Does CPI Granger-Cause WPI? New Extensions from Frequency Domain Approach in Pakistan

Muhammad, Shahbaz and Kumar, A.T.K. and Mohammad, Iqbal Tahir

COMSATS Institute of Information Technology, Lahore, Pakistan, ICFAIUniversity, Tripura, GIFT University, Pakistan

7 May 2012

Does CPI Granger-Cause WPI?
New Extensions from Frequency Domain Approach in Pakistan

Muhammad Shahbaz
COMSATS Institute of Information Technology, Lahore, Pakistan
Email: shahbazmohd@live.com

Aviral Kumar Tiwari
Faculty of Management Studies, ICFAI University, Tripura, India
Email: aviral.eco@gmail.com

Mohammad Iqbal Tahir
GIFT University Gujranwala, Pakistan, and
Griffith University, Brisbane, Australia
Email: iqbaltahir@gift.edu.pk

Abstract:

The present study significantly contributes to the economic literature by investigating the direction of causality between WPI and CPI by applying frequency domain causality approach developed by Lemmens et al. (2008) based on spectral approach. We use monthly frequency data covering the period of 1961-2010 in case of Pakistan. Our results provide evidence of cointegration between the variables. Furthermore, we find unidirectional causal relationship running from CPI to WPI that varies across frequencies i.e., CPI Granger-causes WPI at lower, medium as well as higher level of frequencies reflecting long-run, medium and short-run cycles. This implies that CPI should be a leading indicator for important policy decisions pertaining to monetary or fiscal policies in Pakistan.

Keywords: WPI, CPI, Frequency Domain Approach

Accepted for publication in *Economic Modelling*, 2012, forthcoming issue

I. Introduction

The objective of this paper is to re-assess the causality relationship in case of Pakistan between wholesale price and consumer price indices by using nonparametric frequency domain causality approach developed by Lemmens et al., (2008). The prime objective of monetary policy is to stabilize price levels in an economy. A hike in inflation will reduce the purchasing power of general population especially among middle income and poor segments of the population and hence influence their economic wellbeing (Rao and Bukhari, 2011). That is why central banks have been given enough independence to stabilize the prices. Central banks usually controls price hikes through monetary policy.

In Pakistan, variety of price indices are calculated by following survey based measures. The measures of general price levels such as consumer price index, wholesale price index, GDP deflator and sensitive price index are being constructed by the State Bank of Pakistan (SBP)[1]. These indices help in constructing national income and product account measures (Cecchetti et al. 2009). They are also used to convert data from nominal to real terms in order to examine real performance of macroeconomic indicators. The wholesale price index shows the value of goods at first commercial transaction while at retail level the consumer price index measures the price of goods and services (Rao and Bukhari, 2011). The traditional view is that the wholesale price index leads the consumer price index. This shows that the movement of wholesale prices is from supply side and production process to demand side. This transmission mechanism has been discussed in Shahbaz et al. (2010).

The findings of our analysis confirm that both series are integrated at I (1) and cointegration exists between the variables for a long run relationship. The causality results from frequency domain approach show that the consumer price index (CPI) does lead the wholesale price index (WPI) in case of Pakistan. These findings are also validated by innovative accounting approach as variance decomposition approach reveals that a standard deviation innovative shock in CPI explains WPI by 52.68% while WPI contributes to CPI by 17.97% through its innovative shocks. Shahbaz et al. (2010) and Rao and Bukhari (2011) do not agree with our findings. However, we argue on the reliability of our results over the previous work as this study uses more advanced frequency domain approach developed by Lemmens et al. (2008) based on spectral approach.

The rest of the paper is organized as follows: Section II presents the literature review; section III details the methodology and data sources; section IV discusses the results, and conclusion and policy implications are drawn in section V.

II. Literature Review

Existing literature reveals that wholesale prices play a vital role to increase the consumer prices in an economy. This implies that unidirectional causality should run from wholesale prices to consumer prices. For example, Hatanaka and Wallace (1979), Engle (1978), Silver and Wallace (1980), Guthrie (1981), Colclough and Lange (1982), Cushing and McGarvey (1990), Clark (1995) and, Samanta and Mitra (1998) consider both variables to explore the direction of

[1] See Rao and Bukhari, (2011) for more details.

causality and provide inconclusive findings. Caporale et al. (2002) collect data for G7 countries and examine the causal relationship between wholesale and consumer prices. Their results indicate that wholesale prices Granger-cause consumer prices. Caporale et al. (2002) also highlight two estimation issues that arise when testing for a causal relationship between consumer and wholesale prices: selecting the "correct" model in the context of which causality relationships are analyzed and carrying out tests that result in invalid statistical inferences. That is why Caporale et al. (2002) apply Toda and Yamamoto (1995) causality approach because it does not require any pre-testing of stationarity and cointegration properties of the series. Their results indicate the presence of feedback hypothesis between the two variables and this relationship exists once the monetary transmission mechanism is ignored.

In case of other country studies, Akdi et al. (2006) investigate the relationship between the consumer price index and the wholesale price index using the Turkish data. Their empirical evidence shows cointegration between the series and both variables Granger-cause each other under the umbrella of feedback hypothesis. In case of Mexico, Sidaoui et al. (2009) examine causality relation between producer prices and consumer prices. Their study shows cointegration between the variables. The causality analysis indicates feedback effect between the two series in the long run as well as in the short run. In case of Pakistan, Shahbaz et al. (2009) document the long run relationship between producer price and consumer price indices. Their study shows bidirectional causality between the two variables but strong causality is running from producer prices to consumer prices. In case of Malaysia, Ghazali et al. (2009) investigate whether producer prices Granger-cause consumer prices by applying Engle-Granger (1987) and Toda-Yamamoto (1995) approaches. Their results indicate that unidirectional causality is found running from producer prices to consumer prices.

Furthermore, Shahbaz et al. (2010) conduct a study to test the causality between wholesale prices and consumer prices. They document that variables are integrated at I (1) and cointegration for long run exists. Their results report that wholesale prices and consumer prices Granger-cause each other but causal relation is dominant from wholesale prices to consumer prices validating the hypothesis documented by Cushing-McGarvey (1990). Rao and Bukhari (2011) also examine the causal relation between wholesale price and consumer price indices by using month frequency data for the period 1978-2010. Their empirical exercise confirms the presence of long run relation between both variables. Furthermore, they document that short run changes are temporary and both series converge to long run stable equilibrium with CPI as an appropriate indicator of inflation. Finally, Akcay (2011) examines the direction of causality between producer price index and consumer price index by applying Toda and Yamamoto (1995) causality approach. The empirical evidence confirms unidirectional causal relation from producer price index to consumer price index in Finland and vice versa in case of France. The feedback effect is found in case of Germany for both variables and neutral hypothesis exists in case of Netherlands and Sweden.

It is worth noting that most previous studies are limited in scope to the applications of linear models. However, economic events and regime changes such as changes in economic environment, changes in monetary and/or fiscal policy can cause structural changes in the pattern of inflation (i.e., WPI and/or CPI) for a given time period under study. This creates room for a nonlinear rather than linear relationship between WPI and CPI. Therefore, in the present study we make an attempt to analyze the issue in a nonlinear framework by using a nonparametric approach developed by Lemmens et al. (2008). Use of this approach allows us to decompose the Granger-causality (GC) in the frequency domain. In frequency domain approach, the key idea is that a stationary process can be described as a weighted sum of sinusoidal components with a certain frequency ω. As a result, one can analyze these frequency components separately. As such, instead of computing a single GC measure for the entire relationship, the GC is calculated for each individual frequency component separately. Thus, the strength and/or direction of the GC can be different for each frequency. To the best of our knowledge, the analysis of GC between CPI and WPI has not yet been explored in the frequency domain both in the developing or developed country context.

III. Methodology and Data Collection

Time series analysis in the frequency domain (spectral analysis) can supplement the information obtained from the time-domain framework (Granger 1969, and Priestley 1981). Spectral analysis highlights the cyclical properties of the data. We implement Lemmens et al. (2008) in testing the Granger Causality (GC) over the spectrum using bivariate framework. This test is revised version of Pierce (1979). This GC test in the frequency domain relies on a modified version of the coefficient of coherence. The estimates are obtained non-parametrically and used to 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 (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.

$$\Theta^x(L)X_t = C^x + \Phi^x(L)u_t \tag{1}$$

$$\Theta^y(L)Y_t = C^y + \Phi^y(L)v_t \tag{2}$$

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

Let $S_u(\lambda)$ and $S_v(\lambda)$ be the spectral density functions (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 $\gamma_u(k) = \mathrm{Cov}(u_t, u_{t-k})$ 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 behind 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, originating in the cyclical components in the frequency band ($\lambda, \lambda + d\lambda$).

The cross spectrum represents the cross covariogram of two series in frequency domain and 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 $C_{uv}(\lambda)$, called cospectrum and $Q_{uv}(\lambda)$, called quadrature spectrum are respectively, the real and imaginary parts of the cross-spectrum and $i = \sqrt{-1}$. Here $\gamma_{uv}(k) = \mathrm{Cov}(u_t, v_{t-k})$ represents the cross-covariance of u_t and v_t at lag k. The spectrum $Q_{uv}(\lambda)$ between the two series u_t and v_t at frequency λ can be interpreted as the covariance between the 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 1994, p.274). 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 $\hat{\gamma}_{uv}(k) = \hat{COV}(u_t, v_{t-k})$ the empirical cross-covariances, and with window weights w_k, for $k = -M,..,M$. Equation (6) is called the *weighted covariance estimator*, and the weights w_k are

---

[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 1994, p.159).

selected as the Bartlett weighting scheme i.e. $1-|k|/M$. The constant M determines the maximum lag order considered. The spectra of Equations (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 $0<\lambda<\pi$ under appropriate rescaling 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 Equation (7) provides a measure of the strength of the linear association between the two time series, frequency by frequency, but not on the direction of the relationship between the two processes. Lemmens et al. (2008) decomposed the cross-spectrum (Equation 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.,

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

[3] For the end points $\lambda=0$ and $\lambda=\pi$, one only has one degree of freedom since the imaginary parts of the spectral density estimates cancel out.

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 to v_t which is given by the second part of Equation (10), i.e.

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

The Granger coefficient of coherence is then given by

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

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

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

with $\hat{S}_{u\Rightarrow v}(\lambda)$ as in Equation (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 (Equation 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, for $0<\lambda<\pi$ is given by,

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

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 in 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

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

Later, we compute Granger coefficient of coherence given by Equation (13) and test the significance of causality using use of Equation (15).

The data of wholesale price index (WPI) and consumer price index (CPI) has been obtained from International Financial Statistics (CD-ROM, 2011). We have used monthly frequency data over the period from 1961 to 2010.

IV. Empirical Results and Their Discussion

First of all descriptive statistics of variables[4] have been analyzed to see the sample properties and Pearson's correlation analysis is conducted to see whether there is any evidence for co-movement of both series.[5] We find that correlation is very high and its value is 0.99. In the next step stationary property of the data series of all test variables has been tested through PP test and results are reported in Table 1. Table 1 reports that both variables have unit root problem at their level form while they are stationary at their first differenced form.

Table 1: Estimation of Unit Root Tests

Variables	PP unit root test with intercept		PP unit root test with intercept and trend		Lee-Strazicich unit root test with one structural break	
	T-Statistic	Prob-value	T-Statistic	Prob-value	T-Statistic (Crash model) (k)	T-Statistic (Break model) (k)
$\ln CPI_t$	0.713(10)	0.9924	-2.069(10)	0.5614	-2.923 (12) [1973:12]	-3.647 (12) [1976:07]
$\Delta \ln CPI_t$	-19.986(7)*	0.0000	-20.006(7)*	0.0000	-3.336** (11) [1967:06]	-5.318* (11) [1978:07]
$\ln WPI_t$	0.623(2)	0.9903	-2.575(2)	0.2917	-2.196 (12) [1972:02]	-3.229 () [1976:03]
$\Delta \ln WPI_t$	-15.994(10)*	0.0000	-15.993(10)*	0.0000	-3.377** (12) [1987:05]	-7.252* (12) [1973:01]

Note: The asterisks * and ** denote the significant at 1% and 5% level respectively. The figure in the parentheses is the bandwidth for the PP unit root test and it is determined by the Schwert (1989) formula. Here we have presented results of Lee-Strazicich unit root test with one structural break only as second break in both models were insignificant in level series. Therefore, two breaks analysis of the variables with first difference form is not carried out. In parentheses are the break dates and "k" denotes the lags chosen for analysis.

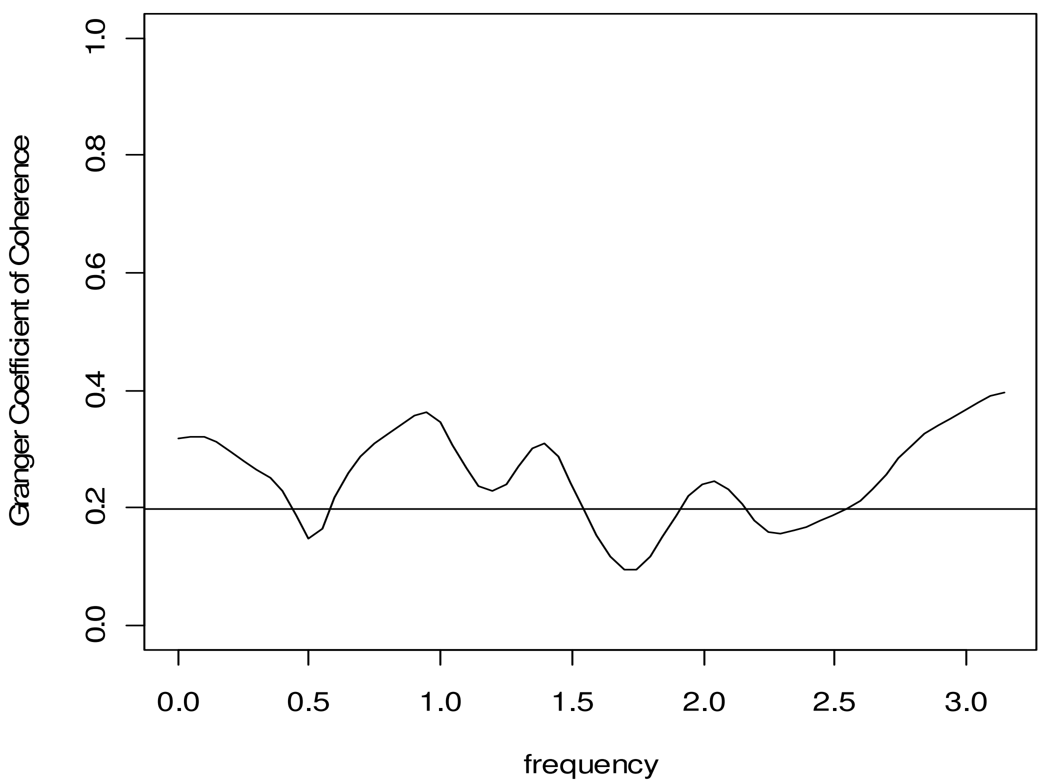
The next step is to investigate the long run relationship between the series by applying ARDL bounds testing approach. The results of ARDL bounds testing are reported in Table 4 (in the Appendix). The lag length selection of the variables for a suitable ARDL model to calculate F-statistic is based on Akaike Information Criteria (AIC). AIC provides better results and has superior predicting properties as compared to other tests (Lütkepohl, 2006) and lag order is 8. The results in Table 4 show that our calculated F-statistics exceed upper critical bounds generated by Pesaran et al. (2001) at 1% level of significance. Pesaran et al. (2001) created the upper and lower critical bounds for large sample (T = 500 to T = 40, 000) and Narayan (2005) generated the critical bounds for small sample (T = 30 to T = 80). We have used bounds developed by Pesaran et al. (2001) as our sample size is large. Our empirical exercise indicated two cointegrating vectors once WPI and CPI are treated as predicting variables. This shows that

[4] Time series plot and descriptive statistics of the variables are presented in Figure 3 and Table 3 respectively, in the Appendix. Table 3 in the Appendix indicates that the two variables do not have log normal distribution and therefore, provides scope for our nonlinear analysis.
[5] Results are reported in Table 3 in the Appendix.

long run relationship exists between wholesale price and consumer price indices in case of Pakistan over the period of 1961-2010.

In the next step, we analyze Granger-causality (GC) between CPI and WPI in the frequency domain framework. GC is analyzed by adopting log differenced data (after seasonal adjustment) of the variables so that series become stationary. Furthermore, the two log differenced variables have been filtered using ARMA models to obtain the innovation series. We have used lag length[6] $M = \sqrt{T}$. 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. Figure 1 presents the result of Granger coefficient of coherence for causality running from CPI to WPI.

Figure 1: Granger Causality from CPI to WPI. (The line parallel to the frequency axis represents the critical value for the null hypothesis at the 5% level of significance).

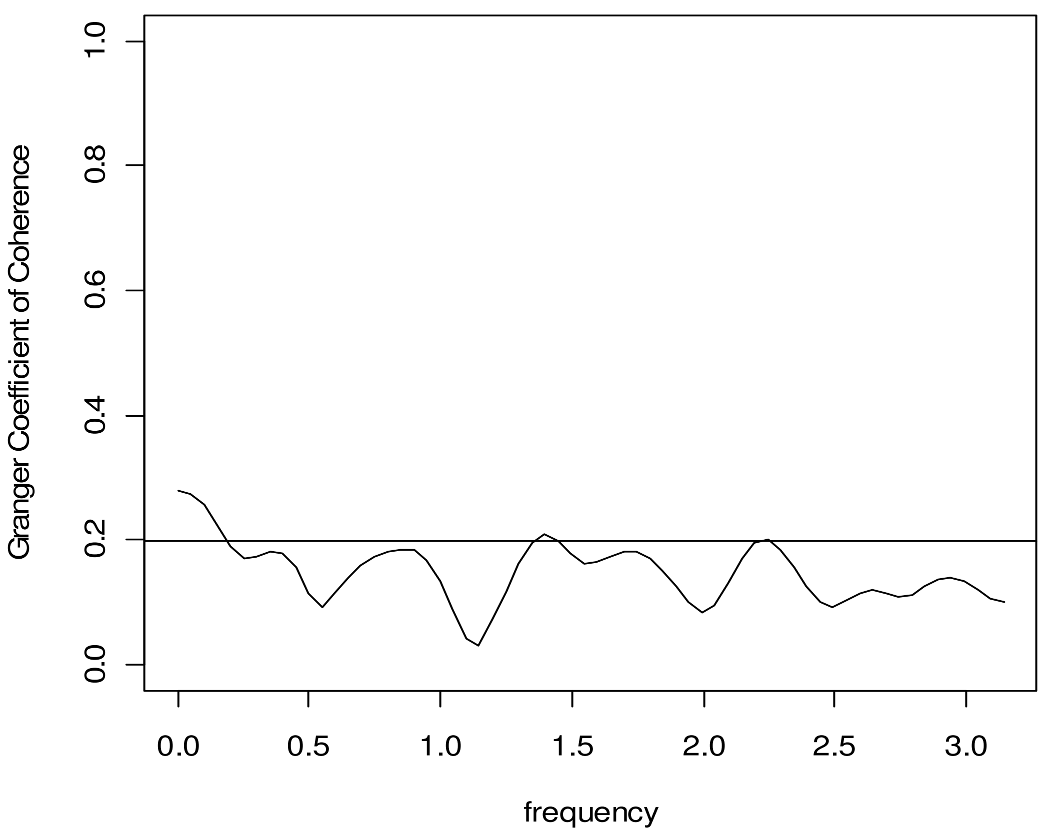


[6] Following Diebold (2001, p.136) we take M equal to the square root of number of observations T.

Figure 1 shows that at 5% level of significance, CPI Granger-causes WPI at lower, medium as well as higher levels of frequencies reflecting very long-run, medium as well as short-run cycles. That is long-, medium-, and short-run business cycles in WPI are Granger-caused by CPI.

Similarly, Figure 2 reports the result of Granger coefficient of coherence for causality running from WPI to CPI. However, Figure 2 provides no evidence of Granger-causality from WPI to CPI at 5% level of significance at all levels of frequencies[7]. Though some business cycles are evident in the CPI at the intermediate level yet WPI does not show significant evidence of Granger-causality to CPI (with the only exception of the frequency level 1.4).

Figure 2: Granger Causality from WPI to CPI. (The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance).



[7] Of course, there is some evidence where Granger coefficient of coherence just crosses the critical value of 5% level of significance. However, it is at very high frequencies and therefore, business cycle is of very small periodicity.

Variance Decomposition Approach (VDA)

The Granger causality tests do not present the relative strength of causality results ahead of the selected sample period. In this situation, findings by causality tests do not help policy makers in formulating comprehensive policy to control inflation in the country. The main objective of the State Bank of Pakistan is to stabilize price levels in the country by implementing an appropriate monetary policy. The variance decomposition approach seems to help policy makers by providing relative strength of causality results ahead of the selected sample period.

Table 2: Variance Decomposition Approach (VDA)

Period	Variance Decomposition of $\ln CPI_t$		Variance Decomposition of $\ln WPI_t$	
	$\ln CPI_t$	$\ln WPI_t$	$\ln CPI_t$	$\ln WPI_t$
1	100.0000	0.0000	17.1115	82.8884
2	97.8713	2.1286	20.6217	79.3782
3	96.6760	3.3239	24.7635	75.2364
4	93.1164	6.8835	28.8036	71.1964
5	91.9433	8.0566	32.5980	67.4020
6	90.9504	9.0495	37.3831	62.6168
7	90.2594	9.74055	41.1019	58.8980
8	88.4741	11.5258	43.7795	56.2204
9	87.0775	12.9224	45.7970	54.2029
10	85.7675	14.2324	47.5167	52.4832
11	84.7996	15.2003	48.8459	51.1540
12	83.8608	16.1391	49.9673	50.0326
13	83.1913	16.8086	50.9068	49.0931
14	82.5587	17.4412	51.8147	48.1852
15	82.0343	17.9656	52.6810	47.3189

The results reported in Table 2 show that a standard deviation innovation shock in CPI explains 82.03 per cent of CPI itself and the rest is contributed by innovation shocks stemming in WPI. The innovative shocks in CPI attribute to WPI by 52.68 per cent and the rest is contributed by own innovative shocks of WPI i.e. 47.32 per cent. This indicates the unidirectional causality running from CPI to WPI. Overall, our findings confirm that findings by frequency domain approach are robust and superior to other traditional causality approaches. The results of impulse response function are shown in Figure 4 (in the Appendix).

V. Conclusions and Policy Implications

In the present study we analyze Granger causality between CPI and WPI for Pakistan by using monthly data covering the period from 1961 to 2010. We find that both variables are nonstationary in log level form and stationary in log first difference form. Our results show that in case of Pakistan causal relations between CPI and WPI vary across frequencies. We also find that CPI Granger-causes WPI at lower, medium as well as higher levels of frequencies reflecting very long-run, medium as well as short-run cycles. Contrary to that we find that WPI does not Granger-cause CPI at 5% level of significance at all levels of frequencies.

The unique contribution of the present study lies in decomposing the causality on the basis of time horizons and demonstrating causality at lower, medium as well as long-run cycles from CPI to WPI and no cycles from WPI to CPI. These results have important implications for Pakistan for planning of inflation related policies. For example, our finding that CPI Granger-causes WPI at lower, intermediate and higher level frequencies implies that CPI should be a leading indicator for important policy decisions pertaining to monetary or fiscal policies. It also suggests that by looking at this link policy makers may be better prepared to avoid, or at least mitigate, the negative consequences of producers' inflation i.e. WPI.

References

1. Akcay, S., (2011), ‘The causal relationship between producer price index and consumer price index: Empirical evidence from selected European countries’, International Journal of Economics and Finance, 3, 227-232.
2. Akdi, Y., Berument, H. and Cilasun, S. M., (2006), ‘The relationship between different price indices: Evidence from Turkey,’ Physics A, 360, 483-492.
3. Caporale, G.M., Katsimi, M. and Pittis, N. (2002), ‘Causality links between consumer and producer prices: Some empirical evidences,’ Southern Economic Journal, 68, 703-711.
4. Cecchetti, S.G., Kohler, M., Upper, C. (2009), ‘Financial Crises and Economic Activity’, NBER Working Papers 15379, National Bureau of Economic Research, Inc.
5. Clark. T. (1995), ‘Do producer prices lead consumer prices? Federal Reserve Bank of Kansas City Economic Review, 80, 25-39.
6. Colclough, W. G and M. D. Lange, (1982), ‘Empirical evidence of causality from consumer to wholesale prices,’ Journal of Econometrics, 19, 379–384.
7. Cushing, M. J and M. G, McGarvey, (1990), ‘Feedback between wholesale and consumer price inflation: A reexamination of the evidence,’ Southern Economic Journal, 56, 1059-1072.
8. Diebold, F. X., (2001), ‘Elements of forecasting (2nd Ed.). Ohio: South-Western.
9. Engle, R. F, (1978), ‘Testing price equations for stability across spectral frequency bands,’ Econometrica, 46, 869–881.
10. Engle, R.F., and C.W.J. Granger, (1987), ‘Cointegration and error correction representation: Estimation and testing,’ Econometrica, 55, 251-276.
11. Ghazali, M. F., Yee, O. A., Muhammad, M. Z., (2008), ‘Do producer prices cause consumer prices? Some empirical evidence’, International Journal of Business and Management, 3, 78-82.
12. Granger, C. W. J., (1969), ‘Investigation of causal relations by econometric models and cross-spectral methods,’ Econometrica, 37, 424-438.
13. Guthrie, R. S., (1981), ‘The relationship between wholesale and consumer prices,’ Southern Economic Journal, 47, 1046-1055.
14. Hamilton, J. D., (1994), ‘Time series analysis’. Princeton University Press, Princeton, NJ.
15. Hatanaka, M and T. D. Wallace, (1979), ‘Multicollinearity and the estimation of low order moments in stable lag distributions,’ In Evaluation of Econometric Models, J Kmenta and J Ramsay (eds.), New York: Academic Press.
16. Lemmens, A., Croux, C. and Dekimpe, M. G. (2008), ‘Measuring and testing Granger causality over the spectrum: An application to European production expectation surveys,’ International Journal of Forecasting, 24, 414-431.
17. Lütkepohl, H., (2006), ‘Structural vector autoregressive analysis for cointegrated variables,’ AStA Advances in Statistical Analysis, 90, 75-88.
18. Narayan, P. K., (2005), ‘The savings and investment nexus for China: Evidence from co-integration tests,’ Applied Economics, 37, 1979-1990.
19. Pesaran, M. H., Shin, Y. and R. J. Smith, (2001), ‘Bounds testing approaches to the analysis of long run relationships’, Journal of Applied Econometrics, 16, 289-326.
20. Pierce, D. A., (1979), ‘R-squared measures for time series,’ Journal of the American Statistical Association, 74, 901-910.

21. Priestley, M. B. (1981), 'Spectral analysis and time series'. London: London Academic Press.
22. Rao, N. M., Bukhari, S. K. H., (2011), 'Asymmetric shocks and co-movement of price indices', SBP Working paper no.38.
23. Samanta, G and Mitra, S., (1998), 'Recent divergence between wholesale and consumer prices in India- a statistical exploration,' RBI Occasional Papers, 19.
24. Schwert, G.W. (1989), 'Tests for unit roots: A monte carlo investigation', Journal of Business & Economic Statistics, 7, 147-159.
25. Shahbaz, M., Awan, U. R and Nasir, M. N., (2009), 'Producer and consumer prices nexus: ARDL bounds testing approach,' International Journal of Marketing Studies, 1, 78-86.
26. Shahbaz, M., Wahid, A. N. M. and Haider, A. (2010), 'Empirical psychology between wholesale price and consumer price indices: the case of Pakistan,' The Singapore Economic Review, 55, 537-551.
27. Sidaoui, J, Capistran, C., Chiquiar, D. and Ramos-Francia, M. (2009), 'A note on the predictive content of PPI over CPI inflation: The case of Mexico,' Working Paper 2009-14, Banco de Mexico.
28. Silver, J. L and T. D, Wallace, (1980), 'The lag relationship between wholesale and consumer prices- An application of the Hatanaka-Wallace procedure,' Journal of Econometrics, 12, 375–387.
29. Toda, H. Y and T. Yamamoto, (1995), 'Statistical inference in vector autoregressions with possibly integrated processes,' Journal of Econometrics, 66, 225–250.

Appendix

Table 3: Descriptive Statistics and Correlation Matrix

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	$\ln WPI_t$	$\ln CPI_t$
$\ln WPI_t$	2.9512	2.99673	5.0862	1.05431	1.2170	-0.0699	1.7101	40.1899	1.0000	0.9997
$\ln CPI_t$	3.0790	3.1376	5.0314	1.3029	1.1337	-0.0953	1.7152	40.2767	0.9997	1.0000

Table 4: Statistical Output for Cointegration Test (Bounds Test)

Estimation Models	Lag Length	F-Statistics	Lower - Upper Bound at 1%	Lower - Upper Bound at 5%	Lower - Upper Bound at 10%
$F_{CPI} = CPI / WPI)$	7	9.139*	3.34 - 4.63	2.69 - 3.83	2.38 - 3.45
$F_{WPI} = WPI / CPI)$	7	7.537*	3.34 - 4.63	2.69 - 3.83	2.38 - 3.45
$F_{CPI} = CPI / WPI)$	8	8.123*	3.25 - 4.43	2.55 - 3.68	2.26 - 3.34
$F_{WPI} = WPI / CPI)$	8	6.596*	3.25 - 4.43	2.55 - 3.68	2.26 - 3.34
Note: * denotes rejection of the null at 1% significance level. Critical values bounds are used computed by Pesaran et al. (2001).					

Figure-3: Time Series Plots of the Variables

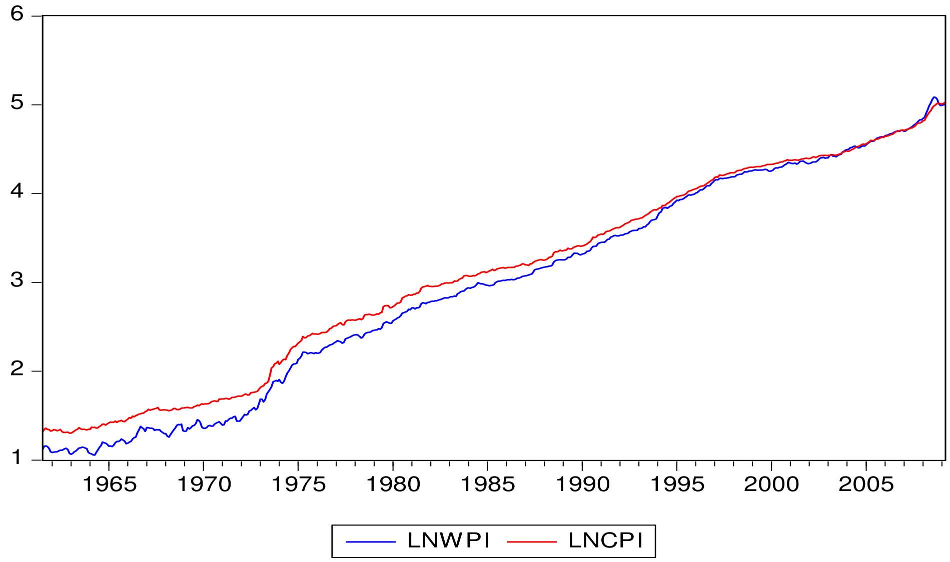


Figure-4: Impulse Response Function