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Causality between Prices, Output and Money in India: An Empirical Investigation in the Frequency Domain

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Abstract

The causation between output and prices has been intensively investigated in the Indian context. Decomposing the money-output causality by frequency is likely to be highly revealing about the underlying macroeconomic processes. In this paper, we examine this issue using a bivariate methodology developed by Lemmens et al. (2008) in order to decompose Granger causality between money supply, prices and output in the frequency-domain. The evidence suggests that money supply granger causes output over the short-run, but over the business cycle frequencies and in the long run, money supply Granger causes prices, not output.

Key Words: Money; Inflation; Granger causality; Frequency-domain.

JEL Code(s): **E3, E5**

I Introduction

What is the strength and direction of relationships involving nominal magnitudes like money, and prices, and real output? This question has been extensively investigated in previous studies mainly using the Granger causality framework in the time domain, but there are no studies (for India) that decompose Granger causality by frequency. Different theoretical perspectives have differing predictions regarding the short and long term trade-offs between money, output and prices. Hence, a decomposition of the causality relationships over time is extremely important in understanding the underlying macroeconomic processes and consequently, in conducting monetary policy.

A number of hypotheses regarding the causal relationship, between money and income and between money and prices, with plausible theoretical arguments have been formulated in the past. The quantity theory of money argues that money is an exogenous variable. Cagan (1965) argues that money supply exhibits both endogenous and exogenous properties. For short-run and cyclical fluctuation, Cagan (1965) proposed a relation in which the money supply is endogenously determined by changes in the real sector. However, he asserts that in the long-run secular trend movements in money supply are independent of real sector and are determined exogenously. Friedman (1963) famously said: "inflation is always and everywhere a monetary phenomenon". In the monetarist view, increase in money supply, may lead to increase in output in the short-run, but in the long-run it influence only prices. Monetarists discard the existence of long-run Phillips curve trade-off, while allowing for the possibility of short-run trade-off as expectations adjust. An extreme rational expectation formulation denies even the short-run Phillips curve trade-off and argues that only an unexpected rise in money supply will lead to change in output, whereas the expected change in money supply will lead to a rise in relative nominal prices with no real effects (Lucas, (1972) and (1973)). On the other hand, nominal rigidities models by incorporating rational expectations had shown that monetary shocks do have real effects (Fischer, (1977), Phelps and Taylor, (1977), Taylor, (1979)). These models assume that long-term contracts, through fix wages or prices, prevent the realisation of advantageous transactions that were unpredictable when these contracts were being made but are realised or become predictable during the term of the contracts. The other forms of nominal rigidities models that have been suggested in influencing the output-inflation trade-off include menu costs (Mankiw (1985) and Akerlof and Yellen (1985)), information gathering and processing costs (Mankiw and Reis (2002)). The different theoretical predictions have varied implications for causality between nominal and real magnitudes over varying time horizons. The monetarist position implies a short-run trade-off between real and nominal magnitudes, with money supply impacting prices alone in the long-run. The rational expectations school would rule out short-run as well as long-run causality from anticipated money supply to output. The different Keynesian models, emphasising rigidities, lead to theoretical short-run or short-run as well as long-run causation from money supply to output depending upon whether the structural rigidities are short-term or long-term. Which of these positions best describes the Indian context can only be determined by an empirical methodology that is capable of distinguishing between causality in the short-run and the long-run. The commonly used time domain methodologies of determining direction and strength of causality do not decompose causality by different time horizons. This weakness constitutes a limitation on the empirical understanding of the money-income and money-prices causality in the Indian context.

In addition to the need to decompose causality according to different time horizons in order to distinguish between different macroeconomic processes operating in the Indian context, there is an additional policy benefit from undertaking a decomposition of causality between nominal and real magnitudes according to different time horizons. In conducting monetary policy, either central banks use money supply as an "intermediate target" variable or as an "information" variable, it is essential that there at least exist some reliably exploitable relation between money supply and income or money supply and prices, so that observed fluctuations in money provides a systematic implication for income or prices in the future. From an information-variable perspective or from an intermediate-target perspective, it is important to understand how these causal relationships pan out over different temporal horizons.

The Reserve Bank of India (RBI) broadly followed a monetary targeting rule from the mid-1980s onwards till around 1997-98 and broad money (M3) served as the intermediate target variable (Report on Currency and Finance, 2001-2002, para 5.16). The growing complexities of monetary management, by the latter half of the 1990s, in the context of ongoing liberalisation in the financial sector and opening up of the Indian economy, required that the process of policy formulation should be based on a wider range of inputs rather than on a single M3 aggregate. Accordingly, in 1998 Reserve Bank of India (RBI) adopted a multiple indicator approach for policy initiatives, whereby a set of economic variables was to be monitored along with the growth rate of money supply. However, even though the Reserve Bank of India (RBI) adopted an indicator approach for policy initiatives, the use of M3 money continued to be an important "information variable" of monetary policy stance (Report on Currency and Finance, 2005-2006, para 3.5). This makes it imperative to understand the temporal dimensions of the money, prices and output causal relations.

Given this background our study intends to investigate the money and output and money and price causality in frequency domain. The plan of the paper is as follows. Section 2 provides a brief review of empirical studies on money, output and price causality in India. Section 3 discusses the data and outlines the GC methodology over the spectrum proposed by Lemmens et al. (2008). Section 4 investigates the causal relations between money, output and prices in the frequency domain. Section 5 concludes the essay.

II Causality Between Money, Output and Prices in India: A Review

Several studies examine the causal link between money and output and between money and prices in the Indian context. Ramachandra (1983, 1986) using annual data, found that money causes real income and price level, price level causes real income and nominal income causes money. Sharma (1984) investigated the causality between price level and money supply (M1 and M2) using Granger (1969) and Sims (1972) methods for the period 1962-1980 and established bi-directional causality between M1 and Price level as well as M2 and price level. Although he found that causality from M1 to Price level was much stronger than the reverse causality from price levels to M1. Nachane and Nadkarni (1985) found unidirectional causality from money stock to prices based on their study on quarterly data over the period 1960-1961 to 1981-1982, with causality between real income and money stock remaining inconclusive. Singh (1990) set up bidirectional causality between money stock (M3) and prices (WPI) and revealed comparatively less significant causality from money supply to prices. Biswas and Saunders (1990) also found bidirectional causality or feedback between money supply (M1, M2) and price level (WPI), using quarterly data for two periods: 1962-1980 and 1957-1986. They contradicted Sharma's (1984) findings of comparatively weaker reverse causality between M1 to Price level. Masih and Masih (1994) found that money supply was leading and price was the lagging variable for the period 1961-1990. During the period of their study prices had a feedback effect on money supply but not strong enough to be statistically significant at 5 percent probability level. Rangarajan (1998) modelled the relationship between money, output and prices covering the period 1970-71 to 1992-93 and established that it was possible in the Indian context to predict the average inflation rate in the medium term on the basis of the reduced form money demand equation. Das (2003) examined relationship between money, price and output in India and provided the evidence that there exists bidirectional causality between money and prices and unidirectional causality between money and output, with causality running from money to output. Ashra et al. (2004) established bidirectional causality between price (GDP deflator) and M3. Ramachandran (2004) found that M3 growth could be used as one of the predictors of future prices.

The available studies for India provide mixed results regarding causality between money and income and between money and prices. A feature shared by all the studies is that they are all time domain investigations of causality. However, the strength of Granger causality (hereafter GC) and its direction may vary by frequency. Therefore, it may be worthwhile to follow Granger's (1969) suggestion that a spectral-density approach of GC would give a richer and more comprehensive picture than a one-shot GC measure that is supposed to apply across all periodicities. Our study attempts to investigate the causality between money and income and between money and prices in the frequency domain which can uncover further layers of complexity by allowing us to look into what happens at different periods of interest.

III Methodology and Empirical Evidence

III.1 Data

We have used monthly data for the period 1993:1 to 2009:9. We have considered broad money (M3) as measure of money supply reported at the end of the month by Reserve Bank of India (RBI). Output or income has been proxied by IIP manufacturing and prices by WPI manufacturing, with base year 1993-94. Data on all these variables was collected from Reserve Bank of India (RBI) database on Indian economy (RBI Website). All the three variables, IIP, WPI and M3, have been logarithmic transformed.

We first test for stationarity of for the three series IIP, WPI and M3. We have applied the Beaulieu and Miron methodology for testing unit roots in monthly data (see Beaulieu and Miron, 1993). Beaulieu and Miron (1993) used the approach developed by Hylleberg et al. (1990) to derive the mechanics of another procedure for testing seasonal unit roots using monthly data. The unit roots test results are presented in Table 1.

Table 1 Beaulieu and Miron test for integration at seasonal and non-seasonal frequencies

	0	π	$\pm\pi/2$	$\mp 2\pi/3$	$\pm\pi/3$	$\mp 5\pi/6$	$\pm\pi/6$
IIP (Stat.)	-1.71	-4.42	11.77	12.83	16.12	14.63	10.67
(P-value)	(0.1)*	(0.01)	(0.1)*	(0.1) *	(0.1) *	(0.1)*	(0.1)*
WPI (Stat.)	-1.84	-2.76	19.28	13.49	11.27	12.16	10.07
(P-value)	(0.1)*	(0.04)	(0.1)*	(0.1)*	(0.1)*	(0.1)*	(0.1)*

M3 (Stat.)	-1.16	-2.96	22.89	13.35	8.42	28.08	23.95
(P-value)	(0.1)*	(0.03)	(0.1)*	(0.1)*	(0.1)*	(0.1)*	(0.1)*

In the parenthesis, associated P-value has been given. The (*) reflects that we can not reject the null hypothesis of presence of unit roots at 5% level of significance. The test has been performed using the R software. (R Development Core Team (2008). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.)

The result in table 1 shows that all the variables were non stationary in levels. Therefore we cannot reject the null hypothesis i.e. presence of unit roots at seasonal frequencies as well as at zero frequency in all the three time series, IIP, WPI and M3. Following from the above result, all the three variables were seasonally differenced and further first differenced, which leaves us with 188 observations. The differenced series $\Delta_{12}\Delta$ of IIP, WPI and M3 were found stationary (not reported for brevity).

III.2 The causality test methodology

Analysing time series in frequency domain i.e. spectral analysis could be helpful in supplementing the information obtained by time-domain analysis (Granger, (1969) and Priestley, (1981)). Spectral analysis highlights the cyclical properties of data. In our study, we follow the bivariate GC test over the spectrum proposed by Lemmens et al. (2008). They have reconsidered the original framework proposed by Pierce (1979), and proposed a testing procedure for Pierce's spectral GC measure. This GC test in the frequency domain relies on a modified version of the coefficient of coherence, which they estimate in a nonparametric fashion, and for which they derive the distributional properties.

Let X_t and Y_t be two stationary time series of length T. The goal is to test whether X_t Granger causes Y_t at a given frequency λ. Pierce's measure for GC (Pierce (1979)) in the frequency domain is performed on the univariate innovations series, u_t and v_t, derived from filtering the X_t and Y_t as univariate ARMA processes, i.e.

$$\Theta^x(L)X_t = C^x + \Phi^x(L)u_t \qquad (1)$$

$$\Theta^y(L)Y_t = C^y + \Phi^y(L)v_t \qquad (2)$$

where $\Theta^x(L)$ and $\Theta^y(L)$ are autoregressive polynomials, $\Phi^x(L)$ and $\Phi^y(L)$ are moving average polynomials and C^x and C^y potential deterministic components. The obtained innovation series u_t and

v_t, which are white-noise processes with zero mean, possibly correlated with each other at different leads and lags. The innovation series u_t and v_t, are the series of importance in the GC test proposed by Lemmens et al (2008)[1].

Let $S_u(\lambda)$ and $S_v(\lambda)$ be the spectral density functions, or spectra, of u_t and v_t at frequency $\lambda \in]0, \pi[$, defined by

$$S_u(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_u(k) e^{-i\lambda k} \tag{3}$$

$$S_v(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_v(k) e^{-i\lambda k} \tag{4}$$

where $\gamma_u(k) = \text{Cov}(u_t, u_{t-k})$ and $\gamma_v(k) = \text{Cov}(v_t, v_{t-k})$ represent the autocovariances of u_t and v_t at lag k. The idea of the spectral representation is that each time series may be decomposed into a sum of uncorrelated components, each related to a particular frequency λ [2]. The spectrum can be interpreted as a decomposition of the series variance by frequency. The portion of variance of the series occurring between any two frequencies is given by area under the spectrum between those two frequencies. In other words, the area under $S_u(\lambda)$ and $S_v(\lambda)$, between any two frequencies λ and $\lambda + d\lambda$, gives the portion of variance of u_t and v_t respectively, due to cyclical components in the frequency band ($\lambda, \lambda + d\lambda$).

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[1] In Granger-Sims causality test, popularised by Sims (1972), the joint behaviour of time series is described as: a variable X will Granger-cause the variable Y if the set of correlations between current innovations in Y and lagged innovations in X is significant.

[2] The frequencies λ_1, λ_2, ….., λ_N are specified as follows:

$$\lambda_1 = 2\pi / T$$
$$\lambda_2 = 4\pi / T$$
$$.$$
$$.$$

The highest frequency considered is $\lambda_N = 2N\pi / T$

where $N \equiv T/2$, if T is an even number and $N \equiv (T-1)/2$, if T is an odd number (see Hamilton, p.159, 1994).

The cross spectrum represents the cross covariogram of two series in frequency domain. It allows determining the relationship between two time series as a function of frequency. Let $S_{uv}(\lambda)$ be the cross spectrum between u_t and v_t series. The cross spectrum is a complex number, defined as,

$$S_{uv}(\lambda) = C_{uv}(\lambda) + iQ_{uv}(\lambda)$$

$$= \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{-i\lambda k} \tag{5}$$

where $C_{uv}(\lambda)$ is called cospectrum and $Q_{uv}(\lambda)$ is called quadrature spectrum are respectively, the real and imaginary parts of the cross-spectrum and $i = \sqrt{-1}$. Here $\gamma_{uv}(k)=$ Cov (u_t, v_{t-k}) represents the cross-covariance of u_t and v_t at lag k. The cospectrum $Q_{uv}(\lambda)$ between two series u_t and v_t at frequency λ can be interpreted as the covariance between two series u_t and v_t that is attributable to cycles with frequency λ. The quadrature spectrum looks for evidence of out-of-phase cycles (see Hamilton, p.274, 1994). The cross-spectrum can be estimated non-parametrically by,

$$\hat{S}_{uv}(\lambda) = \frac{1}{2\pi} \left\{ \sum_{k=-M}^{M} w_k \hat{\gamma}_{uv}(k) e^{-i\lambda k} \right\} \tag{6}$$

with $\hat{\gamma}_{uv}(k) = \widehat{COV}(u_t, v_{t-k})$ the empirical cross-covariances, and with window weights w_k, for $k = -M,..,M$. Eq. (6) is called the *weighted covariance estimator*, and the weights w_k are selected as, the Bartlett weighting scheme i.e. $1-|k|/M$. The constant M determines the maximum lag order considered. The spectra of Eq. (3) and (4) are estimated in a similar way. This cross-spectrum allows us to compute the coefficient of coherence $h_{uv}(\lambda)$ defined as,

$$h_{uv}(\lambda) = \frac{|S_{uv}(\lambda)|}{\sqrt{S_u(\lambda) S_v(\lambda)}} \tag{7}$$

Coherence can be interpreted as the absolute value of a frequency specific correlation coefficient. The squared coefficient of coherence has an interpretation similar to the R-squared in a regression context. Coherence thus takes values between 0 and 1. Lemmens et al. (2008) have shown that, under the null hypothesis that $h_{uv}(\lambda)=0$, the estimated squared coefficient of coherence at frequency λ, with $0<\lambda<\pi$ when appropriately rescaled, converges to a chi-squared distribution with 2 degrees of freedom[3], denoted by χ_2^2.

$$2(n-1)\hat{h}_{uv}^2(\lambda)\xrightarrow{d}\chi_2^2 \tag{8}$$

where $\rightarrow^d$ stands for convergence in distribution, with $n=T/\left(\sum_{k=-M}^{M} w_k^2\right)$. The null hypothesis $h_{uv}(\lambda)=0$ versus $h_{uv}(\lambda)>0$ is then rejected if

$$\hat{h}_{uv}(\lambda)>\sqrt{\frac{\chi_{2,1-\alpha}^2}{2(n-1)}} \tag{9}$$

with $\chi_{2,1-\alpha}^2$ being the $1-\alpha$ quantile of the chi-squared distribution with 2 degrees of freedom.

The coefficient of coherence in Eq. (7) gives a measure of the strength of the linear association between two time series, frequency by frequency, but does not provide any information on the direction of the relationship between two processes. Lemmens et al (2008) have decomposed the cross-spectrum (Eq.5) into three parts: (i) $S_{u\Leftrightarrow v}$, the instantaneous relationship between u_t and v_t; (ii) $S_{u\Rightarrow v}$, the directional relationship between v_t and lagged values of u_t; and (iii) $S_{v\Rightarrow u}$, the directional relationship between u_t and lagged values of v_t, i.e.,

$$\begin{aligned} S_{uv}(\lambda) &= [S_{u\Leftrightarrow v}+S_{u\Rightarrow v}+S_{v\Rightarrow u}] \\ &= \frac{1}{2\pi}\left[\gamma_{uv}(0)+\sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k}+\sum_{k=1}^{\infty}\gamma_{uv}(k)e^{-i\lambda k}\right] \end{aligned} \tag{10}$$

The proposed spectral measure of GC is based on the key property that u_t does not Granger cause v_t if and only if $\gamma_{uv}(k)=0$ for all $k<0$. The goal is to test the predictive content of u_t relative v_t to which is given by the second part of Eq. (10), i.e.

[3] For the endpoints $\lambda=0$ and $\lambda=\pi$, one only has one degree of freedom since the imaginary part of the spectral density estimates cancels out.

$$S_{u\Rightarrow v}(\lambda) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k}\right] \qquad (11)$$

The Granger coefficient of coherence is then given by,

$$h_{u\Rightarrow v}(\lambda) = \frac{\left|S_{u\Rightarrow v}(\lambda)\right|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \qquad (12)$$

Therefore, in the absence of GC, $h_{u\Rightarrow v}(\lambda) = 0$ for every λ in $]0,\pi[$. The Granger coefficient of coherence takes values between zero and one, Pierce (1979). Granger coefficient of coherence at frequency λ is estimated by

$$\hat{h}_{u\Rightarrow v}(\lambda) = \frac{\left|\hat{S}_{u\Rightarrow v}(\lambda)\right|}{\sqrt{\hat{S}_u(\lambda)\hat{S}_v(\lambda)}}, \qquad (13)$$

with $\hat{S}_{u\Rightarrow v}(\lambda)$ as in Eq. (6), but with all weights w_k =0 for $k \geq 0$. The distribution of the estimator of the Granger coefficient of coherence is derived from the distribution of the coefficient of coherence Eq. (8). Under the null hypothesis $\hat{h}_{u\Rightarrow v}(\lambda) = 0$, the distribution of the squared estimated Granger coefficient of coherence at frequency λ, with $0 < \lambda < \pi$ is given by,

$$2(n'-1)\hat{h}^2_{uv}(\lambda) \xrightarrow{d} \chi^2_2 \qquad (14)$$

where n is now replaced by $n' = T/\left(\sum_{k=-M}^{-1} w_k^2\right)$. Since the w_k s', with a positive index k, are set equal to zero when computing $\hat{S}_{u\Rightarrow v}(\lambda)$, in effect only the w_k with negative indices are taken into account. The null hypothesis $\hat{h}_{u\Rightarrow v}(\lambda) = 0$ versus $\hat{h}_{u\Rightarrow v}(\lambda) > 0$ is then rejected if

$$\hat{h}_{u\Rightarrow v}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n'-1)}} \qquad (15)$$

Afterward, we compute Granger coefficient of coherence given be Eq. (13) and test the significance of causality by making use of Eq. (15).

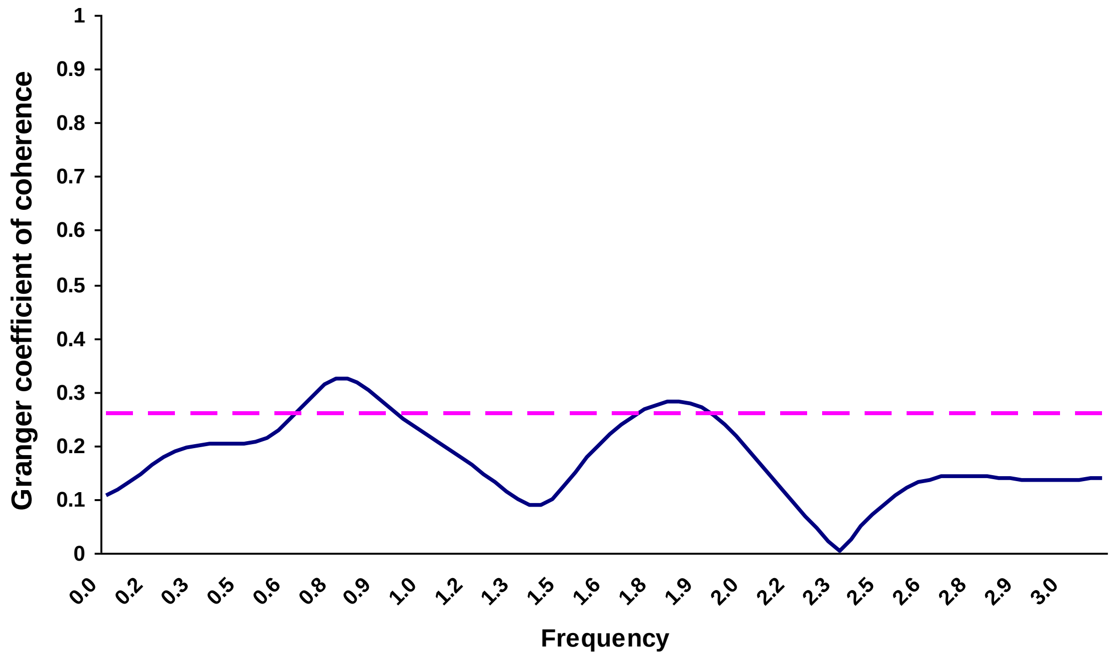
III.2 Empirical findings

All the three differenced series (i.e. $\Delta_{12}\Delta$ of the series) of IIP, WPI and M3 have been filtered using ARMA models to obtain the innovation series. Below we present the Granger causality results between money-output and money-prices using the innovation series for IIP, WPI and M3 after ARMA. We have used lag length[4] $M = \sqrt{T}$. The frequency (λ) on the horizontal axis can be translated into a cycle or periodicity of T months by $T = 2\pi / \lambda$ where T is the period. After ARMA filtering the series and adjusting for lags, we are left with 176 observations. Therefore, we can consider $N = 88$ cycles of different frequencies, with the shortest possible cycle of 2 months and longest cycle of 176 months.

Figure 1 presents the result of Granger coefficient of coherence for causality running from money supply to output. Figure 1 shows that at 5 percent level of significance, money supply Granger causes output at higher frequencies reflecting short-run cycles. The causality running from money supply to output is significant between frequencies corresponding to 3-4 months cycles and then between frequencies corresponding 6-10 months cycle. The Granger coefficient of coherence suggests that the causality running from money to output between frequencies corresponding to 3-4 months cycles is relatively weak compared to frequencies corresponding 6-10 months cycles. The peak of Granger coefficient of coherence is reached at the frequency corresponding to 8 months. However, the results in figure 1 indicate that at 5 percent level of significance, money supply does not Granger causes output at frequencies corresponding to more than a year.

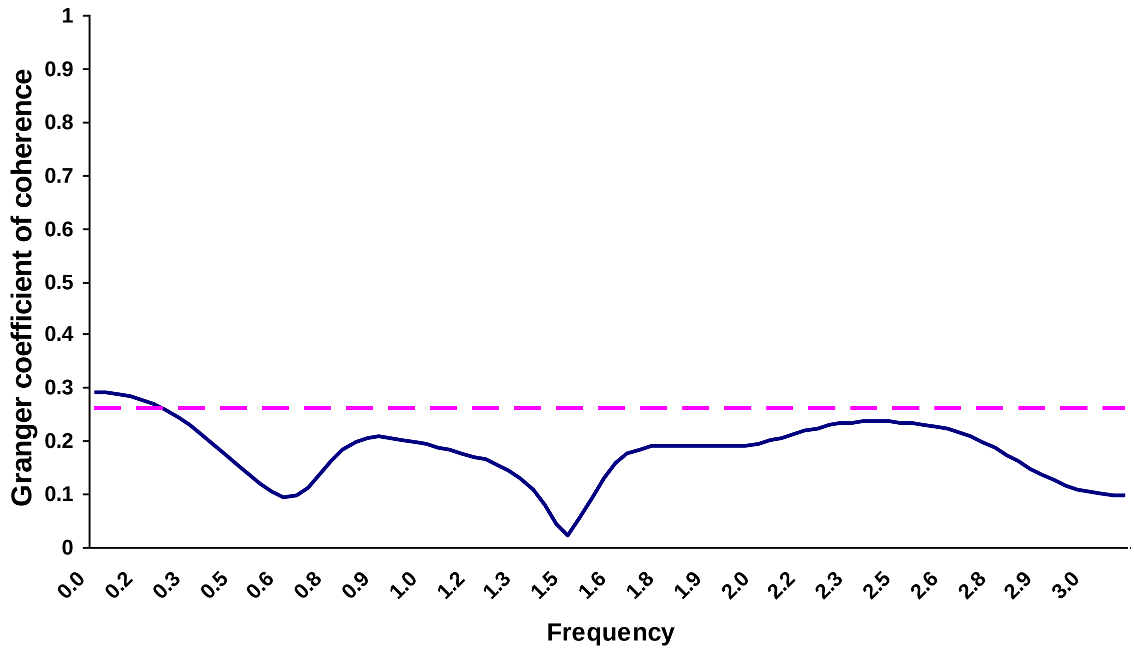
Figure 1. Granger causality from money supply to output. The dashed line represents the critical value for the null hypothesis, at the 5% level of significance.

[4] Following Diebold (2001, p.136) we take M equal to the square root of number of observations T.



Based on the results obtained in figure 1, we can say that money supply provides significant predictive power for future output movement within a year, but money supply does not appear to be an indicator of interest for future output movement beyond a year.

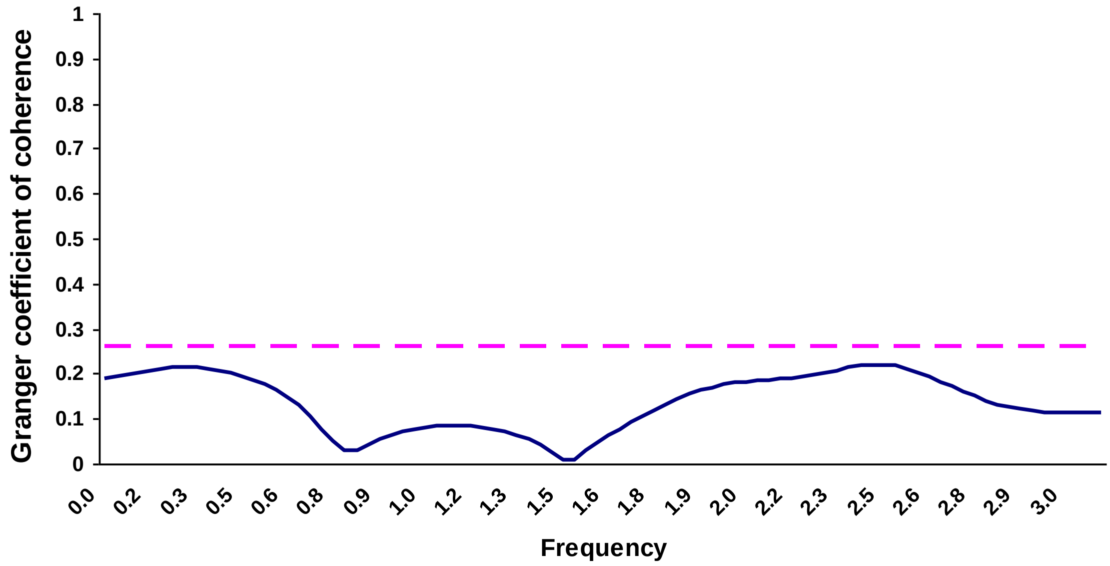
Figure 2. Granger causality running from money supply to prices. The dashed line represents the critical value for the null hypothesis, at the 5% level of significance.



In Figure 2, Granger coefficient of coherence for causality running from money supply to prices has been presented. Figure 2 suggests that the estimated Granger coefficient of coherence rises at frequency corresponding to 3 months cycles, but at these frequencies the coefficient of coherence is not significant at 5 percent level. However, figure 2 suggests that the Granger coefficient of coherence is significant at 5 percent level at lower frequencies. At frequencies corresponding to 29 months cycle to 176 months cycle, we find money supply significantly Granger causes prices. This reflects that money supply Granger causes prices over the business cycle frequencies and also in the long-run. The Granger coefficient of coherence attains the maximum value at frequency corresponding to 176 months. It follows from the results obtained in figure 2 that money supply constitutes significant predictive power for tracking the future inflation, over the business cycle frequencies and at frequencies corresponding to long-run.

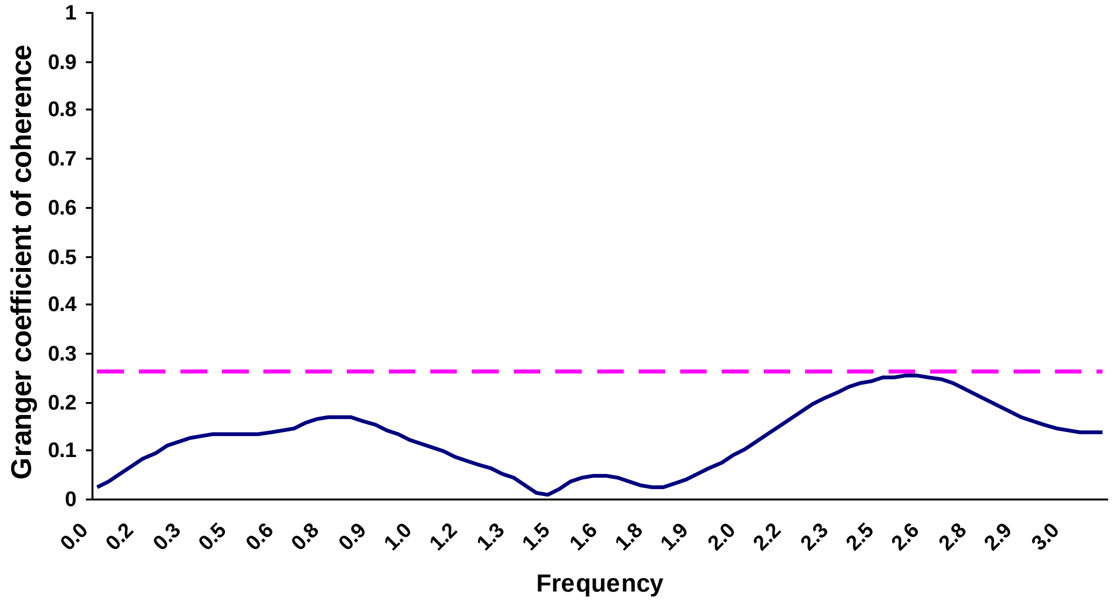
Figure 1 and 2 presents the results for causality running from money to output and causality running from money to prices. Now, we move to the question regarding reverse causality. Figure 3 presents the results for Granger causality running from output to money supply. The result indicates that at 5 percent level of significance output does not Granger causes money supply, at higher as well as at lower frequencies. Though, the Granger coefficient of coherence jumps at frequencies corresponding to 3 months cycles but does not cross the significance level. Therefore we cannot reject the null hypothesis of no causality running from output to money at 5 percent level of significance, at all the frequencies.

Figure 3. Granger causality from output to money supply. The dashed line represents the critical value for the null hypothesis, at the 5% level of significance.



We now test for feedback running from prices to money supply and figure 4 presents the result. The result reported in figure 4 clearly reveals that the null hypothesis of no Granger causality running from prices to money supply cannot be rejected at 5 percent level of significance, at all the frequencies. Though, at frequencies corresponding to 3 months cycles, causality running from prices to money supply rises, but the Granger coefficient of coherence is not strong enough to reject the null hypothesis at 5 percent level of significance. This finding goes well with the earlier finding of Masih and Masih (1994), that feedback effect of prices on money supply were not strong enough to be statistically significant at 5 percent probability level.

Figure 4. Granger causality running from prices to money supply. The dashed line represents the critical value for the null hypothesis, at the 5% level of significance.



The results evolving from this study suggests that in India, over the post reform period, money supply seems to provide reliable prediction power for future output movement within a year period but not in the long- run. The feedback running from output to money supply is not significant at any of the frequencies. The causality running from money supply to prices over the business cycle frequencies as well as in the long-run indicates that at these frequencies money supply seems to provide reasonable information regarding the movement of future prices in India. The feedback running from prices to money supply is not significant at all the frequencies. Therefore, money Granger causes output in short-run but over the business cycle frequencies and in the long-run it Granger causes prices. This finding highlights that the monetarist proposition works well in India. The finding of unidirectional causality running from money to output and money to prices indicates that money supply remains exogenous. The exogeneity of money supply indicates that monetary authority can use money supply as an effective monetary policy instrument.

IV Concluding Remarks

The salient feature of this study has been the spectral approach to uncovering the causality relation between money and output and money and prices by making use of monthly data covering the period of 1993:1 to 2009:9.

Our results show that causal and reverse causal relations between money and output and money and prices vary across frequencies. The causality running from money to output remains a short-run phenomenon. The relationship between money and output remained unidirectional for our sample period, with causality running from money supply to output. Our study also finds a unidirectional causality between money and prices, with causality running from money supply to prices, supporting the monetarist proposition. The unique contribution of the present study lies in decomposing the causality on the basis of time horizons and demonstrating that short run causality from money supply to output, long run causality from money supply to prices, as well as lack of long run causality from money supply to output, all co-exist.

Since the late 1990's, the Reserve Bank of India has been emphasising a multiple indicators approach, where a host of macroeconomic variables ,such as, inter alia, interest rates, credit flows, exchange rate were given policy perspectives. However, M3 remains an important indicator of monetary policy stance. Expansionary monetary policy has real effects in the short run, but over the business cycle and over the longer term, money supply drives prices. Our results have re-emphasised the tradeoff between short run countercyclical benefits and the longer term price stability issues that face monetary authorities. These results are consistent with nominal price rigidity in the short run, but full nominal price flexibility at the business cycle frequency as well as in the long run. On the other hand, output in the long run is likely to be determined by real factors rather than by nominal variables.

Appendix I

We have used WPI manufacturing as measure of price Index because it excludes primary products (whose prices are more vulnerable to temporary supply shocks) and fuel and energy (whose prices are often administered). Excluding primary products and fuel and energy from WPI, allows us to over come the variation in prices caused due to structural influences, e.g. crop failures, commodity shortage, administered pricing policies etc. In selection of output variable GDP would have been a better measure but using that as a measure of output would leave us with too few observation since it is available quarterly only from the mid 1990's. The use of IIP for the manufacturing sector is more suitable as a measure of output and has nearly 80 percent weight in IIP General Index. The reason for opting for manufacturing sector IIP is that demand of credit mainly comes from manufacturing sector compared to Mining and Electricity. Moreover, the latter two sectors, inspite of their importance to the economy, have been excluded since their responsiveness to aggregate demand changes is likely to be rather sluggish, especially over the higher frequencies. Including these sectors might obscure the short-run changes. Though, while using IIP of manufacturing sector as a measure of output we are aware of its limitations.

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