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Causality between wholesale price and consumer price indices in India

An empirical investigation in the frequency domain

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Abstract

Purpose – The purpose of this study is to attempt to analyze Granger causality in the frequency domain framework between producers' prices measured by wholesale price index (WPI) and consumers' prices measured by consumer price index (CPI) in the context of India.

Design/methodology/approach – Analysis was carried out in the framework of time series and for analysis Johansen and Juselius's maximum likelihood approach for cointegration was applied after confirming that variables are integrated of order one, i.e. I(1) through the Lee and Strazicich unit root test. Finally, Granger causality was tested in the frequency domain by utilizing a recently developed approach of Lemmens *et al.* over the period January 1957-February 2009.

Findings – The paper finds that CPI Granger cause WPI at a lower, intermediate as well as higher levels of frequency, reflecting very long-run, intermediate as well as short-run cycles. By contrast WPI Granger cause CPI at 5 percent level of significance was found at intermediate frequencies, reflecting significant intermediate cycles.

Research limitations/implications – The study reveals that CPI is a leading indicator of producers' prices and inflation (i.e. WPI). This gives an indication that Indian policy analysts ought to control for factors affecting CPI in order to have control on WPI since WPI is used for making various macroeconomic indicators in real terms.

Originality/value – The main contribution of the paper is to show the evidence of bidirectional causality between WPI and CPI. Furthermore, use of a recent approach developed by Lemmens *et al.* for Granger causality in the frequency domain in this study is also relatively new. To the best of the author's knowledge there is no such study in this area either for developed or developing economy to date.

Keywords Consumer price index, Wholesale price index, Granger causality, Cointegration, Frequency domain, Structural change, Retail price index, Wholesaling

Paper type Research paper

1. Introduction

There have been a number of studies to identify the causal direction between consumers' prices and producers' prices. This is particularly because these prices are used for various purposes, for example, these indices help in constructing national income and product account measures (Cecchetti *et al.*, 2009). Producers' prices

JEL classification – E31, C32

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(particularly the wholesale price index (WPI)) are used to convert nominal data series into real terms in order to examine real performance of macroeconomic indicators. These real data series are used in various research works either by the independent researchers, or some agency- or project-based research. Finally, policy implications derived from the research are adopted by the government or monetary authority of a nation in some way or other that ultimately affects the development process of an economy and welfare of society. For example, the central bank of a country tries to stabilize inflation through its monetary policy because a hike in inflation will reduce the purchasing power of the general population, especially the middle income and poor segments, and hence influence its economic wellbeing (Rao and Bukhari, 2011). This will ultimately reduce the welfare of society and harm the development process of the nation. Hence, in such a situation the question of the direction of Granger causality (GC) between consumers' prices and producers' prices should be answered. Not only that, but there may also be a situation where one-shot measure of GC (either developed in a linear and/or nonlinear framework) might be unable to give a possibly true answer as, for different frequency bands, the direction of GC may vary. It is also important to note that the traditional GC test only measures precedence and information content, but does not indicate causality in its conventional sense (Tiwari, 2012). Hence, in the present study we employed a frequency domain GC test to obtain a more reasonable answer to the critical question faced by policy makers.

As Goyal and Tripathi (2010) argued:

> [because] consumer prices are a weighted average of the prices of domestic and of imported consumption goods, and producer prices feed into final consumer prices, wholesale price inflation should cause consumer price inflation.

They further added that there should also be a long-term relationship among between consumer and wholesale price inflation and the exchange rate. According to the traditional view, the WPI leads the consumer price index (CPI) and this transmission mechanism has been discussed in Shahbaz *et al.* (2010). To explain the causal relationship running from wholesale price to consumers' prices Cushing and McGarvey (1990)[1] have developed theoretical basis. They argued that since primary goods are used as input with a lag period in the production process of consumption goods wholesale prices will lead consumer prices independently. Hence, from the above arguments it is proved that WPI may Granger cause CPI. These kinds of dynamics appear particularly when the transmission mechanism moves from the supply side or production processes to the demand side or consumption behavior. There are several reasons to support this argument. For example, since the retail sector adds value with a lag to existing production and uses existing domestic or imported materials as production input, the price of final consumer goods will depend on the price at which raw materials, or what is called production inputs, are purchased. Further, the price of production inputs depends on domestic demand and supply of the production inputs in the one hand and imported inputs on the other. Hence price of production inputs in turn depends on the prices of the imported goods, the nominal exchange rate, the level of indirect taxes, the marginal cost of retail production and interest rates.

However, in contrast to this wisdom Colclough and Lange (1982) claimed that the causal relationship from CPI to WPI did not receive much attention in the literature. They developed a building block from the theory of derived demand to demonstrate a situation wherein WPI may Granger cause CPI. The authors argued that, since demand for inputs are determined by demand for final goods and services between competing utility items, this indicates that opportunity cost of resources and intermediate materials is reflected by the production cost that influences the demand for final goods and services. This argument implies that CPI should determine or affect WPI. Further, Cushing and McGarvey (1990) assumed that demand for primary goods depends on expected future prices of consumer goods. This assumption implies that current demand and past expectations of current demand determine consumer price, and expected future demand determines producer price. Changes in the demand for final goods have an impact on input prices; therefore CPI leads to WPI. Furthermore, development was made by Caporale *et al.* (2002) in this direction. They documented that CPI may Granger cause WPI through the labor supply channel, which may also reflect through supply shocks in the labor market provided that wage earners in the wholesale sector want to preserve the purchasing power of their incomes. This effect occurs with a lagged period, and it probably depends on the nature of wage-setting process along with expectations of machinery formation. Hence Cushing and McGarvey (1990) developed a generalized approach that explains the bidirectional causal relationship. That is due to a lag period in the production process of consumption goods wholesale prices leading consumer prices and a change in the current demand having an impact on input prices and therefore providing evidence that CPI leads WPI.

Hence, we find that, theoretically, CPI may Granger cause WPI or WPI may Granger cause CPI or both (CPI and WPI) may Granger cause each other. However, empirical evidence has been inconclusive in regard to this. Further, for example, when the transmission mechanism moves from the supply side to the demand side with various frequencies (which are the real world case) the empirical evidence and policy recommendations based on one-shot measure of GC are truly misleading. Further, GC measures precedence and information content, but does not indicate causality in its conventional sense (Tiwari, 2012). Importantly, the extent and direction of causality differs between frequency bands (Granger and Lin, 1995). Hence, in this study, by utilizing frequency domain approach of GC we are trying to obtain a more reasonable answer to this real world problem. Therefore, this study has made an attempt to investigate whether in India CPI Granger causes WPI or WPI Granger causes CPI or both causes one another at different frequencies.

The rest of the paper is organized as follows. Section 2 presents a brief review of literature followed by methodology adopted in this paper for analysis and a data source in Section 3. Section 4 presents data analysis and Section 5 concludes.

2. A brief review of literature

The studies analyzing the relation between CPI and WPI using time series techniques have found some kind of stable relationship between the two series because of inter-linkages between the wholesale market and the retail market. Guthrie (1981) used percentage monthly change for the US economy in the WPI and the CPI from January 1947 to December 1975 for analysis. Guthrie also divided the entire period into two equal five-year periods, 1966-1970 and 1971-1975. The author found that there is a relationship between changes in WPI and changes in CPI, and that this relationship can be described by a Pascal distributed lag model. Additionally, the author also documented that WPI changes take longer to work themselves into CPI changes than they did 25 years ago and that a longer mean response time is associated with higher rates of inflation. Further, the author argued that the amount of effect of the WPI changes translated into CPI changes has also increased over the years, although this rate is not studied universally for all the time periods. Jones (1986), by using Wald test of GC for the US economy for the period January 1947-December 1983 and also for two sub periods (January 1947-June 1971 and May 1974-December 1983), found evidence of bidirectional causality between WPI and CPI. Further, Jones recommended that for a bivariate model consisting of CPI and WPI simultaneous equation approach is the appropriate way to estimation. Cushing and McGarvey (1990) indicated that feedback from WPI to CPI is greater than that from CPI to WPI for the period from January 1952 through December 1987 in the USA by using the Engle-GC test. The authors concluded that the magnitude of feedback from producer to consumer prices is greater than that from consumer to producer prices, to the extent that a one-sided Granger causal pattern can be assumed, as consumer prices have very little incremental power. They also argued that the addition of the money supply does not produce significant changes, the feedback from producer to consumer prices still dominates, and that such a causal ordering is perfectly consistent with a flexible price model with strong demand effects. Clark (1995) examined relationships between PPI and CPI by using VAR forecasting models over the period 1959:Q2-1994:Q4 in the USA. His analysis revealed that changes in PPI did not systematically help to predict CPI changes. In other words pass-through effect between PPI and CPI is weak. Caporale *et al.* (2002) investigated the causality issue using Toda and Yamamoto (1995) for G7 countries for the period January 1976-April 1999. The authors found that PPI led CPI in France and Germany and that in the USA it was other way around, i.e. CPI led PPI. Further, for cases of Italy, Japan and the UK feedback relations were found and for Canada the direction of causality was not recognized. Further, Caporale *et al.* (2002) claimed that bidirectional causality only exists when the causality links reflecting the monetary transmission mechanism are ignored. Akdi *et al.* (2006) investigate the long- and the short-run relationships between the CPI and the WPI using Turkish data for the period January 1987-August 2004. Their findings suggest that the conventional tests of Engle and Granger (1987) and Johansen (1988) give mixed results. They also employed the periodogram method to test whether there is a cointegrating relationship between two indices. Results of the periodogram method suggest that there is no cointegration between PPI and CPI in Turkey. Moreover, they found a short-run relationship between WPI and CPI in Turkey. Ghazali *et al.* (2008) examined the Granger causal relationship between CPI and producer price index (PPI) in Malaysia by using monthly data from January 1986 to April 2007. The authors utilized Johansen's cointegration method to test for cointegration and both Engle Granger and Toda-Yamamoto causality tests were used to find the Granger causal relationship. The author found that there is long-run equilibrium relationship between these two variables and there is unidirectional causality running from PPI to CPI. Shahbaz *et al.* (2009) investigated the relationship between PPI and CPI using monthly data (1992M1-2007M6) for Pakistan. The authors employed autoregressive distributed lag (ARDL) bounds testing and the Johanson cointegration approach to determine the long-run relationship between PPI and CPI. The authors also used Toda and Yamamoto's (1995) approach to determine causality between PPI and CPI. Their results have verified the existence of a long-run relationship between producer and consumer prices. They also found that there is bidirectional causality, but it is stronger from producer to consumer prices. Sidaoui *et al.* (2009) examined the causal relationship between producer prices and consumer prices for Mexico for the period February 1994-June 2009. The authors utilized the methodology proposed by Engle and Granger (1987) to test for cointegration and vector error correction for testing the causality direction and finally they utilized out-of-sample GC test for forecasting purpose. Their study shows cointegration between the variables. The authors concluded (based on in-sample and out-of-sample tests of GC, using an error correction model) that, in the case of Mexico, information on the PPI seems to be useful to improve forecasts of CPI inflation. In particular, CPI inflation responds significantly to dis-equilibrium errors with respect to the long-run relationship between consumer and producer prices. Shahbaz *et al.* (2010) used ARDL bounds testing and Johansen's approach to test for the existence of a long-run relationship for Pakistani economy during the period 1992-2007 with monthly frequencies. The causality was detected by utilizing Toda and Yamamoto's (1995) approach between WPI and CPI. The authors found evidence of cointegration between WPI and CPI based on the ARDL bounds testing and Johansen's framework. Furthermore, the causality test based on Toda and Yamamoto (1995) clearly showed that there prevails a bidirectional causal relationship between WPI and CPI, and that its behavior running from WPI to CPI is comparably stronger. Akçay (2011) examined the causal relationship between PPI and CPI for the five selected European countries, using seasonally adjusted monthly data from August 1995 to December 2007. The author employed Toda and Yamamoto's (1995) causality test approach to investigate causality and found a unidirectional causality running from PPI to CPI in Finland and France, bidirectional causality between two indices in Germany and no significant causality in the case of The Netherlands and Sweden. Rao and Bukhari (2011) also examined the causal relation between WPI and CPI by using monthly data for the period 1978-2010. Their empirical exercise confirmed 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.

In the case of the Indian economy, Samanta and Mitra (1998) applied cointegration and GC tests for two sub periods: April 1991-April 1995 and May 1995-May 1998. A stable long-run relationship between CPI and WPI existed during 1991-1995, but not thereafter. On the other hand Shunmugam (2009) examined the time lag with which CPI responds to a change in WPI, the causal relationship between the two series, and if they are cointegrated in the long run, over 1982-2009, and for pre- and post-liberalization periods for India. Shunmugam (2009) found evidence of cointegration over the entire period of study but in the pre- and post-liberalization period evidence of cointegration was not found. Goyal and Tripathi (2010) extended these two literatures available for the Indian economy, including other important variables (such as exchange rate) affecting WPI and CPI and found evidence of both long- and short-run relationships. They also evaluated the existence of structural breaks and utilized a variety of indices. The authors found that: WPI inflation (primary articles) Granger causes CPI (all commodities) inflation; CPI (all commodities) inflation Granger causes WPI (general) inflation; CPI inflation (food) Granger causes WPI (general) inflation; CPI (all commodities) inflation Granger causes WPI (manufactured goods) at 10 percent significance level; CPI inflation (food) Granger causes WPI (manufactured goods) inflation; WPI (fuel) inflation Granger causes WPI (manufactured goods) inflation; and exchange rate change Granger causes CPI food inflation.

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 structure changes in the pattern of inflation (i.e. WPI and/or CPI) for a given time period under study. This creates a room for a nonlinear rather than linear relationship between WPI and CPI. Therefore, in the present study we made an attempt to analyze the issue in the nonlinear framework by using a recently developed nonparametric approach of Lemmens *et al.* (2008). Use of this approach allows us to decompose the GC in the frequency domain. In frequency domain, 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. This analysis will make it possible to determine whether the predictive power is concentrated at the quickly fluctuating components or at the slowly fluctuating components. 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 either for the developing, or the developed country context.

3. Data source and methodology

For the analysis we obtained data of WPI and CPI from the IMF (2010) CD ROM with monthly observations covering the period January 1957-February 2009.

3.1 Linear cointegration analysis

Prior to testing for a long-run cointegration relationship between the time series, it is necessary to test for their order of integration and establish that they are integrated in the same order. The unit root test performed here is that of Phillips and Perron (1988)[2] and robustness is checked through Lee and Strazicich's (2003, 2004) unit root test, which incorporates endogenously determined structural breaks in the data. The most popular approach to linear cointegration analysis is Johansen's framework (Johansen and Juselius, 1990). In this study, consider a two-dimensional VAR (p) time series x_t with possible time trend and the model is defined by:

$$x_t = \eta_t + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + \xi_t \tag{1}$$

where the error term, ξ_t is assumed to be Gaussian, η_t is a two-dimensional vector of constants and x_t is an integrated process of order 1, i.e. $I(1)$. Since x_t is nonstationary, an error-correction model (ECM) for the VAR (p) process is:

$$\Delta x_t = \eta_t + \prod x_{t-1} + \phi_1^* \Delta x_{t-1} + \cdots + \phi_{p-1} x_{t-p+1} + \xi_t \tag{2}$$

where $\phi_j^* = -\sum_{i=i+1}^{p} \phi_i$, $j = 1, \ldots, p-1$ and $\prod = \phi_p + \phi_{p-1} + \cdots + \phi_1 - I = -\phi(1)$. The term $\prod x_{t-1}$ in equation (2) is referred as the error-correction term, where the coefficient, $\prod$ contains information about long-run relationships between the variables. Three cases are of interest in considering the ECM in equation (2). If rank $(\prod) = 2$, the matrix $\prod$ has full rank and x_t is stationary. The ECM model is not informative and x_t can be studied directly. If rank $(\prod) = 0$, this implies that the matrix $\prod$ is a null matrix and x_t is not cointegrated. Then equation (2) corresponds to a traditional differenced vector time series model. Finally, if rank $(\prod) = 1$, there exists one cointegrating vector; in this case, $\prod = \alpha\beta'$, where α and β are 2×1 matrices. This means that x_t is cointegrated with one linearly independent cointegrating vector and equation (2) can be interpreted as an ECM.

The likelihood ratio (LR) test for the hypothesis of r cointegrating vectors is proposed by Johansen (1988). The cointegrating rank, r, can be tested with two statistics, namely trace and maximal eigenvalue. However, Cheung and Lai (1993) suggested that the trace test shows more robustness to both skewness and excess kurtosis in the residuals than the maximal eigenvalue test. Hence, we are guided by the trace statistic.

The limiting distributions of cointegration tests depend on the deterministic function μ_t in the dynamic model. The choice of the appropriate specification was based on the Pantula principle (Johansen, 1992, 1995). The Pantula principle[3] chooses both the correct rank order and the deterministic component. This principle can be summarized as follows. Three models are estimated and the results are presented from the most restrictive to the least restrictive alternative. The models employed are Model 2, which includes intercept in the cointegration relation, Model 3, which allows deterministic trends in level, and Model 4, which allows for trend in the cointegration space. The test procedure then is to move through from the most restrictive model to the least and at each stage compares the trace test statistic to its critical value. The selection process only stops at the first instance where the null hypothesis is not rejected.

3.2 Motivation and approach of causality analysis in the frequency domain

Analysing time series in frequency domain, i.e. spectral analysis could be helpful in supplementing the information obtained by time-domain analysis (Granger, 1969; 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.

It is noteworthy that the Granger (1969) approach to the question of whether variable X causes variable Y is to determine how much of the current variable Y can be explained by past values of variable Y, and then to see whether adding lagged values of variable X can improve the explanation. In other words, variable Y is said to Granger cause variable X if variable X helps in the prediction of variable Y, or if the coefficients on the lagged values of variable X are statistically significant[4]. However, Tiwari (2012) documented that one-shot GC test only measures precedence and information content, but does not indicate causality in its conventional sense. Further, Granger and Lin (1995) documented that the extent and direction of causality differs between frequency bands. Lemmens *et al.* (2008) argued that a stationary series is effectively the sum of uncorrelated components, each of which is associated with a single frequency ordinate, and allows the full causal relationship to be decomposed by frequency. The traditional approach to GC tacitly ignores the possibility that the strength and/or direction of the GC (if any) can vary over different frequencies (Lemmens *et al.*, 2008). Granger (1969) suggested that a spectral-density approach would give a better and more complete picture than a one-shot GC measure that is supposed to apply across all periodicities (for example, in the short run, over the business-cycle frequencies, and in the long run).

Therefore, in the study we have adopted the Lemmens *et al.* (2008) approach to GC to use in the frequency domain[5]. Their work is based on spectral-density approach, which is slightly different from the other approaches such as the partial directed coherence (PDC) measure. The approach provides an elegant interpretation of the frequency domain GC as a decomposition of the total spectral interdependence between two series (based on the bivariate spectral density matrix, and directly related to the coherence) into a sum of "instantaneous", "feedforward" and "feedback" causality terms. The innovativeness of this measure of GC is that it can be applied across all periodicities (for example, in the short run, over the business-cycle frequencies, and in the long run) and hence, one can get to know exactly for which periodicity one variable can Granger cause the other, which the popular one-shot measure of GC test (developed either in linear or nonlinear framework) fails to measure (Tiwari, 2012). This approach is important in our application because of few concerns. For example, if we follow theoretical basis of Cushing and McGarvey (1990), which says that primary goods are used as input with lag period in production process of consumption goods and hence wholesale prices leads consumer prices. However, in this case what is the lag period is not defined. Of course, this lag will not be same in each production cycle and it will create a non-linear lead-lag relationship between WPI and CPI. Apart from that, as consumer prices are a weighted average of the prices of domestic and imported consumption goods, which of course will not be constant or growing with some constant rate and hence, create a nonlinear feed-back relationship. Hence, we hope use of Lemmens *et al.*'s (2008) approach might be able to handle these inconsistencies in the lead-lag relationship between WPI and CPI and give reasonably fair results. Lemmens *et al.*'s (2008) approach can be defined as follows.

Let X_t and Y_t be two stationary time series of length T. The goal is to test whether X_t Granger cause 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.:

$$\Theta^x(L)X_t = C^x + \Phi^x(L)u_t \tag{3}$$

$$\Theta^y(L)Y_t = C^y + \Phi^y(L)v_t \tag{4}$$

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).

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:

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

$$S_v(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_v(k) e^{-i\lambda k} \tag{6}$$

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[6]. 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 $(\lambda, \lambda + d\lambda)$.

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:

$$S_{uv}(\lambda) = C_{uv}(\lambda) + iQ_{uv}(\lambda) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty} \gamma_{uv}(k)e^{-i\lambda k} \tag{7}$$

where $C_{uv}(\lambda)$ is called cospectrum and $Q_{uv}(\lambda)$ is called quadrature spectrum and 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 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 which is attributable to cycles with frequency λ. The quadrature spectrum looks for evidence of out-of-phase cycles (Hamilton, 1994, p. 274). The cross-spectrum can be estimated non-parametrically by:

$$\hat{S}_{uv}(\lambda) = \frac{1}{2\pi}\left\{\sum_{k=-M}^{M} w_k \hat{\gamma}_{uv}(k)e^{-i\lambda k}\right\} \tag{8}$$

with $\hat{\gamma}_{uv}(k) = \widehat{COV}(u_t, v_{t-k})$ the empirical cross-covariances, and with window weights w_k, for $k = -M, \ldots, M$. Equation (8) 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 equations (5) and (6) are estimated in a similar way. This cross-spectrum allows us to compute the coefficient of coherence $h_{uv}(\lambda)$ defined as:

$$h_{uv}(\lambda) = \frac{|S_{uv}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \tag{9}$$

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^2 in a regression context. Coherence thus takes values between 0 and 1. Lemmens *et al.* (2008) have shown that under the null hypothesis $h_{uv}(\lambda) = 0$, the estimated squared coefficient of coherence at frequency λ, with $0 < \lambda < \pi$ when appropriately rescaled, converges to a χ^2-distribution with two degrees of freedom[7], denoted by χ^2_2:

$$2(n-1)\hat{h}^2_{uv}(\lambda) \xrightarrow{d} \chi^2_2 \tag{10}$$

where $\xrightarrow{d}$ stands for convergence in distribution, with:

$$n = \frac{T}{\left(\sum_{k=-M}^{M} w_k^2\right)}$$

The null hypothesis $h_{uv}(\lambda) = 0$ versus $h_{uv}(\lambda) > 0$ is then rejected if:

$$\hat{h}_{uv}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n-1)}} \tag{11}$$

with $\chi^2_{2,1-\alpha}$ being the $1 - \alpha$ quantile of the χ^2-distribution with two degrees of freedom. The coefficient of coherence in equation (9) 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 (equation (5)) into three parts: $S_{u\Leftrightarrow v}$, the instantaneous relationship between u_t and v_t; $S_{u\Rightarrow v}$, the directional relationship between v_t and lagged values of u_t; and $S_{v\Rightarrow u}$, the directional relationship between u_t and lagged values of v_t, i.e.:

$$\begin{aligned} S_{uv}(\lambda) &= [S_{u\Leftrightarrow v} + S_{u\Rightarrow v} + S_{v\Rightarrow u}] \\ &= \frac{1}{2\pi}\left[\gamma_{uv}(0) + \sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k} + \sum_{k=1}^{\infty}\gamma_{uv}(k)e^{-i\lambda k}\right] \end{aligned} \tag{12}$$

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 equation (12), i.e.:

$$S_{u\Rightarrow v}(\lambda) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k}\right] \tag{13}$$

The Granger coefficient of coherence is then given by:

$$h_{u\Rightarrow v}(\lambda) = \frac{|S_{u\Rightarrow v}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \tag{14}$$

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:

$$\hat{h}_{u\Rightarrow v}(\lambda) = \frac{\left|\hat{S}_{u\Rightarrow v}(\lambda)\right|}{\sqrt{\hat{S}_u(\lambda)\hat{S}_v(\lambda)}}, \tag{15}$$

with $\hat{S}_{u\Rightarrow v}(\lambda)$ as in equation (8), 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 (10). 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:

$$2(n' - 1)\hat{h}^2_{uv}(\lambda) \xrightarrow{d} \chi^2_2 \tag{16}$$

where n is now replaced by:

$$n' = \frac{T}{\left(\sum_{k=-M}^{-1} w_k^2\right)}.$$

Since the w_ks', 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:

$$\hat{h}_{u\Rightarrow v}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n'-1)}} \tag{17}$$

Afterward, we compute the Granger coefficient of coherence given in equation (15) and test the significance of causality by making use of equation (17).

4. Data analysis and empirical findings

First of all, descriptive statistics of variables[8] have been analyzed to see the sample property, and Pearson's correlation analysis is conducted to see whether there is any evidence for co-movement of both series[9]. We found 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 was tested through PP test and results are reported in Table I.

Table I reports that both variables have unit root at their level form while they are stationary at their first differenced form. Further, we analyzed the stationarity property of both the variables by using a powerful unit root test proposed by Lee and Strazicich (2003, 2004) of two breaks and one break, respectively. Results of the Lee and Strazicich (2003, 2004) unit root test are reported in Table II.

It is evident from Table II that either we incorporate one or two breaks in the crash model or trend break model of Lee and Strazicich (2003, 2004) specification. We found evidence of two structural breaks in both the test series and both series are non-stationary in the level form but stationary in first difference form. Hence, there is strong evidence of the unique order of integration which allows us to proceed with cointegration analysis. Results of cointegration analysis are presented in Table III.

With application of the Pantula principle (and using different lag selection creation) we found that both series do not have a cointegration relationship, which is a surprising finding[10]. However, standard cointegration techniques are biased towards accepting the null of no cointegration and if there is a structural break in the relationship, as Kunitomo (1996) mentioned, these tests may produce

	PP test: constant model		PP test: constant and trend model	
Variables	T-calculated	Prob.-value	T-calculated	Prob.-value
ln CPI_t	0.100834(6)	0.9656	− 2.416046(5)	0.3707
Δln CPI_t	− 14.00179(21)	0.0000	− 13.91194(22)	0.0000
ln WPI_t	− 0.475588(5)	0.8931	− 1.848101(5)	0.6800
Δln WPI_t	− 15.98997(13)	0.0000	− 15.97889(13)	0.0000

Note: The figures in parentheses are the bandwidth for the PP unit root test determined by the Schwert (1989) formula
Source: Author's calculation

Table I. Estimation of unit root tests

Table II.
Results of Lee and Strazicich unit root test with one and two structural breaks

Series	T_{B1}	T_{B2}	S_{t-1}	k	B_{t1}	B_{t2}	D_{t1}	D_{t2}
Model 1: crash model								
One break case								
LnCPI	July 1973	–	−1.8442	24	−0.0115 (−1.4215)	–	–	–
D(LnCPI)	November 1996	–	−5.0223*	23	0.0027 (0.3413)	–	–	–
lnWPI	June 1969	–	−1.7439	24	−0.0203 (−2.0211)	–	–	–
D(lnWPI)	May 1964	–	−4.7324*	23	0.0143 (1.4577)	–	–	–
Two break case								
LnCPI	July 1973	December 1999	−1.9613	24	−0.0115 (−1.4266)	0.0079 (0.9495)	–	–
D(LnCPI)	July 1974	November 1996	−5.2706**	23	0.0137 (1.6917)	0.0028 (0.3541)	–	–
lnWPI	June 1969	June 1976	−1.8252	24	−0.0205 (−2.0477)	0.0176 (1.7977)	–	–
D(lnWPI)	November 1982	December 1996	−4.9864	23	−0.0046 (−0.4698)	−0.0105 (−1.0878)	–	–
Model 2: trend break model								
One break case								
LnCPI	October 1992	–	−3.6281	24	−0.0038 (−0.4785)	–	0.0034* (2.5396)	–
D(LnCPI)	October 1964	–	−5.4107**	23	−0.0200* (−2.4706)	–	0.0074** (4.4916)	–
lnWPI	July 1992	–	−3.2734	24	0.0038 (0.3899)	–	0.0023 (1.5315)	–
D(lnWPI)	August 1967	–	−5.5962**	23	0.0189 (1.8679)	–	−0.0070** (−4.6769)	–
Two break case								
LnCPI	December 1975	August 1996	−4.7200	24	−0.0114 (−1.3866)	−0.0033 (−0.4150)	0.0029** (3.6145)	0.0001 (0.0559)
D(LnCPI)	December 1967	January 1998	−9.1790**	23	0.0520** (6.1552)	−0.0400** (−4.8276)	−0.0192** (−8.5707)	0.0169** (8.6137)
lnWPI	August 1973	October 1998	−5.6388	24	−0.0167 (−1.7348)	−0.0046 (−0.4904)	0.0100** (5.4946)	−0.0047** (−4.4737)
D(lnWPI)	December 1973	July 1980	−8.7213**	23	0.0643** (6.1613)	−0.0261* (−2.6208)	−0.0258** (−8.7307)	0.0206** (8.5646)

Notes: Statistical significance at: *5 percent and **1 percent levels; Model 1 presents results for univariate LM unit root test with one structural break in intercept/constant only and Model 2 presents results for univariate LM unit root test with one structural break in intercept/constant and trend; T_{B1} and T_{B2} – dates of the structural breaks; k – lag length; S_{t-1} – LM test statistic; B_{t1} and B_{t2} – dummy variables for the structural breaks in the intercept; D_{t1} and D_{t2} – dummy variables for the structural breaks in the slope; figures in parentheses are t-values; critical values of S_{t-1} of both test (that is when breaks occur intercept and intercept and trend jointly are reported in Lee and Strazicich (2003, 2004)) two-break and one-break cases, respectively
Source: Author's calculation

"spurious cointegration results". As we have seen from the unit root results, both variables have been the subject of structural changes, and the cointegration test must be based on structural breaks. It is noteworthy that the cointegration test based on exogenously determined structural breaks may also therefore not provide fruitful results; we apply the Gregory and Hansen (1996) cointegration procedure that allows for an endogenously determined structural break in a single equation framework.

It is evident from Table IV that, with the exception of one case, null hypothesis of cointegration is not rejected, hence leading us to conclude that there is an absence of cointegration between WPI and CPI similar to the findings of Goyal and Tripathi (2010). This allows us to adopt Lemmens *et al.*'s (2008) approach to test for GC in the frequency domain as an appropriate method[11]. Therefore, in the next step to analyzng GC between CPI and WPI in the frequency domain framework the entire three log differenced variables have been filtered using auto regressive moving average (ARMA) models to obtain the innovation series. We have used lag length[12] $M = \sqrt{T}$. 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[13]. In order to interpret the results of causality in frequency domain we need to model the entire frequency band that

Hypothesized (no. of CE(s))	Model 2	Model 3	Model 4
Case 1: Ln(WPI) and Ln(CPI)	VAR lag order selection criteria: SIC (Lag 2)		
R = 0	58.19867 (20.26184)	7.952754 (15.49471)	14.40836 (25.87211)
R = 1	4.021226 (9.164546)	1.015050 (3.841466)	5.643295 (12.51798)
Case 2: Ln(WPI) and Ln(CPI)	VAR lag order selection criteria: AIC, HQIC, FPE (Lag 8)		
R = 0	46.75625 (20.26184)	9.448932 (15.49471)	15.74664 (25.87211)
R = 1	4.555962 (9.164546)	1.392756 (3.841466)	5.537604 (12.51798)

Note: Figures in parentheses are the 5 percent critical values of the respective test statistics
Source: Author's calculation

Table III.
Cointegration rank and model selection: trace statistic

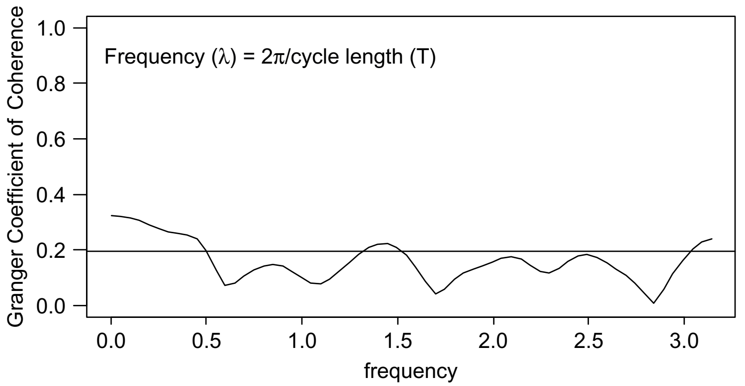
Cointegration test: Gregory-Hansen cointegration tests			
Case 1: Ln(WPI) and Ln(CPI)		Case 2: Ln(WPI) and Ln(CPI)	
Break in intercept: no trend (October 1971)	Test statistics (k)	Break in intercept: no trend (October 1971)	Test statistics (k)
Yes	−3.858 (1)	Yes	−3.777 (1)
Break in intercept: trend included (August 1973)		Break in intercept: trend included (October 1971)	
Yes	−3.970 (1)	Yes	−3.685 (1)
Full structural break (October 1979)	−5.059** (1)	Full structural break (October 1979)	
Yes		Yes	−4.803 (1)

Notes: "k" – lag length; critical values are −5.13 and −4.61 at 1 percent and 5 percent, respectively, for break in intercept and the no trend model; critical values are −5.45 and −4.99 at 1 percent and 5 percent, respectively, for break in intercept when the trend is included in the model and critical values are −5.47 and −4.95 at 1 percent and 5 percent, respectively, for the full structural break model; Mi (where i = 1, 2, . . ., 12) denotes number of months
Source: Author's calculation

Table IV.
Cointegration analysis

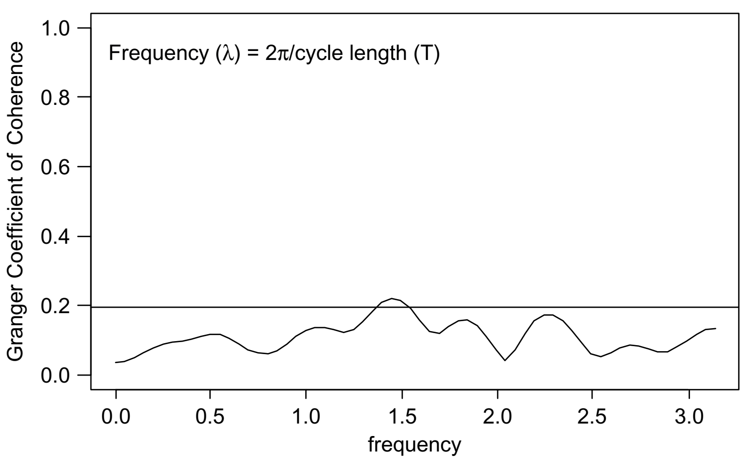
is frequencies in the interval $(0, \pi)$. In others words, the data generating process for CPI and WPI can be divided into three time horizons, that is: short-run (range $\lambda \in (0.0,1.0)$), medium-run (range $\lambda \in (1.0,2.0)$); and long-run (range $\lambda \in (2.0,3.2)$)[14]. These three frequency bands/horizons correspond to cycles of six months and beyond, three months to six months, and two months to three months, respectively. We reported results of GC between WPI and CPI in Figures 1 and 2. These figures report the test statistics, along with their 5 percent critical values (a line parallel to x-axis) for all frequencies (λ) (which are expressed as fraction of π) in the interval $(0, \pi)$.

Figure 1, which shows the result of Granger coefficient of coherence for causality running from CPI to WPI after filtering the variables, shows that at 5 percent level of significance, CPI Granger cause WPI in the range $\lambda \in (0.0,0.5)$, $\lambda \in (1.3,1.5)$ as well as



Note: The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5 percent level of signifiance

Figure 1.
GC from CPI to WPI



Note: The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5 percent level of signifiance

Figure 2.
GC from WPI to CPI

$\lambda \in (3.0,3.2)$ reflecting very long-run (corresponds to 12 months and beyond), intermediate (corresponds to five and four months), as well as short-run (corresponds to 2 months and less) cycles. Although business cycles in CPI of other different periods corresponding to different ranges of frequencies were also evident, those were unable to give significant evidence for prediction of WPI.

Similarly, Figure 2, which shows the result of Granger coefficient of coherence for causality running from WPI to CPI after filtering the variables, provides evidence of GC from WPI to CPI at 5 percent level of significance, in the range $\lambda \in (1.3,1.5)$ a reflecting a significant intermediate (corresponds to five and four months) cycle. Similar to Figure 1, in this case cycles in WPI of different periodicity corresponding to different frequency range were also evident, but those were unable to give significant evidence to predict CPI.

5. Conclusions and policy implications

In the present study we analyzed GC between CPI and WPI for the India by using monthly data covering the period of January 1957-February 2009. We found that both variables are nonstationary in log level form and stationary in log first difference form, however, application of Johansen and Juselius (1990) maximum likelihood approach and Gregory and Hansen (1996) cointegration procedure which allows for an endogenously determined structural break in single equation framework shows that both variables are not cointegrated in the long run.

The finding of stationarity and cointegration between WPI and CPI is very similar to the results of Goyal and Tripathi (2010). Our results show, for the Indian economy, that causal and reverse causal relations between CPI and WPI vary across frequencies. We found that CPI Granger cause WPI at a lower level of frequencies (corresponding to business cycle of 12 months and beyond), intermediate (corresponding to business cycle of five and four months) as well as higher frequencies (corresponding to business cycle of two or less months). By contrast, we found WPI Granger cause CPI at 5 percent level of significance, at intermediate frequencies reflecting significant intermediate cycles (corresponding to a business cycle of five and four months). These findings are partially in contrast to those of Goyal and Tripathi (2010) where the authors found that CPI (all commodities) inflation Granger causes WPI (general) inflation. One can think of three reasons for such a difference in the findings. First, our study is based on a large data set *vis-á-vis* Goyal and Tripathi (2010). Second, use of the approach – whereas Goyal and Tripathi (2010) used simple one-shot GC test, we used a test developed on the frequency domain. Third, our model on the one hand suffers from the omitted variables problem (like exchange rate), but we argue, on the other, if nonlinearity in the data was due to such omitted variables we are able to take these into account in the approach we used.

The unique contribution of the present study lies in decomposing causality on the basis of time horizons and demonstrating this at lower, intermediate as well as long-run cycles from CPI to WPI and intermediate cycles from WPI to CPI. To sum up, our findings provide evidence of unidirectional causality running from CPI to WPI for the business cycle of 12 months and beyond and for business cycles of two and less months. This implies that for planning purposes the Indian Government and/or monetary authority of India (that is the Reserve Bank of India) should consider CPI to predict WPI for one year or more or two months or less. Further, our evidence gives support for the bidirectional causal relationship between WPI and CPI for the business cycle of five and four months. Hence, this implies that for intermediate projections any of the two inflation indices can be used. These findings are very much helpful in inflation targeting policies of RBI and CPI-based wage-indexing policies of the government of India. Further, these results have important implications for the India for planning of inflation related and other policies to be achieved by setting short-term, intermediate and long-term monetary and/or fiscal policy targets. It also suggests that by looking at this link policy makers maybe better prepared to avoid, or at least mitigate, the negative consequences of producers' inflation, i.e. WPI. Theoretically our results support the supply side view of economics for the India case. That is, we found support for the Caporale *et al.* (2002) argument in India which documented that CPI may Granger cause WPI through the labor supply channel, and which may also reflect through supply shocks in labor market provided wage earners in the wholesale sector want to preserve the purchasing power of their incomes. This is because of strong labor unions as well as insufficient flexibility of the Indian labor market (for details on the labor market, see Tiwari (2010, 2011)).

Notes

1. Cushing and McGarvey (1990) concluded that the magnitude of feedback from WPI to CPI is greater than that from CPI to WPI and, therefore, a one-sided Granger causal pattern running from WPI to CPI can be assumed as CPI has very little incremental power. They added that these results are robust to inclusion of the money supply, i.e. the feedback from WPI to CPI was still higher and, therefore, such a causal ordering is perfectly consistent with a flexible price model with strong demand effects.
2. Since PP test has advancements over DF/ADF test in the sense that whereas DF/ADF test use a parametric autoregression to approximate the ARMA structure of the errors in the test regression, PP test correct for any serial correlation and heteroskedasticity in the errors. Therefore, this test is used.
3. In testing ELG hypothesis, among others who employed the Pantula principle in selecting appropriate specification in cointegration test are Love and Chandra (2005) and Dawson (2006).
4. Putting it differently, a process X is said to Granger cause another process Y, when the variance of the error in forecasting future values of Y, using an (optimal) forecast based on the observed values of both X and Y, is strictly smaller than the variance of the prediction error, using an (optimal) forecast based only on the observed values of Y.
5. In statistics, frequency domain describes the domain for analysis of mathematical functions or signals with respect to frequency, rather than time. A very similar definition holds for the GC, as in the time domain. Speaking non-technically, a time-domain graph shows how a signal changes over time, whereas a frequency-domain graph shows how much of the signal lies within each given frequency band over a range of frequencies.
6. The frequencies $\lambda_1, \lambda_2, \ldots, \lambda_N$ are specified as follows:

$$\lambda_1 = \frac{2\pi}{\mathrm{T}}$$

$$\lambda_2 = \frac{4\pi}{\mathrm{T}}$$

   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 (Hamilton, 1994, 159 pp.).
7. 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.

8. Time series plot and descriptive statistics of the variables are shown in Figure A1 and Table AI, respectively, in the Appendix. Table AI indicates that all the two variables do not have log normal distribution and therefore, provides scope for our nonlinear analysis.
9. Results are reported in Table AI.
10. Following Pantula principle, we move with rank = 0 starting from most restrictive model to least restrictive (that is from Model 2 to Model 4) unless null hypothesis for the first time is not rejected. In our case, with rank = 0, for the first time, the null hypothesis is not rejected for Model 3 that implies no cointegration between the two variables.
11. It is interesting to consider the frequency domain GC test within a cointegrating framework. However, unfortunately to the best of our knowledge there is only one test developed by Breitung and Candelon (2006) to this end.
12. Following Diebold (2001, p. 136) we take M equal to the square root of number of observations T.
13. The frequency (λ), of a cycle is related to its period, T, measured in number of observations, by the formula $T = 2\pi/\lambda$; π takes its usual value, i.e. $\pi = 22/7$. Thus, a frequency of $\pi/4$ corresponds to a period of eight observations, or two years given the quarterly observations and eight months for monthly observation.
14. One may consider four bands or time horizons also like very short-run (range $\lambda \in (0,0.5)$), short-run (range $\lambda \in (0.5,1.5)$), medium-run (range $\lambda \in (1.5,2.5)$), and long-run (range $\lambda \in (2.5,3.2)$). But in our case we prefer to consider three time horizons only. This is because it will allow sufficient time in the production process for lag to occur and productivity shocks to have a measurable impact so that cycles can be recognized.
15. The "t-sig" approach has been shown to produce test statistics which have better properties in terms of size and power than information-based methods such as the Akaike Information Criterion or Schwartz Bayesian Criterion (Hall, 1994; Ng and Perron, 1995).
16. We used conventional level of significance that is 10 percent level of significance as a benchmark and fixed $k_{max} = 12$.

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(The Appendices follow overleaf.)

Appendix 1

Variables	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera	ln CPI_t	ln WPI_t
ln WPI_t	3.0637	3.109	4.824466	1.261298	1.113387	−0.078478	1.656891	47.695	0.998329945	1
ln CPI_t	2.9914	2.941	4.847253	1.199965	1.144322	0.032623	1.645467	47.967	1	0.99832994583

Table AI.
Descriptive statistics and correlation matrix

Appendix 2

1. Lee and Strazicich (2003, 2004) LM unit root tests

Let us consider the following data generating process (DGP) in the application of Lagrange Multiplier (LM) unit root tests, Lee and Strazicich (2004) LM tests with one break, and Lee and Strazicich (2004) LM test with two structural breaks:

$$y = \delta Z_t + e_t, \;\; e_t = \beta e_{t-1} + \varepsilon_t \tag{A1}$$

where Z_t is a vector of exogenous variables, δ is a vector of parameters and ε_t is a white noise process, such that $\varepsilon_t \sim NIID(0, \sigma^2)$. First, we will consider the case where there is evidence of one structural break. The crash model that allows shift in level only is described by $Z_t = [1, t, D_t]'$, and the break model that allows for changes in both level and trend is described as $Z_t = [1, t, D_t, DT_t]'$, where D_t and DT_t are two dummies defined as:

$$D_t = 1, \;\; \textit{if}\; t \geq T_B + 1 = 0, \text{otherwise}$$

and:

$$DT_t = t - T_B, \;\; \textit{if}\; t \geq T_B + 1 = 0, \text{otherwise}$$

where T_B is the time period of the break date.

Next, let us consider the framework that allows for two structural breaks. The crash model that considers two shifts in level only is described by $Z_t = [1, t, D_{1t}, D_{2t}]'$, and the break model that allows for two changes in both level and trend is described as $Z_t = [1, t, D_{1t}, DT_{1t}, D_{2t}, DT_{2t}]'$, where D_{jt} and DT_{jt} for j = 1, 2 are appropriate dummies defined as above, namely:

$$D_{jt} = 1, \;\; \textit{if}\; t \geq T_{Bj} + 1 = 0, \text{otherwise}$$

and:

$$DT_{tj} = t - T_{Bj}, \;\; \textit{if}\; t \geq T_{Bj} + 1 = 0, \text{otherwise}$$

where T_{Bj} is the jth break date.

The main advantage of Lee and Strazicich's (2003, 2004) approach to unit root test is that it allows for breaks under the null ($\beta = 1$) and alternative ($\beta < 1$) in the DGP given in equation (1). This method uses the following regression to obtain the LM unit root test statistics:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta \tilde{S}_{t-j} + u_t \tag{A2}$$

where $\tilde{S}_t = y_t - \tilde{\Psi}_t - Z_t \tilde{\delta}, t = 2, \ldots, T$; $\tilde{\delta}$ denotes the regression coefficient of Δy_t on ΔZ_t and $\tilde{\Psi}_t = y_t - Z_1 \tilde{\delta}, y_1$ and Z_1 are first observations of y_t and Z_t respectively. The lagged term $\Delta \tilde{S}_{t-j}$ is included to correct for likely serial correlation in errors. Using the above equation, the null hypothesis of unit root test ($\phi = 0$) is tested by the LM *t*-statistics. The location of the structural break or structural breaks is determined by selecting all possible breaks for the minimum *t*-statistic as follows:

$$\ln f \tilde{\tau}(\bar{\lambda}_i) = \ln_\lambda f \tilde{\tau}(\lambda), \;\; \text{where}\; \lambda = T_B/T.$$

The search is carried out over the trimming region ($0.15T$, $0.85T$), where T is sample size and T_B denotes date of structural break. We determined the breaks where the endogenous two-break LM *t*-test statistic is at a minimum. The critical values are tabulated in Lee and Strazicich (2003, 2004) for the two-break and one-break cases respectively. To select the lag length (k) we use the "t-sig" approach[15] proposed by Hall (1994). This involves starting with a predetermined upper bound *k*. If the last included lag is significant, *k* is chosen. However, if k is insignificant[16], it is reduced by one lag until the last lag becomes significant. If no lags are significant k is set equal to zero.

2. Gregory and Hansen (1996) cointegration test

The Gregory and Hansen (1996) cointegration procedure allows for an endogenously determined structural break in single equation framework. The test presents three models, whereby the shifts can be:

In either intercept alone (C):

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha^T y_{2t} + e_t \tag{A3}$$

where $t = 1, \ldots, n$.

In both trend and level shift (C/T):

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \beta t + \alpha^T y_{2t} + e_t \tag{A4}$$

And a full shift of the regime shift model (C/S):

$$y_{1t} = \mu_1 + \mu_2 \varphi_{t\tau} + \alpha_1^T y_{2t} + \alpha_2^T y_{2t} \varphi_{t\tau} + e_t \tag{A5}$$

where $t = 1, \ldots, n$ and μ_1, β_1 and α_1 are the intercept, trend and slope coefficients respectively before the regime shift and μ_2, β_2 and α_2 are the corresponding changes after the break. The dummy variable $\varphi_{t\tau}$ is defined as:

$$\varphi_{t\tau} = \begin{cases} 0, & if\ t \leq \{\eta\tau\} \\ 1, & if\ t > \{\eta\tau\} \end{cases}$$

where unknown parameter $\tau \in (0,1)$ denotes the (relative) timing of the change point, and { } denotes integer part.

Following the procedure suggested by Herzer and Felicitas (2006), we estimated all the models for each possible break date in the data set (for each τ). Then we perform a unit root test on the estimated residuals $\hat{e}_{t\tau}$ and the smallest value of the unit root test statistics was used for testing the null hypothesis of no cointegration between exports and imports, against the alternative hypothesis of cointegration in the presence of an endogenous structural break. The asymptotic critical values are tabulated in Gregory and Hansen (1996) Lag-length in cointegration equation is based on SIC and AIC (in our case AIC).

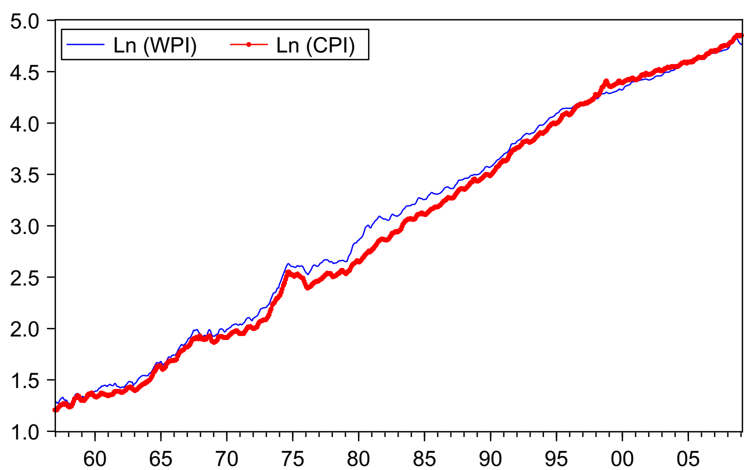

Figure A1.
Time series plots of the variables