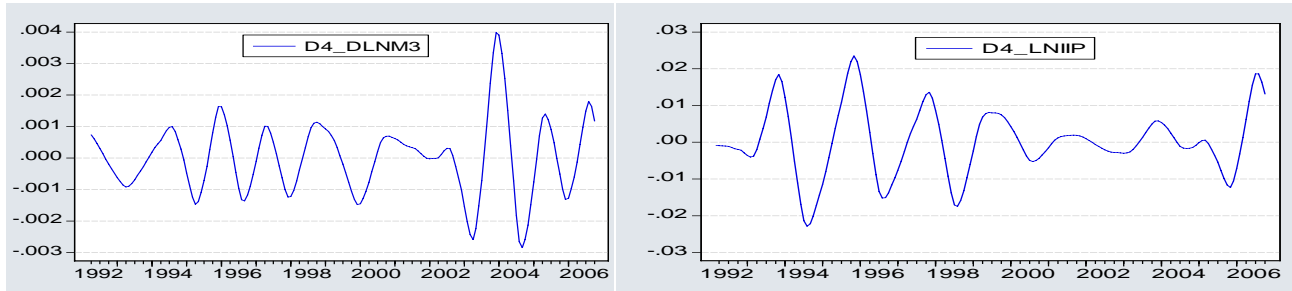
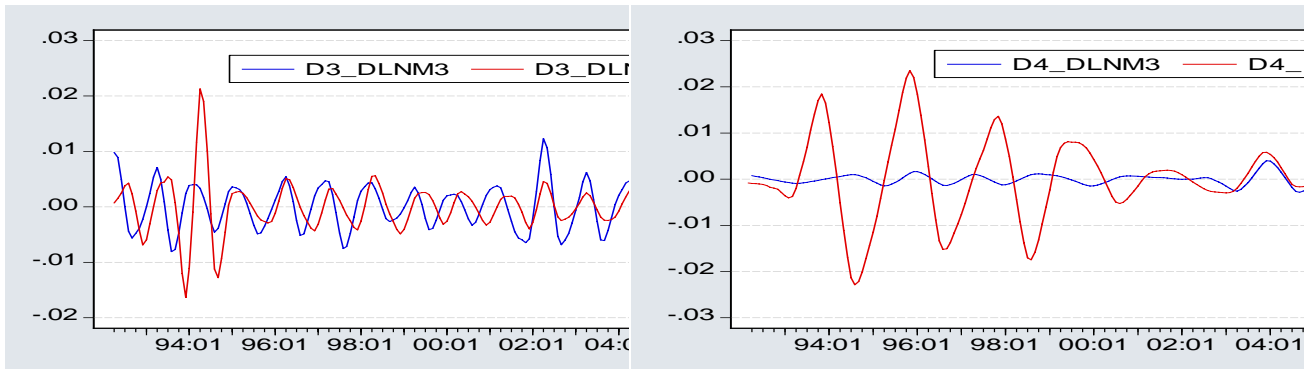

Figure 2(a)

Figure 2(b)

Figure 3(a) & 3(b)

These figure bring out the following interesting features that

(i) For crystal D_3 the two series of interest viz. $\Delta Ln(M3)$ and $\Delta Ln(WPI)$ move continuously in and out-of-phase[24] as follows:

Period	1992:03-1994:03	1994:04-1999:07	1999:08-2002:06	2002:07-2004:12	2005:01-2006:10
Phase	Out-In	In-Out	Out-In	In-Out	Out-In

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[24] This is due to the difference in the dominant periodicities at crystal D_3 for $\Delta Ln(M3)$ and $\Delta Ln(WPI)$ which are respectively 6.7 months and 5 months respectively.

(ii) For crystal D_4 also, *the* two series of interest viz. $\Delta Ln(M3)$ and $\Delta Ln(IIP)$ move continuously in and out-of-phase[25] as follows:

Period	1992:03-1998:03	1998:04-2004:06	2004:07-2006:10
Phase	*In-Out*	*Out-In*	*In-Out*

To account for the varying phase relationships, we conduct separate Granger causality tests over each distinct part of the cycle. For crystal, D_3 five such distinct phases are identified, whereas for crystal D_4, there are three distinct phases. However, because the total number of observations in some of these phases are too few to permit meaningful causality testing, we concentrate only on the following two phases for the crystal D_3

Period 1994:05- 1999:08 In-Out   *Period 1999:09 - 2002:07 Out-In*

and further for crystal D_4, we single out for attention the two phases

Period: 1992:03-1998:04 In-Out   *Period 1998:05 – 2004:07 Out-In*

The results of conducting Granger causality tests for each of these phases are displayed in Table 6.

TABLE 6: Granger Causality Results: Variation by Phases

Crystal : D_3		Time Period	
		1994:05- 1999:08	1999:09 - 2002:07
Phase Relationship $\rightarrow$		In-Out	Out-In
$\Delta Ln(M3)$ does not cause $\Delta Ln(WPI)$	F-Statistics	8.8482** (0.0001)	5.1366** (0.0047)
$\Delta Ln(WPI)$ does not cause $\Delta Ln(M3)$	F-Statistics	0.7504 (0.5900)	2.7377 (0.0543)
Crystal : $D4$		Time Period	
		1992:03-1998:04	1998:05 – 2004:07
Phase Relationship $\rightarrow$		In-Out	Out-In
$\Delta Ln(M3)$ does not cause $\Delta Ln(IIP)$	F-Statistics	2.82496* (0.0245)	3.2555* (0.0199)
$\Delta Ln(IIP)$ does not cause $\Delta Ln(M3)$	F-Statistics	6.3647** (0.0001)	1.0248 (0.4120)

Notes: (*) and (**) denote significance at 5% and 1%.Figures in parentheses indicate P-values.

Interestingly, this further breakdown indicates (see Table 6) that the nature of the causal relationship does show changes over the different phases. For example, (crystal D_4) money growth uni-directionally Granger-causes output growth in the Out-In phase, whereas in the In-

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[25]The dominant periodicities at crystal D_4 for $\Delta Ln(M3)$ and $\Delta Ln(IIP)$ are 10 months and 22 months respectively.

Out phase there is feedback. Similarly, (at crystal D_3) money growth leads inflation when the two series are moving out of phase, whereas when the two series are moving into phase there is also in evidence a mild feedback from inflation to money growth. Thus part of the explanation of the disagreement between the band-spectral and wavelet results could lie in the fact of the nature of the relation itself being phase-dependent (see e.g. Ramsey & Lampart (1998)).

6. Conclusion

There has been a marked reduction in the importance of monetary aggregates in the conduct of monetary policy in the wake of the on-going process of financial liberalization in developed countries as well as EMEs. This de-emphasis sits somewhat uneasily with those macro-economic theories that assign a prime causal role to monetary phenomena in explanations of inflation. Further, as shown by Christiano *et al* (2007), even if monetary aggregates play no useful role in the monetary transmission mechanism, this does not constitute an argument for their abandonment. Such aggregates could still play a useful role in anchoring inflationary expectations and guard against some of the negative consequences of an inflationary targeting regime in the presence of nominal rigidities such as wage frictions. Thus it is a worthwhile exercise to carefully scrutinize the empirical role of monetary aggregates in the macro-economy. In the context of an EME, such an examination assumes even greater significance, since the role of monetary aggregates is even less understood here, many such economies being in transition from a stage of *financial repression* to one of *financial openness.* These and other similar considerations underscore the *rationale* for studies such as this.

In examining the causal significance of monetary aggregates in the macro-economy, earlier research had been focused on two important *puzzles* viz. sensitivity of the results to the choice of the sample period (Eichenbaum & Singleton (1986), Christiano & Ljungqvist (1987) etc.), and to the model specification[26] (Bernanke (1986), Stock & Watson (1989) , Friedman & Kuttner (1993) etc.), the Sims' *puzzle* being a specific instance of the latter. Developments in spectral and wavelet analysis opened up the additional possibility of examining the varying role of money across distinct time horizons and indeed studies such as Artis et al (1992), Ramsey & Lampart (1998), Kim & In (2003) etc. bear out this possibility empirically.

Our benchmark results reinforce the first two *puzzles* noted above. The results alter significantly if the period of analysis is extended beyond April 2004 to October 2006, to include the recent high growth phase. As the high growth phase is widely expected to be persistent, we included it in our period of analysis (see Section 3). The sensitivity of the benchmark causality results to the model specification are well brought out in Table 3, which shows that the causality results are indeed affected by the variables included in the model. In

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[26]This also includes issues like the choice of the appropriate interest rate as well as the treatment of trend.

particular there is a clear indication of the existence of *Sims' puzzle*[27]. But the most interesting aspects of the paper refer to the decomposition of the underlying benchmark causality results across different time horizons. There is substantial agreement among the results following from the two alternative decompositions (see Tables 3 and 4). The money-output relationship seems to be characterized by feedback for short-term cycles of upto 16 months duration and then again for longer-term cycles of between 32 months and 64 months duration. The secular relationship (time periods exceeding 64 months) seems to be one of unidirectional causality from output to money growth. Similarly there is unidirectional causation from inflation to money growth at the short end of the cyclical span (upto 8 months) and over the longer end (32 to 64 months). The secular relationship seems to be characterized by feedback between the two series.

The two decomposition methods however show different results for cycles in the range of 8-16 months (for the money-inflation relation) and in the range of 16-32 months (for the money-output relation). Probing this discrepancy further brings out the interesting phenomenon of *phase drift* and the sensitivity of the causality results to whether the series are moving *into phase* or *out of phase.*

The wavelet decomposition was also utilized to throw further light on the issue of *Sims' puzzle*. It was found that the *puzzle* was absent throughout the business cycle span (upto 64 months) but surfaced strongly at the secular time scale (crystal S_5) (see Table 5).

The role of monetary aggregates in predicting macroeconomic movements has been a subject of enduring fascination for economists. In recent years the issue has acquired substantive policy connotations. However spectral and wavelet analysis can uncover further layers of complexity in the underlying relationships by permitting a look into what happens at different time horizons of interest. Our results for example show that causal relations can vary across frequencies and timescales, and causality reversals across differing decompositions occur all too frequently to be ignored as data vagaries. At the moment it is difficult to explain such causality reversals within existing theoretical structures, as the latter almost invariably proceed within broad time classifications such as the *short, medium* and *long* runs. There is no denying that the next big stage in the development of macroeconomic theory will be one in which time horizons can be graded on a much finer scale than hitherto and in which phenomena like causality reversal across different time periods, varying time scales and successive business cycle stages will get a fair share of attention.

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[27]This puzzle is discussed in Section 3 of the paper.

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