Chapter 3: Investigating causality between foreign inflows and macroeconomic indicators for the Indian economy

3.1 Introduction

Capital inflows should contribute to faster economic growth in developing countries by enhancing domestic savings and transferring technological knowledge. Each country may have its unique traits, hence the experiences of managing capital inflows. The nature of causality between foreign inflows and macroeconomic and monetary indicators in the post-liberalized Indian economy is attempted to be studied in this chapter. Most existing country-specific empirical research studies provide mixed results of pieces of evidence of causality (Agarwal, 1997; Alfaro, 2007). There are multiple views established by researchers about capital inflows and the economic performances of the host countries. According to Ahmad et al. (2009), “the determinants of net private capital inflows to emerging market economies (EMEs) since 2002. Our main findings are: First, growth and interest rate differentials between EMEs and advanced economies and global risk appetite are statistically and economically important determinants of net private capital inflows. Second, there have been significant changes in the behavior of net inflows from the period before the recent global financial crisis to the post-crisis period, especially for portfolio inflows, partly explained by the greater sensitivity of such flows to interest rate differentials since the crisis. Third, capital controls introduced in recent years do appear to have discouraged both total and portfolio net inflows. Finally, we find positive effects of unconventional U.S. monetary policy on EME inflows, especially portfolio inflows. Even so, U.S. unconventional policy is one among several important factors influencing flows.” India's capital flows and economic growth were investigated for possible cointegration and causality by

Bhattacharya et al. (2012). They performed a VAR framework cointegration test and applied a VECM, GC test, and impulse response (IRF) analysis. They observed a bi-directional causality between different types of foreign inflows (foreign direct investment, external assistance, and other capital) and economic growth, whereas, for FPI, they observed unidirectional causality. Chandrashekhar and Shanmugan, K. (2018) investigated the causality between capital inflows (net FDI and net FPI) with many major macroeconomic variables using a frequency domain approach with quarterly data series. They found a mixed result for the different variables. The study finds that the capital inflows Granger causes money supply both in the short and long run whereas GDP, import, export, exchange rate, and WPI in the short run. The Granger causality test failed to observe causality between foreign capital inflows and foreign exchange reserves and between foreign capital inflows and interest rate. Given the ongoing debate of capital inflows and economic performance, it is crucial to investigate foreign inflows' role in India and their relevance for economic growth. India started opening up its economy after 1991, and nearly two decades had passed. Hence, one may find an excellent rationale to revisit these relations as the economy has undergone many systemic and structural changes during this period.

It was evident that these developments would further enhance our interest in exploring the effects of capital flows and the far-reaching impact on India’s Macroeconomic indicators. Decomposing GC over the frequency allows disentangling potential causal relationships over variable frequencies to generate new insights, unlike traditional GC tests. However, with changing frequencies, the strength of the GC test and direction also varies.

Therefore, this study follows Granger's (1969) spectral-density approach of the GC test to obtain comprehensive estimates than a one-shot (point estimator) GC measure that applies uniformly across periodicities. The study uses the GC test under frequency domain methodologies for analyzing causality between foreign capital inflows (FDI and FPI separately) and macroeconomic indicators to uncover further layers of complexity in different periods of interest. In all apparent probabilities, an empirical analysis capable of making a clear distinction between the short-run and the long-run causality would be a relatively better measure to describe the dynamics involved in the time-series domain for the Indian context. The commonly used time-domain methodologies to determine direction and strength of causality fail to decompose causality by the time horizon. Hence, the decomposition of a causal relationship with different frequencies and time helps understand the impact of capital flows on the macroeconomic parameters.

We analyzed if the observed fluctuations in datasets have any causal link with foreign capital inflows and intend to unveil the causality direction, i.e.bi-directional or uni-directional. This study will add to the existing literature on understanding the nexus between India's capital inflows and macroeconomic parameters. However, it may be stated that this study stands to be the first empirical attempt to investigate the relationship between foreign capital inflows and macroeconomic parameters for the Indian economy using the Granger causality test in the frequency domain.

The analysis has used the following variables to represent capital inflows and macroeconomic indicators. The growth rate is reparented by GDP series, such that M3- Money supply, CMR-

Interest rate, WPI- inflation, exports, imports, FPI, and FDI as foreign capital inflows.

3.2 Test for seasonal unit roots in the data series

We have used the frequency domain econometric approach for empirical investigation. The analysis uses quarterly time series data collected periodically. These data usually exhibit seasonality. Therefore, it is natural to investigate seasonal unit roots in the series and check whether they exist in seasonally unadjusted quarterly data variables at frequencies different from the long run. The data will appear in seasonality if the spectrums of the process have peaks at specific frequencies. Many tests are available for seasonal unit roots, but seasonal unit root tests, Hylleberg, Engle, Granger, Yoo (1990) test (henceforth: Hegy test) are proposed for quarterly data of seasonal unit roots. Therefore, to check for a unit root in quarterly linear time series variables, we used the HEGY test. It detects seasonal unit roots at different seasonal frequencies, including at zero frequency. HEGY procedure can test for the presence of unit roots at multiple frequencies individually without assuming the existence of unit roots in data series. HEGY uses simple *t* and *F* statistics to test seasonal unit roots. This test is fundamentally based on an idea similar to the Dickey-Fuller test (1979 and 1981) for a unit root in a cross-section of frequency. The regression equation employed here to obtain the tests statistics includes a constant, a linear trend, and a seasonal dummy and is estimated by choosing appropriate lags. The regression equation has lags of the dependent variable. The maximum number of lags considered in the analysis is based on the minimum criteria of "AIC" (Akaike Information Criterion).

The test design discriminates against the presence of unit roots at different frequencies on the unit circle. Simultaneously, it is also sensitive to variability in the size of frequency. The critical goal of applying this testing procedure is to test any seasonal unit root in a univariate series. The test check for the seasonality if there is any unit root present in the series. To test the hypothesis HEGY test makes use of the Dickey-Fuller framework. The null hypothesis: roots for series lie on the unit circle vs. alternative hypothesis root for series lie outside the unit circle. In particular, the goal is to test for unit roots without taking a stand on the presence of seasonal or zero frequency unit-roots. This test is carried out using R packages “uroot.”

Table 1: HEGY test coefficients for seasonal unit roots in quarterly series data

Variables	Ypi1	Ypi2	Ypi3	Ypi4
GDP (Stat.)	-0.078	-0.028	-0.196	0.002
(P-value)	(0.10)*	(0.10)*	(0.10)*	(0.50)*
WPI (Stat.)	-0.014	-3.87	0.315	-0.739
(P-value)	(0.10)*	-0.01	(0.10)*	-0.01
FXR (Stat.)	-0.033	-0.606	0.128	-0.703
(P-value)	(0.10)*	(0.10)*	(0.10)*	-0.01
EXR (Stat.)	-0.066	-0.745	-1.093	-1.339
(P-value)	-0.01	-0.01	(0.10)*	-0.01
CMR (Stat.)	-0.195	-0.507	-0.519	0.177
(P-value)	(0.10)*	-0.01	(0.10)*	(0.78)*
M3 (Stat.)	-0.128	-0.572	-0.017	0.536
(P-value)	-0.01	-0.01	(0.10)*	(0.97)*
IMP (Stat.)	-0.036	-0.618	-0.227	-0.509
(P-value)	(0.10)*	-0.01	(0.10)*	-0.01
EXP (Stat.)	-0.113	-0.298	-0.345	-1.628
(P-value)	(0.10)*	(0.10)*	(0.10)*	-0.01
FDI (Stat.)	-0.147	-0.234	-0.613	-0.411
(P-value)	(0.05)*	(0.10)*	-0.01	-0.01
FPI (Stat.)	-0.253	-2.766	-0.563	-0.149
(P-value)	-0.01	-0.01	(0.10)*	(0.36)*

***Note**, Associated P-value for each variable has been given in the parenthesis. The (*) reflects that we cannot reject the null hypothesis of unit roots' presence at 5% level of significance.*

The result of the HEGY test on log-transformed series of variables is presented in table.19. At first, it is worth mentioning that the null hypothesis at zero frequency regarding unit root for the series GDP, WPI, FXR, CMR, IMP, EXP, and FDI cannot be rejected. This indicates that there is a unit root in the long run for these variables. The null hypothesis for EXR, M3, and FPI may be rejected at zero frequency and at 1% significance level for the unit root. The null hypothesis cannot be rejected for log-transformed GDP series at any frequency, but the same for other series may be rejected at higher frequencies.

3.3 The causality test methodology

Time-domain is a concept very much used and perceived in our everyday life. Time continuously marches forward; hence we are very comfortable and familiar with this. A plot of time typically represents this phenomenon. Whereas the frequency domain is an observable phenomenon at continuous frequency, it is initially generated to deal with electronic and electrical analysis signals but later on applied to social science research, economics, and finance. They represent signals by the frequency components that make them up continuous Fourier time series in time waveform, which can be broken into a series of cosines and sines to create a frequency domain.

Time-domain analysis, i.e., analysis of time series data in the frequency domain, is supplemented by spectral analysis (Granger, (1969) and Priestley, (1981)). This follows the bivariate Granger Causality test by Lemmens et al. (2008). We computed the

Granger coefficient of coherence and tested the significance of causality. The higher the estimated Granger coefficient of coherence at a particular frequency, the more substantial the evidence of Granger causality, and the size of the coefficients throws light on the strength of variation in the same direction of the causality at a particular frequency or over frequency domain.

3.4 Empirical findings

Granger causality testing based on frequency domain analysis is an efficient tool widely used to establish relationships among variables in multivariate dynamic processes. The stationarity of the time series variables considered in the model is a precondition for traditional time-domain-based GC tests and spectral GC tests. Classical Granger test results failed to provide clear evidence about co-movements in the presence of short-run and long-run cyclical and seasonal fluctuations. The test procedure produces a single statistic for the predictability of the causal relationships between variables. Simultaneously, it conveniently ignores the possibility of changes in causal relationships between variables with changing frequencies. The study employs the SARIMA process for each pair of bi-variate time series frequency domain chosen appropriately based on the structure of stationarity and the lags. It should also be noted here that the lags chosen had been scrutinized for the normality of innovation. All the variables are log-transformed, except CMR, which is analyzed in base form (without any statistical transformation). The importance of this technique is that each variable is considered an independent variable. Each variable is tested to identify the process wherein independent variables paired with appropriate dependent variables are selected as a causal variable for examining the causality through Stepwise Multiple Linear Regression. This would help the researcher to prioritize the variables for analysis. An ARIMA process to control a seasonal time series called SARIMA model is estimated using R-package called “forecast.” The SARIMA model has been utilized successfully for modeling and forecasting quarterly macroeconomic variables.

To deal with seasonalities, the traditional ARIMA model is further extended to a general multiplicative seasonal ARIMA (p,d,q);(P, D, Q)s model. Where (p,d,q) is the non-seasonal part, and (P, D, Q) is the seasonal part of the model. “s” is the number of periods per season. In our case, it is a maximum of 4. The forecasting performance of the chosen SARIMA model is measured using Paired T-test. Paired T-test determines whether they vary from each other significantly or not. This analysis also considers the assumptions that the paired differences are independent and identically normally distributed. AIC and BIC results obtained are used as the model selection criterion.

The results of the frequency domain in the GC test are presented in Table 20 below. The result supports the traditional Granger causality analysis even from the viewpoint of frequency domain estimates produced. Frequency domain analysis helps in untangling directions and strengths of causalities at changing frequencies. Decomposition of causality by frequencies helps understand causal relationships between FDI and the macroeconomic variables and FPI and the macroeconomic variables separately.

Table 2: SARIMA result of macroeconomic indicators

Series: Gross Domestic Product

Forecast method: ARIMA(0,1,2)(1,0,0)[4] with drift				
	ma1	ma2	sar1	Drift
Coefficients	-0.3439	-0.4245	0.9251	0.0166

Standard error	0.1216	0.1417	0.0381	0.0049
Log likelihood=153.2		AIC=-296.4	BIC=-285.76	

Series: Wholesale Price Index

ARIMA(0,1,1)(0,0,1)[4] with drift			
	ma1	sma1	Drift
Coefficients	0.5022	0.3122	0.0103
Standard error	0.1124	0.1237	0.0032
Log likelihood=180.63	AIC=-353.26	BIC=-344.75	

Series: Foreign Exchange Reserves

ARIMA(1,2,1)		
	ar1	ma1
Coefficients	0.3859	-0.9211
Standard error	0.1446	0.0609
log likelihood=95.4	AIC=-184.8	BIC=-178.47

Series: Exchange Rate (Rupee Vs US Dollar)

ARIMA(0,1,0)(1,0,0)[4] with drift		
	sar1	Drift
Coefficients	-0.2054	-0.0062
Standard error	0.1211	0.0040
log likelihood=116.21AIC=-226.41BIC=-220.03		

Series: Call Money Rate

ARIMA(0,0,1) with non-zero mean		
	ma1	Intercept
Coefficients	0.5675	1.8944
Standard error	0.0965	0.0059

log likelihood=131.7	AIC=-257.4	BIC=-250.97	

Series: Broad Money Supply (M3)

ARIMA(1,1,0)(1,0,0)[4] with drift

	ar1	sar1	Drift
Coefficients	-0.2624	0.6028	0.0359
Standard error	0.1230	0.0966	0.0032
Log likelihood=177.78	AIC=-347.57	BIC=-339.06	

Series: Import

ARIMA(0,1,1) with drift

	ma1	Drift
Coefficients	0.2157	0.0339
Standard error	0.1224	0.0150
log likelihood=56.21 AIC=-106.42	BIC=-100.04	

Series: Export

ARIMA(0,1,0)(1,0,0)[4] with drift

	sar1	Drift
Coefficients	0.2849	0.0259
Standard error	0.1238	0.0162
log likelihood=59.03 AIC=-112.07	BIC=-105.69	

Series: Foreign Inflows (Foreign Direct Investment and Foreign Portfolio Investment)

ARIMA(0,1,1) with drift

	ma1	Drift
Coefficients	-0.2346	0.0424

Standard error	0.1282	0.0256
log likelihood=-4.49AIC=15.99BIC=22.37		

Following the above results, all the variables have been filtered using SARIMA models. After adjusting for lags, we were left with 61 observations. Therefore, in our case, N = 61. We computed the spectral decomposition of all the series using the innovation for variables under consideration.

3.4.1 Causality between foreign inflows and whole price index

Figure 7 presents the Granger coefficient of coherence for causality running from foreign inflows to WPI. Figure 7 shows that at a 5 % level of significance[1], foreign inflows Granger causes WPI at higher frequencies reflecting short-run cycles. The causality running from foreign inflows to WPI is significant between frequencies corresponding to 4 -7 quarters cycles. The estimated coherence coefficient peaks, i.e., 0.38 at the frequency corresponding to the 5-quarter cycle. Therefore, we may infer that foreign capital inflows Granger causes WPI in the short run, but its impact is not visibly observed in the long run.

1 ***The dashed line represents the critical value for the null hypothesis, at the 5% level of significance.***

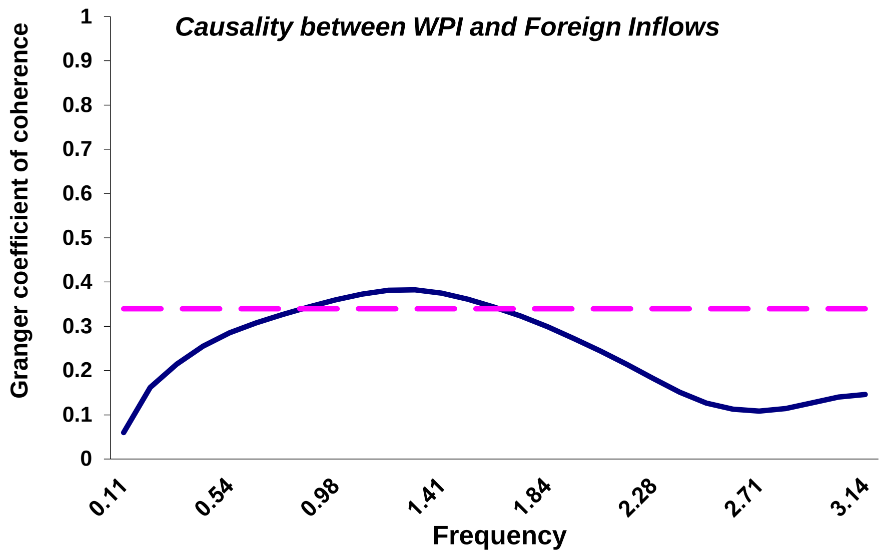

Figure 1: Granger coefficient of coherence for causality between Foreign Inflows and WPI

In the short run, capital inflows are not appropriately adjusted through sterilization. The domestic monetary base may get adjusted in such a manner that it produces price effect and not the output effect and therefore produces short-run inflation. On the contrary, sterilization becomes evident in production in the long run and therefore clears excess demand, which puts less pressure on inflation. It may be inferred that the long-run dynamics of the causality are thus absent due to the impact of sterilization on production.

3.4.2 Causality between foreign inflows and money supply

Granger causality test for money supply from foreign capital inflows at 5% level of significance shows that capital inflows granger causes money supply at a frequency corresponding to a four-five quarter cycle and then from a twenty to fifty-eight quarters cycles. Therefore, we can infer that foreign capital inflows Granger causes money supply at both the short-run and long-run frequencies of cycles. The Granger coefficient of coherence reaches its peak, i.e., 0.47 at frequencies corresponding to long-run cycles, highlighting that the causality running from foreign capital inflows to money supply becomes much more robust at longer cycles (figure 8).

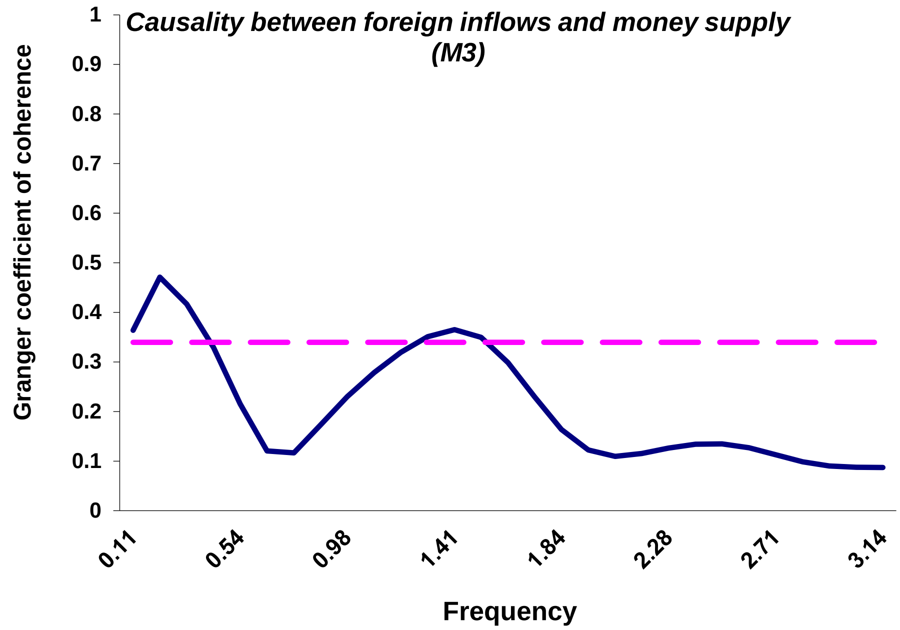

Figure 2: Granger coefficient of coherence for causality between Foreign Inflows and Money supply

Under the managed float exchange rate regime system, Reserve Bank intervenes in the exchange market to correct disequilibrium. The bank has two choices either change the international reserve or change the exchange rate. Hence, the Reserve Bank of India makes a delicate balance between these two choices depending upon other accompanied economic circumstances and complexity of display of financial market disequilibrium. The analysis suggests that foreign inflows influence the money supply both in the short and long run.

3.4.3 Causality between foreign inflows and import

Figure 9 presents causality running from foreign capital inflows to import. Changes in foreign capital inflows Granger cause import at frequencies three to fifty-eight quarters cycles at 5% level of significance. Therefore, we argue that the foreign capital inflows push imports in the long run, not vice-versa. In the long run, foreign capital inflows enhance the import appetite of the capital recipient country, whereas the change in import is not significant in the short run. It can be established that the long-run relationship exists between capital flows and imports, i.e., capital flows increase imports but with lags.

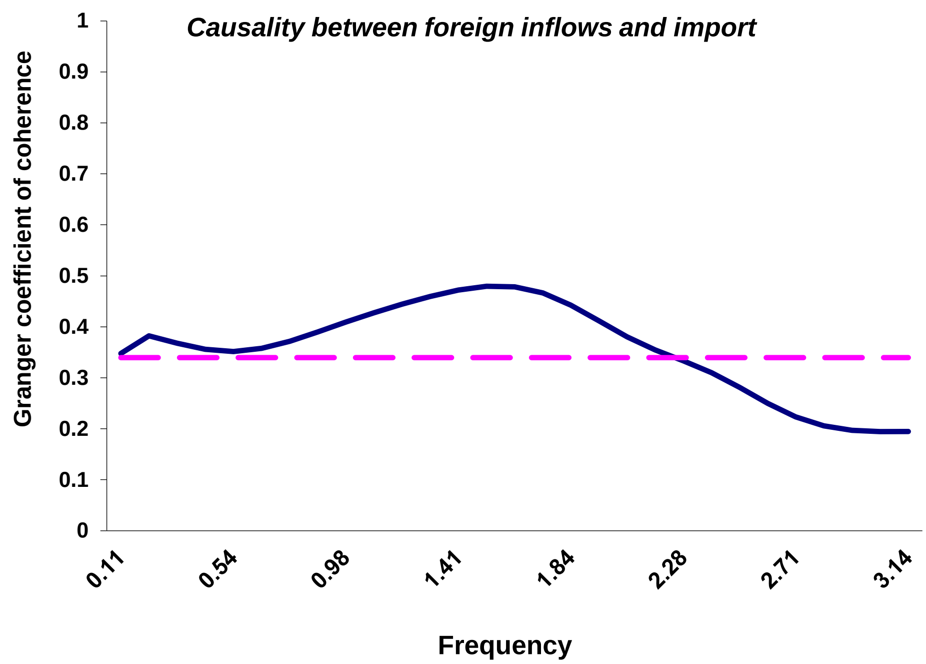

Figure 3: Granger coefficient of coherence for causality between Foreign Inflows and Imports

3.4.4. Causality between foreign inflows and GDP

Figure 10 presents the results of feedback running from foreign capital inflow to GDP. The causality running from foreign capital inflows to GDP is significant but relatively weak, as evidenced by the coefficient of coherence between frequencies corresponding to two to three-quarters cycles. However, the causality frequencies corresponding to the four to fifty-eight quarter's cycle is relatively strong. The coefficient of coherence reaches its peak at 14th quarter. This summarizes that foreign capital inflows have a significant on future GDP movements. It implies that in the long run, foreign capital inflows are likely to support economic growth. The finding validates one of the important postulates of this study that "capital inflows associated are with faster income growth only in the long run."

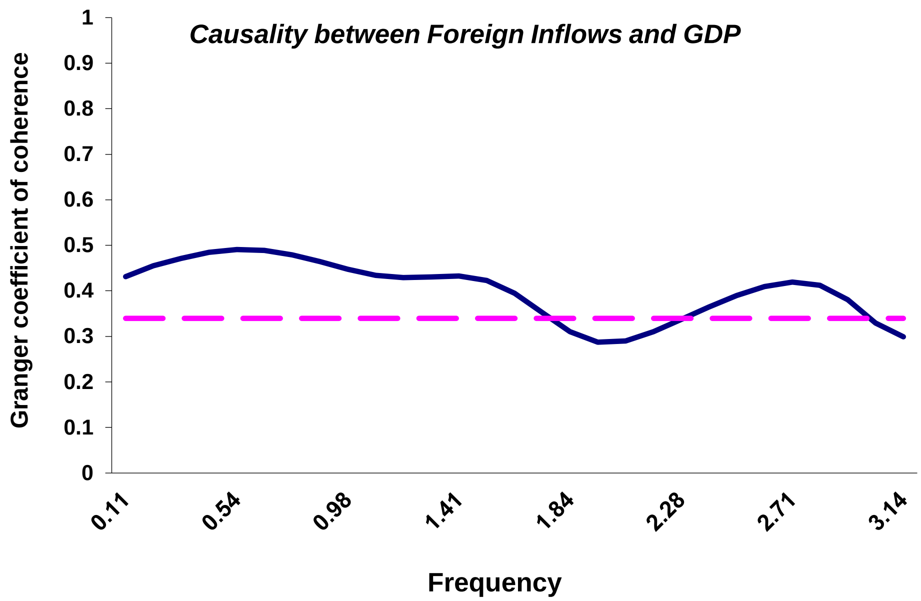

Figure 4: Granger coefficient of coherence for causality between Foreign Inflows and GDP

3.4.5. Causality between foreign inflows and foreign exchange reserves

Figure 11 present the causality from foreign capital inflow to foreign exchange reserves which are significant at 5% level of significance. The result is significant only at frequencies corresponding to one-two quarter cycles. It implies that foreign capital inflow drives foreign exchange reserves only in the short run. The international forex reserves play the role of a stabilizer for capital flows in the short run. Forex reserve of the country increases with the increase in foreign capital flows only in the short run and reverts to the average level in the long run.

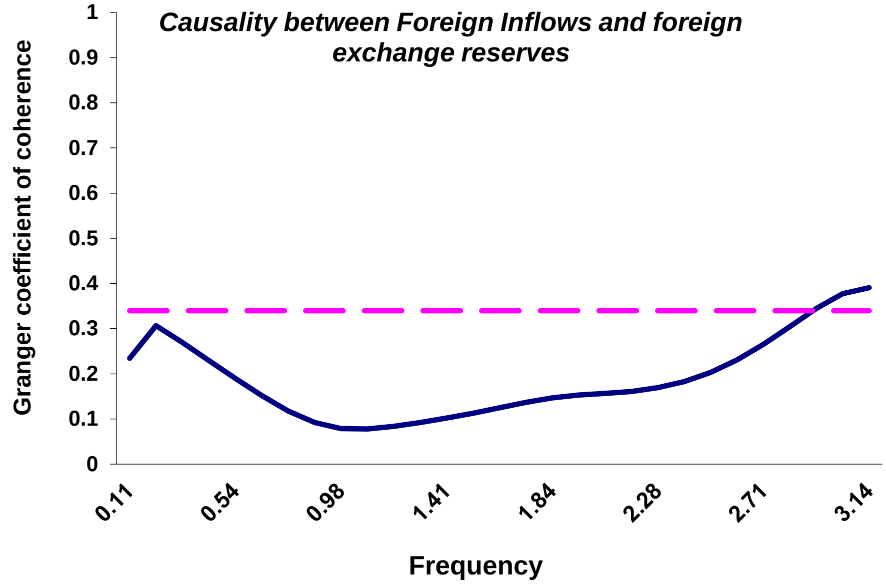

Figure 5: Granger coefficient of coherence for causality between Foreign Inflows and foreign exchange reserves

3.4.6 Causality between foreign inflows and exchange rate

The results reported in figure 12 show Granger causality running from foreign capital inflows to exchange rate, and this reveals the causality at frequencies corresponding to two-three quarters cycles. Therefore, one can argue that in the short-run foreign capital inflows, Granger causes exchange rate. It indicates that the inflows in the form of foreign capital in the short-run make the rupee stronger, but its impact tapers gradually and vanishes in the long run.

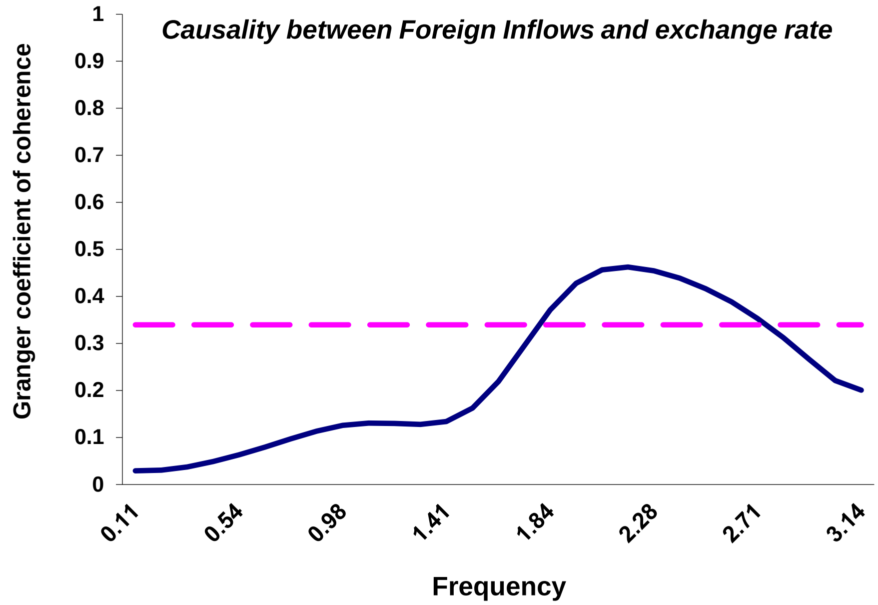

Figure 6: Granger coefficient of coherence for causality between Foreign Inflows and exchange rate

3.4.7 Causality between foreign inflows and export

Diagram-13 presents the Granger causality test results between foreign capital inflows and exports. The result is significant at a 5% level of significance. The result shows causality only at frequencies corresponding to cycles longer than three quarters and becomes much stronger after a year. This could be interpreted as a more than one-year gestation between foreign inflow and export.

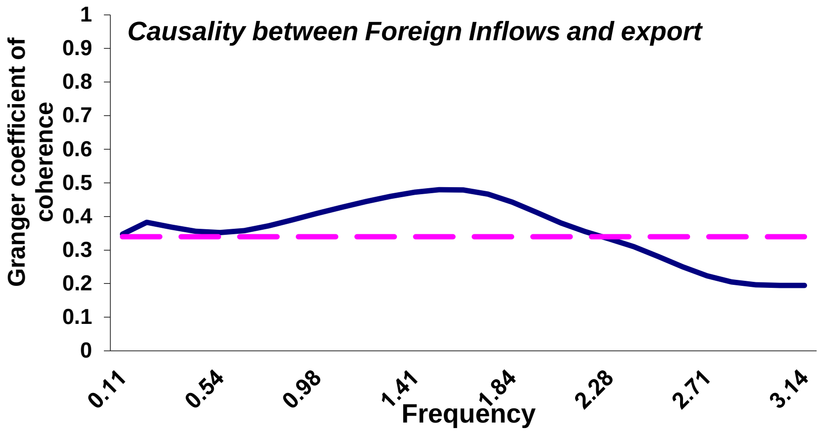

Figure 7:Granger coefficient of coherence for causality between Foreign Inflows and export

3.4.8 Causality between foreign inflows and *interest rate*

Figure 14 presents the Granger causality between foreign capital inflows and interest rate. Foreign capital inflows do not Granger cause interest rate at any frequencies at a significance level of 5 percent. However, the coherence coefficient improves after three to fourth quarter cycles but still fails to cross the significance level. Therefore, the null hypothesis of no causality between foreign capital inflows and the interest rate is not significant at a 5 % level at any frequency. Further, this implies that at a 5% level of significance, the foreign inflows do not Granger-cause interest rate at lower or higher frequencies.

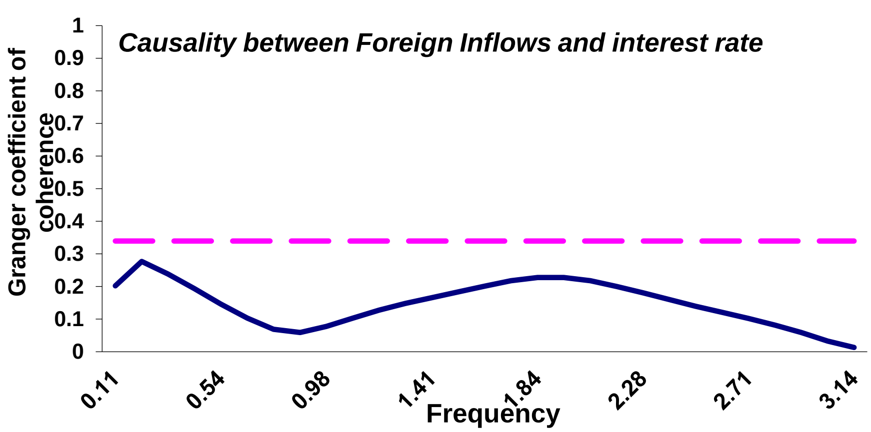

Figure 8: Granger coefficient of coherence for causality between Foreign Inflows and interest rate

3.5 Conclusion

Our findings provide important implications for India's macroeconomic and monetary policy management, especially in managing capital flows. It offers granular details about the behavior of major macroeconomic variables for an economy allowing for inflows of foreign capital. GC test is widely used for the long-term economic study. The results from the frequency domain approach based on the spectral analysis could help supplement the information obtained by the commonly used time-domain analysis. Theoretically, increasing evidence about the nature of the relationship between two-time series varies with the changing frequencies. This study's salient feature has been using the frequency-domain approach to uncover the causality relation between foreign capital inflows and macroeconomic indicators of the recipient countries using quarterly data. The results establish the causal and inverse causal relations between foreign capital inflows and macroeconomic indicators at multiple frequencies of increasing orders. Capital inflows Granger causes money supply in the short and long run, whereas GDP, import, export, exchange rate, and WPI in the short run. The Granger causality test failed to observe the causality between foreign capital inflows and foreign exchange reserves and foreign capital inflows and interest rates. The unique contribution of this study is that it decomposes the causality based on time horizons and demonstrates the causality between capital inflows and other macroeconomic indicators for India.