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

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Abstract:

Whether money supply Granger causes, 'output and prices' has been intensively investigated in the Indian context. However, the question involves settling of the issue over the short -run, business cycle as well as in the long -run, because the behavior of the Phillips curve depends upon whether a long -run or a short -run relationship is being investigated. In this paper, we examine the issues using a bivariate methodology developed by Lemmens et al. (2008) in order to decompose Granger causality between money supply, prices and output in frequency-domain. We conclude that there is evidence for money-output trade-off over the short -run, but in the long -run, money supply determines prices, not output. The empirical results also indicate that output and prices does not Granger causes money supply reflecting exogeneity of money supply.

Keywords: Granger causality, Frequency-domain, Money supply, Monetarist, RBI,

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Introduction

Does money have a role in determining real output and prices? This relationship has been extensively investigated in previous studies and yet the debate is unsettled regarding the size and nature of the effects of monetary policy on income and prices, in short-run as well as in the long-run. It may be that money supply could be independent of real income and prices, and being an exogenous variable it influences the real income and prices. On the other hand, real income and prices may be the major determinant of supply of money, reflecting endogeneity of the money supply. Moreover, these relationships and their strength may vary in short-run and in long-run. A number of hypotheses regarding the causality relationship among these variables with plausible theoretical arguments have been formulated in the past.

The proponents of quantity theory model assume that money supply is exogenous. While 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 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. In 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. The monetarist discards the existence of long-run Phillips relation and in their view, money is the cause and prices are the effects in the long-run.

Theoretical arguments and hypotheses regarding money supply, output and price behaviour in the macroeconomy requires empirical investigation in settling down the issue, in a manner in which short-run and long-run causality, if any, can be distinguished. Granger Causality (hereafter GC) is a well established technique for measuring causality and applying GC over the spectrum may prove to be useful in measuring the strength and direction of the causality, which could vary over the frequencies. Granger (1969) was the first to suggest that a spectral-density approach would give a richer and more comprehensive picture than a one-shot GC measure that is supposed to apply across all periodicities. Thus measuring the bivariate GC over the spectrum has merit compared to the one-shot GC test.

This paper aims to study the causality relationship between money, output and price in Indian context. The plan of the paper is as follows. Section 1 briefly reviews the existing literature on money, output and price causality in Indian context. Section 2 outlines the GC methodology over the spectrum and data used in this study. Section 3 presents the GC results related to money, output and prices. Section 4 concludes the paper.

1. Literature review

The causality link between prices, output and money has been vigorously investigated in India, for different time period. The foundation of this debate lies in its importance for conducting monetary policy and its role in macroeconomic theory, but the magnitude of this debate reflects the differences in conclusions arrived by earlier researchers. **Ramachandra** (1983, 1986) using annual data for the period 1951-71, found that money causes real income and price level, price level causes real income and nominal income causes money. He took money stock measure as annual average of monthly values as sum of coins, currency and net demand deposits with the commercial and co-operative banks. **Sharma** (1984) investigated the causality between price level and money supply

(M_1 and M_2) using Granger (1969) and Sims (1972) statistical technique for the period 1962-1980 and established bidirectional causality between M_1 and Price level as well as M_2 and Price level. Although he found the causality from M_1 to Price level was much stronger than the reverse causality between Price levels to M_1. **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. In their study the causality results between real income and money stock remained inconclusive. **Singh** (1990) set up bidirectional causality between money stock (M_3) 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 (M_1, M_2) and price level (WPI) by using quarterly data for two periods: 1962-1980 and 1957-1986. They made use of Hsiao's (1981) lag selection criteria and contradicted Sharma's findings of comparatively weaker reverse causality between M_1 to Price level. **Masih** and **Masih** (1994) revealed 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% probability level. **Ashra, Chattopadhyay** and **Chaudhuri** (2004) established bidirectional causality between price (GDP deflator) and M_3.

The available study for India provides us mixed results in context of money, output and price causality direction and strength. Therefore our study is an effort to find out money, price and output causality direction as well as the strength of causality over the spectrum in order to solve the puzzle of short-run and long-run.

2. Methodology and Data

The dynamic behaviour of economic time series has been widely analysed in the time-domain. However, analysing the time series in frequency-domain i.e spectral analysis could be helpful in supplementing the information obtained by time-domain analysis (Granger and Hatanaka, 1964; Priestley, 1981; Press et al., 1986; Medio, 1992). Spectral analysis lies on the remark that most regular behaviour of a time series is periodic; thus, the periodic components embedded in the analyzed series can be determined by computing their periods, amplitude, and phase (Ghil et al., 2002). Spectral analysis is a powerful tool for inspecting cyclical phenomena and highlighting lead-lag relations among series. Cross spectral analysis allows a detailed study of the correlation among series (Iacobucci, (2003).

The purpose of this study is to test the direction and strength of GC between money supply, output and prices in frequency-domain. Therefore we have applied the bivariate GC test over the spectrum proposed by Lemmens et al. (2008). Pierce (1979) proposed an R-squared measure for time series and decomposed it over each frequency of the spectrum, resulting in a measure for GC at every given frequency. Lemmens et al. (2008) reconsidered the original framework proposed by Pierce (1979), and proposed an easy testing procedure for Pierce (1979) spectral GC measure. This GC test in the frequency domain relies on a modified version of the coefficient of coherence, which they have estimated in a nonparametric fashion, and for which they have derived 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 (1979) measure for GC 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.

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

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

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 series u_t and v_t are building block for the GC test proposed by Lemmens et al.

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

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

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

where $\gamma_u(k) = \mathrm{Cov}(u_t, u_{t-k})$ and $\gamma_v(k) = \mathrm{Cov}(v_t, v_{t-k})$ 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.

To investigate the relationship between the two stochastic processes under consideration, they consider the cross-spectrum, $S_{uv}(\lambda)$, between u_t and v_t. This is a complex number, defined as,

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

$$= \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{-i\lambda k} \qquad (3)$$

where the cospectrum $C_{uv}(\lambda)$ and the quadrature spectrum $Q_{uv}(\lambda)$ are, respectively, the real and imaginary parts of the cross-spectrum. Here $\gamma_{uv}(k)=$ Cov (u_t, v_{t-k}) represents the cross-covariance of u_t and v_t at lag k. The cross-spectrum can be estimated non-parametrically by,

$$\hat{S}_{uv}(\lambda)=\frac{1}{2\pi}\left\{\sum_{k=-M}^{M} w_k \hat{\gamma}_{uv}(k)e^{-i\lambda k}\right\} \tag{4}$$

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

$$h_{uv}(\lambda)=\frac{|S_{uv}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \tag{5}$$

This coefficient 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. The squared coefficient of coherence has an interpretation similar to the R-squared in a regression context. In particular, Pierce (1979) indicates that the R-squared of a regression of v_t on all past, present, and future values of u_t is the integral, across frequencies, of the squared coefficient of coherence.

Lemmens et al. 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, denoted by χ_2^2.

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

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

$$\hat{h}_{uv}(\lambda) > \sqrt{\frac{\chi_{2,1-\alpha}^2}{2(n-1)}} \tag{6}$$

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

Following Pierce (1979), Lemmens et al decomposed the cross-spectrum (E.q.3) 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.,

$$S_{uv}(\lambda) = [S_{u\Leftrightarrow v} + S_{u\Rightarrow v} + S_{v\Rightarrow u}]$$

$$= \frac{1}{2\pi}\left[\gamma_{uv}(0) + \sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k} + \sum_{k=1}^{\infty}\gamma_{uv}(k)e^{-i\lambda k}\right] \tag{7}$$

The proposed spectral measure of GC is based on the key property that X_t does not Granger cause Y_t if and only if $\gamma_{uv}(k) = 0$ for all $k < 0$. Our goal of testing the predictive content of X_t relative to Y_t is given by the second part of Eq. (7), i.e.

$$S_{u \Rightarrow v}(\lambda) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{-1} \gamma_{uv}(k) e^{-i\lambda k}\right] \tag{8}$$

The Granger coefficient of coherence is then given by,

$$h_{u \Rightarrow v}(\lambda) = \frac{\left|S_{u \Rightarrow v}(\lambda)\right|}{\sqrt{S_u(\lambda) S_v(\lambda)}} \tag{9}$$

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, as shown by Pierce (1979). An estimator for the Granger coefficient of coherence at frequency λ is given by

$$\hat{h}_{u \Rightarrow v}(\lambda) = \frac{\left|\hat{S}_{u \Rightarrow v}(\lambda)\right|}{\sqrt{\hat{S}_u(\lambda) \hat{S}_v(\lambda)}}, \tag{10}$$

with $\hat{S}_{u \Rightarrow v}(\lambda)$ as in Eq. (4), but with all weights w_k for $k \geq 0$ put equal to zero.

In this study we have applied above discussed methodology for the period April 1991 to March 2009, which can be fairly considered as post liberalisation period in India. We have considered broad money (M_3) as a measure of money supply reported at the end of the month by RBI. Output has been proxied by IIP manufacturing and prices by WPI manufacturing. For IIP the base year was 1980-81 and 1993-94, whereas for WPI the base year was 1981-82 and 1993-94[4]. The IIP and the WPI data have been spliced using symmetric mean methodology. Geometric mean has been applied as symmetric mean because it generates a spliced series that is invariant to rebasing of either of the original series (see. Hill and Fox (1997)). Data on all these variables was collected on monthly basis from RBI database on Indian economy, from RBI database on Indian economy (RBI Website) and RBI occasional report, RBI Annual reports etc. All the variables have been taken in their natural logs.

3. Empirical Finding

We investigate whether money supply Granger cause the output or prices or both. Further, we also investigate whether output and prices granger causes money supply or not. Since the test requires stationarity of the time series, we have applied HEGY monthly unit roots test developed by Beaulieu and Miron (see. Beaulieu and Miron (1993)). The seasonal unit roots test results are reported in the Appendix. The test suggests presence of unit roots at seasonal frequency as well as at zero frequency in all the three time series, M_3, IIP and WPI. We have seasonally differenced the three series and then performed first difference on the seasonally differenced series. We filtered the three series using ARMA modeling by making use of AIC and BIC information to obtain white noise processes. Both AIC and BIC suggested the same ARMA model. We

[4] 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 come over 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 few observation. Our excuse for the choice of IIP manufacturing as a measure of output is that, it is available on monthly basis and has nearly 80 percent weight in IIP General. One can argue that why we have dropped mining and electricity sector from IIP. The reason is that demand of credit mainly comes from manufacturing sector compared to Mining and Electricity. Moreover, Mining and Electricity are inputs of production which will get reflected in IIP manufacturing.

compute the Granger coefficient of coherence, given by E.q (10), using lag length[5] $M = \sqrt{T}$.

Fig. 1 shows the Granger coefficient of coherence between M_3 and IIP at all frequency (λ). This coefficient assesses whether and to what extent M_3 Granger causes IIP at that frequency. The higher is the estimated Granger coefficient of coherence, the higher the Granger causality at that particular frequency. The frequency (λ) on the horizontal axis can be translated into a cycle or periodicity of T months by $T = 2\pi / \lambda$ (for monthly data). Fig. 1 shows at M_3 Granger causes IIP at higher frequencies reflecting short-run components. In terms of months M_3 Granger causes IIP at 3-4 months and then at 6-9 months, which clearly reflects within a year movement. The estimated short term Granger coefficient of coherence between M_3 and IIP reaches 50% (at frequency corresponding to 8 month). On the other, at 5% significance level M_3 does not Granger causes IIP at lower frequencies reflecting long -run component.

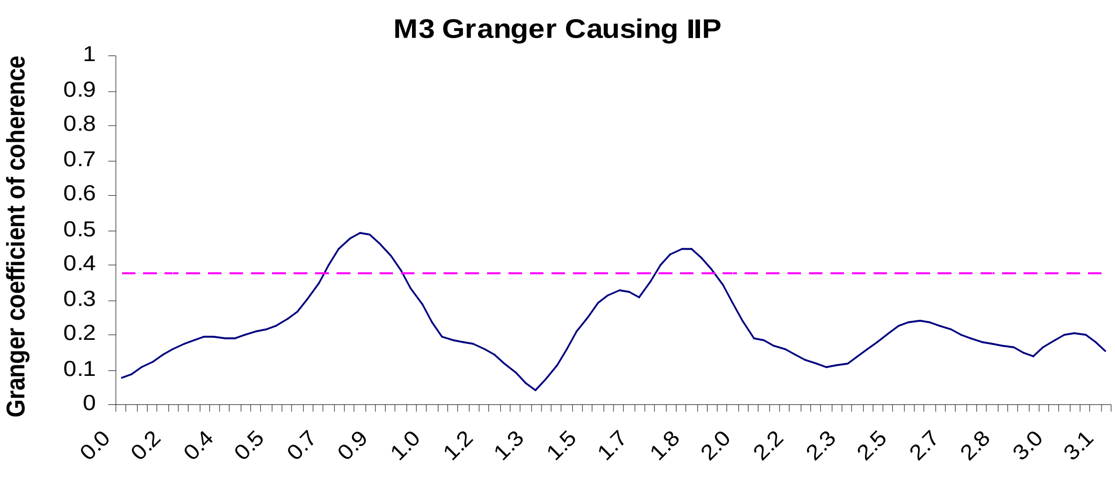

Figure 1. The dashed line represents the critical value, at the 5% level, for the test for no GC.

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

Fig. 2 shows the Granger coefficient of coherence between M_3 and WPI. The estimated Granger coefficient of coherence between M_3 and WPI is not significant in the short -run corresponding to higher frequency. However at lower frequency equivalent to 7-22 quarters, we find M3 significantly Granger causes WPI and the Granger coefficient of coherence between M3 and WPI reaches 42% (at frequency corresponding to 11 quarter).

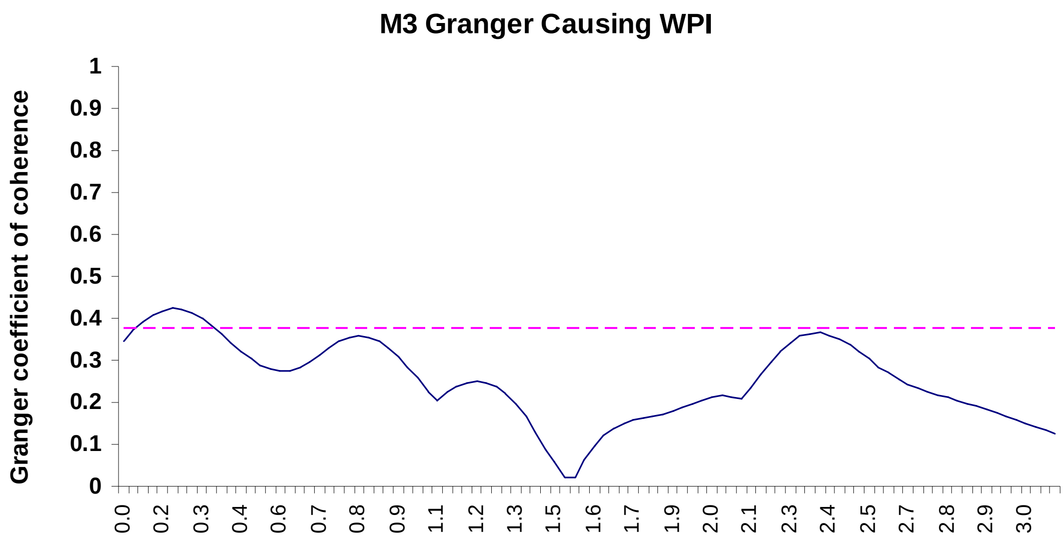

Figure. 2. The dashed line represents the critical value, at the 5% level, for the test for no GC.

The empirical results from above fig.1 and fig.2 suggest that the effect of money supply on output has remained a short–run phenomenon in the post-liberalisation period, in India. On the other hand, effects of money supply on prices get reflected only at business cycle frequency. These finding are in line with monetarist views and substantiate the monetarist proposition in Indian context.

Fig. 3 reports the test result for IIP Granger causing M_3. It is important to note that within our sample period the Granger coefficient of coherence result indicates that IIP does not Granger causes M_3 in short -run as well as in the long -run at 5% significance level. Clearly, there is absence of bidirectional Granger causality between money supply and output in our sample period. The causality between money supply is unidirectional, running from money supply to output.

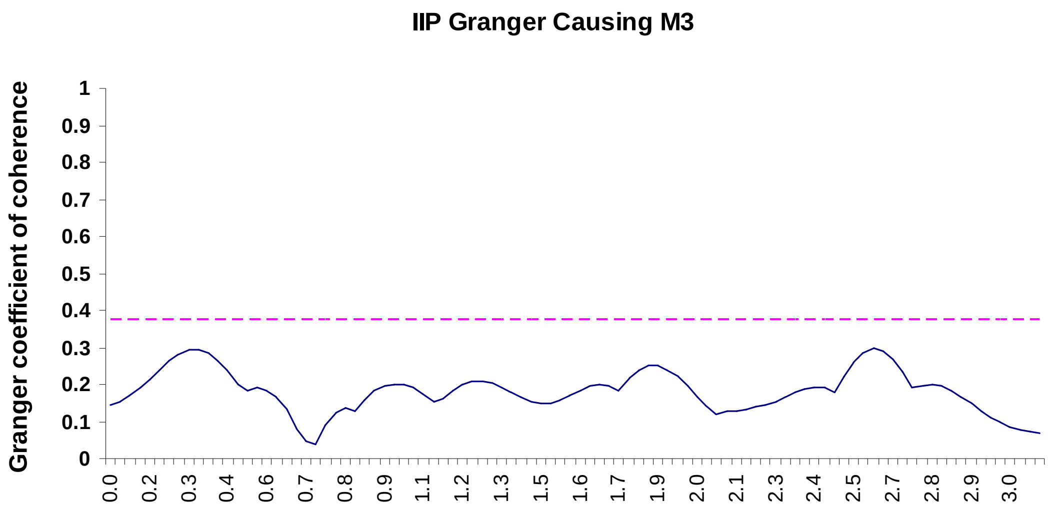

Fig. 3. The dashed line represents the critical value, at the 5% level, for the test for no GC.

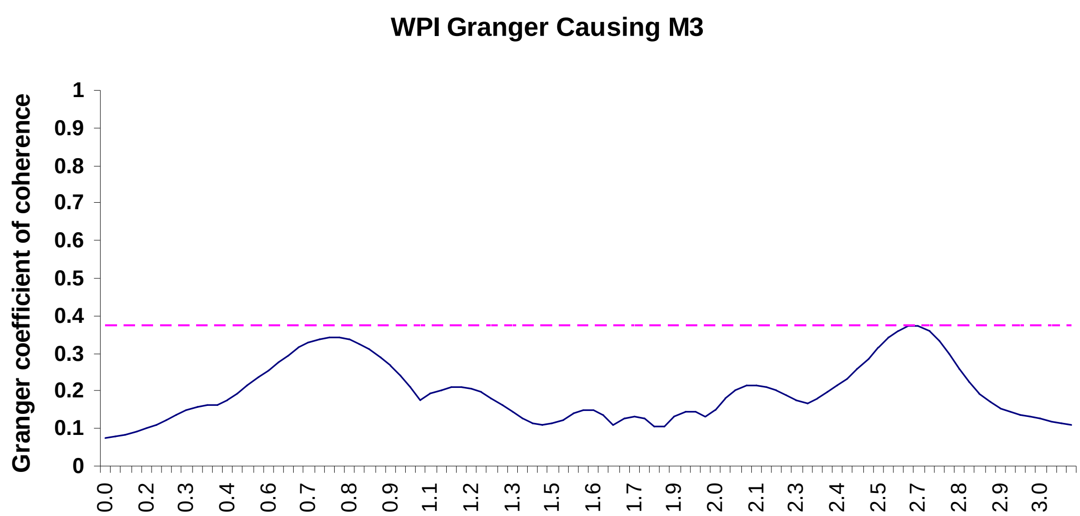

Fig. 4. The dashed line represents the critical value, at the 5% level, for the test for no GC.

Fig. 4 presents the results for the null hypothesis, whether WPI Granger causes M_3 or not. The results clearly suggest that at 5% significance level WPI does not Granger causes $M_{3.}$ This finding is in line with 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% probability level. The Granger causality between money supply to prices is also unidirectional, running from money supply to prices.

The above discussed empirical result indicates that there is no feedback relation between money supply-output and money supply-prices. The causality is unidirectional in both the cases running from money supply to output and prices. However, the strength of causality varies over frequencies. The absence of bidirectional causality between money supply-output and money supply-prices indicates that money supply can be considered as exogenous in our bivariate framework. The implication of this finding is supply of money (M_3) can be considered as an effective control variable.

4. Conclusion

The study investigates the causal relationship between money, output and prices for the post liberalisation period in India. The Granger causality test was performed in bivariate frequency-domain setup. The empirical finding indicates that money supply (M_3) Granger causes output (IIP manufacturing) only in short -run, whereas money supply (M_3) Granger causes prices (WPI manufacturing) at business cycle frequencies. Any feedback running from output (IIP manufacturing) and prices (WPI manufacturing) to money supply (M_3) was rejected in our bivariate setup.

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Appendix

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.)**	-2.05	-4.14	5.46	9.97	7.72	9.86	6.35
(P-value)	(0.1)*	(0.01)	(0.01)	(0.1) *	(0.07)	(0.1)*	(0.02)
WPI (**Stat.)**	-2.69	-2.67	21.02	15.68	8.76	12.13	7.12
(P-value)	(0.1)*	(0.06)	(0.1)*	(0.1)*	(0.1)*	(0.1)*	(0.05)
M_3 (Stat.)	-2.79	-2.81	21.74	14.08	8.88	28.16	25.75
(P-value)	(0.1)*	(0.04)	(0.1)*	(0.1)*	(0.1)*	(0.1)*	(0.1)*

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.)