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An empirical investigation of causality between producers' price and consumers' price indices in Australia in frequency domain

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ABSTRACT

The paper examines Granger-causality between the producers' and the consumers' price using Australian data within the frequency domain framework. For long run relation, the Johansen and Juselius (1990) maximum likelihood approach to cointegration was utilized. The test is also supplemented by the Breitung and Candelon (2006) and Lemmens et al. (2008) method. The quarterly data for the study covers 1969q3 to 2010q4. The findings suggest that consumers' price Granger-causes producers' price at an intermediate level of frequencies reflecting medium-run cycles, whereas producers' price does not Granger-cause consumers' price at any level of frequencies. Our study shows that consumers' price is a leading indicator of producers' price. Given that producers' price is used in making various macroeconomic indicators in real terms, the findings should help the Australian policymakers to gain control over the factors that affect consumers' price. The major contribution of the paper is to demonstrate unidirectional causality from consumers' price to the producers' price. Specifically, results show that consumers' price in Australian may have a significant predictive content in how the producers' price evolve. Furthermore, the application of the Breitung and Candelon (2006) and Lemmens et al. (2008) methodology in testing the Granger-causality in frequency domain is also relatively new.

1. Introduction

Theory predicts that shock to producer prices should ultimately affect consumer prices due to the spillover effect through production chain. Producer prices are normally set as a mark-up over wage costs. Since, mark-up is determined by demand pull, a surge in the mark-up should also influence wage cost because wage rate depends on consumer prices. The causality runs from consumers' price to producers' prices. However, when transmission mechanism moves from the supply or production side to the demand or consumer's side, the reverse causality is also plausible. In other words, Producers Price Index (PPI) may Granger cause Consumers' Price Index (CPI). Thus, the initial response of "cost-push" shocks should appear during the first stages of production chain. As an upshot, it is equally plausible for producer prices to "cause" consumers price. That is, information on producers' price should offer valuable predictive power about consumer prices. Trends in producer prices thus, should be of much value to the central bank authorities in identifying the "cost-push" shocks which they can use to improve the forecast performance of consumer prices inflation. Several reasons justify the causality. For example, the retail sector uses current domestic or imported materials as input, but adds value with a lag. Further, the input prices depend not only on domestic demand and supply, but also on their imports. The latter 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. In reality however, experience suggests that the relationship between producers' and consumers' price is not as obvious as the above arguments may imply. Studies by Clark (1995) and Blomberg and Harris (1995) on the United States show that the PPI did not have a significant predictive power on how the CPI evolves. However, Dion (1999) found some support for a relation between the PPI and the CPI in Canada, although predictive power of the PPI was not the focus of the paper.

The literature on the dynamic interactions between CPI and PPI did not receive adequate attention in the context of time series properties of the data. Most of the earlier studies have assessed Granger-causality between the PPI and the CPI by using Vector Autoregressive (VAR) models in first differences. The procedure relies on the assumptions that price level series are $I(1)$ (consequently inflation rates are stationary) and that PPI and the CPI are not cointegrated.[1] Failure to meet the assumptions implies that the VAR model in the first difference is inappropriate tool for analysis. If the price-level series are $I(2)$, then

[1] The assumption that price series are $I(1)$ implies stationarity of inflation rates; but if this not meet, inefficiency can result. If the aim is to use VAR model to forecast, one might still use non-stationary series. If variables in the VAR system are $I(1)$ and not co-integrated, then we only have efficient results from the first differenced variables. If $I(1)$ variables are co-integrated the choice of the model should be Vector Error Correction Model (VECM).

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the causality analysis should take this property into account, which adds to the complication. Further, in the presence of cointegration, the application of a VAR model in first or second difference of the variables would not be appropriate for estimation due to omitted-variable bias. This happens because of the exclusion of the relevant Error Correction Mechanism (ECM) term (Engle and Granger, 1987). The linear specification may also cause bias and lead to misleading conclusions.

Cushing and McGarvey (1990) developed a theoretical model to examine the causal relationship between wholesale prices and consumers' prices. Shahbaz et al. (2009, pp.79) documented that "the production of final goods in each period uses primary goods produced in lagged period as inputs which indicate that supply-side turbulence in primary goods market influences wholesale and consumer prices in upcoming period". Cushing and McGarvey (1990) argue that wholesale prices will lead consumers' prices independently because primary goods are used as input with a lag period in production process of consumption goods. Colclough and Lange (1982) point out that causality from consumers' to producers' prices did not receive much attention in the literature. They developed a theory based on derived demand and argued that the production cost reflects the opportunity cost of resources and intermediate materials which affects the demand of final goods and services in response. This implies that the consumers' prices should determine the producers' prices. This argument (i.e., the process through consumers' prices should determine producers' prices) was further developed and illustrated by Caporale et al. (2002). They documented that consumers' prices may cause producers' prices through labor supply channel, which may also work through supply shocks in the labor market, provided wage earners in the wholesale sector want to preserve the purchasing power of their incomes. This can happen due to lags, as noted above. Perhaps, the nature of the wage-setting process as well as the mechanism by which expectations are formed play a role in this. The argument in part explains why from theoretical standpoint there may be unidirectional or bidirectional Granger-causality between producers' and consumers' price. Therefore, either producers' or consumers' price, or both may contain information to predict each other.

The objective of the paper is to examine the direction of causality between CPI and PPI using Australian quarterly data from 1969q3 to 2010q4. For long run relation the Johansen and Juselius (1990) maximum likelihood approach has been implemented. The paper contributes by decomposing causality by using time horizons to demonstrate intermediate Granger-causality. These results have important bearings on how Australia might craft inflation related policies. For example, if CPI Granger-causes PPI at intermediate frequencies then CPI should be a leading indicator in policy discussions and in the determination of intermediate macroeconomic targets pertaining to monetary or fiscal policies. The policymakers may use their knowledge to stay better prepared in addressing the negative consequences of producers' price inflation at the intermediate horizon.

This study contributes to the existing literature in several ways. First, methodologically, the approach used here can capture the nonlinear effect and the cyclical nature of the cause and effect relationship between CPI and PPI. To the best of our knowledge, this is the first attempt which employs the approach to understand causality between CPI and PPI. Second, empirically, the results suggest the absence of co-integration between CPI and PPI over the study period for Australia which only reconfirms the fact that PPI is not a useful predictor of CPI movements. The study also detects the strength and direction of the causality in departure from the conventional one-shot measure based on linear models such as, Toda and Yamamoto (1995), VAR and VECM; or nonlinear models such as Baek and Brock (1992). Third, the results lend support Colclough and Lange (1982) and Caporale et al. (2002) for Australia. Fourth, the paper shows the cyclical nature of causal relationship between CPI and PPI over the frequency bands (i.e., period of cycles are defined with frequency bands), which also may be due to market imperfections and/or frictions in the economy.[2] Results of the study point to the weakness of the simple supply–demand relationship alone; and point to the need to use framework that considers cycles in the relationship. Cycles in the relationship between CPI and PPI in Australia appear to originate from the supply as well as the demand side, and significant cycles were detected when they appear from the supply side. Fifth, from the policy point of view, our results show that the supply shocks in the labor market which emanate from the labor supply channel and wage-setting process as well as the mechanism by which expectations are formed play a major role in the Australian economy and therefore, should be addressed by policymakers. This results will also help the Australian central bank to define their inflation targets (particularly, intermediate targets) in terms of a certain measure of CPI.

Rest of the paper is organized as follows. Section 2 briefly reviews the literature followed by data source and empirical methodology used in this paper in Section 3. Findings of the paper are reported in Section 4. Section 5 offers conclusion arising out of the paper.

2. A brief review of literature

It was found that CPI and PPI have some kind of stable relationship between the two series because of inter-linkages between the wholesale market and the retail market. This holds in particular to the studies conducted in the time series framework. For the US economy, Guthrie (1981) used percentage monthly change in the PPI and the CPI covering the period 1947–1975 and sub-periods 1966–70 and 1971–75. Guthrie (1981) found that there is a relationship between changes in the PPI and changes in the CPI and this relationship can be explained by a Pascal distributed lag model. Additionally, Guthrie (1981) documented that PPI changes presently take longer to work themselves into the CPI changes than they did twenty-five years ago and a longer mean response time is associated with higher rates of inflation. Further, the study documented that the amount of the effect of the PPI changes translated into the CPI changes was increased over the years though this rate was not universal for all the time periods studied. Jones (1986), for the US economy, for the period January 1947 to December 1983 and sub periods January 1947 to June 1971 and May 1974 to December 1983 by using Wald test of Granger-causality found evidence of bi-directional causality between the PPI and the CPI. Further, Jones (1986) recommended that for bivariate model, consisting of the CPI and the PPI, simultaneous equation approach is the appropriate way to estimation. Cushing and McGarvey (1990) indicated that feedback from the PPI to the CPI was greater than that from the CPI to the PPI and therefore, the study concluded that the PPI had high incremental power vis-à-vis the CPI.

Contrarily, Clark (1995) concluded that even though pass-through effect from producer prices to consumer prices is weak, causality is unidirectional, running from the PPI to the CPI. Samanta and Mitra (1998) applied cointegration and Granger-causality tests to two sub periods (i) April 1991 to April 1995 and (ii) May 1995 to 1998. The study found a stable long-run relationship between the CPI and the Wholesale Price Index (WPI) during 1991–1995, but not thereafter. Shunmugam (2009) examined the time lag with which the CPI responded to a change in the WPI, the causal relationship between the two series and if they were cointegrated in the long run during 1982–2009 and also for pre- and post liberalization periods in India. Shunmugam (2009) found evidence of cointegration over the entire period of study but not for the pre- and post liberalization periods. Caporale et al. (2002) reported bidirectional causality between the PPI and the CPI (or even no significant links) and claimed that it only

[2] The imperfections in the markets, particularly labor market, arise due to strong labor union and trade union which gradually (depending upon the strength of the labor union or trade union) pass it on to the other markets within the economy. Further, the causal relationship between CPI and PPI may vary depending upon the time-lag taken by the supply-side turbulence to pass on primary goods market and PPI.

existed when the causality links, reflecting the monetary transmission mechanism, are ignored. Ghazali et al. (2008) by using monthly data for the CPI and the PPI, at constant prices of 2000, for the period from January 1986 to April 2007, for Malaysia, found the evidence of unidirectional causality running from the PPI to the CPI. These results are confirmed with the application of both Engle–Granger and Toda–Yamamoto causality tests. Sidaoui et al. (2009) documented on the basis of empirical exercise that the PPI Granger causes the CPI for the Mexican economy in both the long run and the short run. Similarly, for the Pakistan economy, Shahbaz et al. (2009, 2010) found the evidence of bivariate causality between the WPI and the CPI but the causal relation was stronger from the WPI to the CPI vis-à-vis the CPI to the WPI.

It is worth noting that most of the previous studies are limited in their scope, with their applications of linear models. However, economic events and regime changes such as changes in the economic environment, changes in monetary and/or fiscal policy can cause structure changes in the pattern of inflation (i.e., PPI and/or CPI) for a given time period, under study. This creates a room for a nonlinear rather than linear relationship between the PPI and the CPI. This nonlinearity may also arise due to the existence of frictions in the economy and/or asymmetric information flow, which leads to inefficiency of the markets. Therefore, in the present study, we have made an attempt to analyze the issue in nonlinear framework by using Breitung and Candelon's (2006) approach and a recently developed nonparametric approach of Lemmens et al. (2008). Use of these two approaches allows us to decompose the Granger-Causality (GC) in the frequency domain. In the frequency domain, the key idea is that a stationary process can be described as a weighted sum of sinusoidal components with a certain frequency, say 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 direction of the GC can be different for each frequency. To the best of our knowledge, the analysis of GC between the CPI and the PPI has not yet been explored in the frequency domain, either in the context of a developing or developed country.

3. Data source and methodology

For the analysis, we have obtained data of PPI and CPI from the: http://www.rba.gov.au/Statistics/ with quarterly observations covering the period from 1969Q3 to 2010Q4.

3.1. Linear cointegration analysis

It is necessary to test the order of integration of the variables in question and establish that they are integrated of the same order prior to testing for a long run cointegration relationship between the time series. We used in the study Phillips and Perron's (1988, PP) unit root test and the Johansen's cointegration test (Johansen and Juselius, 1990), to test the order of integration[3] and the cointegration, respectively. Let us consider a two-dimensional Vector Autoregressive (VAR) (p) time series $z_t=[CPI_t, PPI_t]'$ with possible time trend which is defined as

$$z_t = \eta_t + \varphi_1 z_{t-1} + \ldots + \varphi_p z_{t-p} + \varepsilon_t \tag{1}$$

where the error term, ε_t, is assumed to be Gaussian, η_t is a two-dimensional vector of constants and z_t is an integrated process of order one i.e., $I(1)$. Hence, an error-correction model for the VAR (p) process can be formulated as

$$\Delta z_t = \eta_t + \Pi z_{t-1} + \varphi_1^* \Delta z_{t-1} + \ldots + \varphi_{p-1} z_{t-p+1} + \varepsilon_t \tag{2}$$

where, $\varphi_j^* = -\sum_{i=i+1}^{p} \varphi_i, j=1,\ldots,p-1$, $\prod = \varphi_p + \varphi_{p-1} + \ldots + \varphi_1 - I = -\varphi(1)$ that contains information about long-run relationships between the variables and $\prod z_{t-1}$ represents the error-correction term. In particular, there are three cases in Eq. (2) of our interest. First, when rank $(\Pi)=2$, the matrix Π is said to have full rank with z_t be a stationary process. Hence, in this case, the error-correction model is not useful and one can study z_t directly. Second, when rank $(\Pi)=0$, this implies that the matrix Π is a null matrix and vector z_t is not a cointegrated process. Therefore, this case of Eq. (2) is just similar to a traditional differenced vector time series model. Lastly, existence of rank $(\Pi)=1$ implies that there exists one cointegrating vector with $\prod = \alpha\beta'$, where α and β are 2×1 matrices. In other words, existence of rank $(\Pi)=1$ implies that z_t is cointegrated with one linearly independent cointegrating vectors and Eq. (2) can be interpreted as an error-correction model. Johansen (1988) had proposed two test statistics, namely, trace and eigenvalue, in order to test for the existence of the cointegration relations. However, we have relied on the trace statistic, following Cheung and Lai's (1993) suggestion.[4] Since the limiting distributions of Johansen's cointegration tests depend on the deterministic function η_t in the dynamic model, we have followed Pantula principle (Johansen, 1992, 1995) for the appropriate specification. This is because the Pantula principle[5] chooses both the correct rank order and the deterministic component. We can summarize the Pantula principle as follows. First, we estimate the three models and present the results from the most restrictive to the least restrictive alternative. The models employed are the model 2, that includes intercept in the cointegration relation; model 3, that includes deterministic trends in level; and model 4, that allows for trend in the cointegration space. Thereafter, we move from the most restrictive model to less restrictive one and at each stage compare the trace test statistic with its critical value. The process only stops, for the first time, when the null hypothesis is not rejected.

3.2. Causality analysis in the frequency domain

It is important to bring in the Granger (1969) approach when dealing with the question of whether CPI_t cause PPI_t is to determine how much of the current PPI_t can be explained by past values of PPI_t, and then to see whether adding lagged values of CPI_t can improve the explanation. PPI_t is said to Granger-cause CPI_t if, CPI_t helps in the prediction of PPI_t, or if the coefficients on the lagged CPI_t's are statistically significant.[6] It is important to mention that the conventional GC tests measure precedence and information content, but do not indicate causality in its conventional sense. Importantly, the extent and the direction of causality differ between frequency bands (Granger and Lin, 1995), which conventional GC tests are unable to diagnose. The fact that a stationary series is effectively the sum of uncorrelated components, each of which is associated with a single frequency

[3] Since, PP test has advancements over DF/ADF test in the sense that where DF/ADF test uses a parametric autoregression to approximate the Autoregressive Moving Average (ARMA) structure of the errors in the test regression, PP test corrects for any serial correlation and heteroskedasticity in the errors. Therefore, this test is used.

[4] Cheung and Lai (1993) have documented that the trace test shows more robustness to both skewness and excess kurtosis in the residuals than the maximal eigenvalue test.

[5] The Pantula principle in selecting appropriate specification in cointegration test was utilized by, among others, Love and Chandran (2005), Dawson (2006) and Lim et al. (2010). Our discussion is broadly based on Lim et al. (2010).

[6] Putting it differently, a process CPI_t is said to Granger-cause another process PPI_t, when the variance of the error in forecasting future values of PPI_t, using an (optimal) forecast based on the observed values of both CPI_t and PPI_t, is strictly smaller than the variance of the prediction error, using an (optimal) forecast based only on the observed values of PPI_t.

ordinate, allows the full causal relationship to be decomposed by frequency (Lemmens et al., 2008). 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) was the first study to give the idea of further disentangling the GC relationship between two time series. Granger (1969) also suggested that a spectral-density approach would give a better-off and more complete picture than a one shot GC measure, that is supposed to apply across all periodicities (e.g., in the short run, over the business-cycle frequencies, and in the long run). Therefore, in the study we have taken the Breitung and Candelon's (2006) approach to GC in the frequency domain.[7] The approach of Breitung and Candelon (2006) is based on the work of Granger (1969) and Geweke (1982), which is slightly different from the other approaches, such as the Partial Directed Coherence (PDC) measure. This approach provides an elegant interpretation of frequency-domain GC as a decomposition of the total spectral interdependence between the 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 (that is in the short run, over the business-cycle frequencies, and in the long run) and as a consequence, one can get to know exactly for which periodicity one variable can Granger-cause the other, which the popular one shot GC tests (developed either in linear or nonlinear framework) fails to measure. Though this approach of analysis has been used in quite a few studies, its scope is limited to studies in the area of monetary policy and stock market with the exception to Tiwari (2012) in the area of public finance. Mention can be made of Assenmacher-Wesche and Gerlach (2007), Assenmacher-Wesche and Gerlach (2008a,b), Assenmacher-Wesche et al. (2008), Lemmens et al. (2008), and Gronwald (2009) in the area of monetary policy and stock market. The Breitung and Candelon's (2006) approach can be explained as follows.

Let z_t be observed at $t=1,\ldots,T$ and it has a finite-order VAR representation of the form

$$z_t = \Theta(L)z_t \tag{3}$$

where $\Theta(L)=I-\Theta_1L-\ldots-\Theta_pL^p$ is a 2×2 lag polynomial with $L^kz_t=z_{t-k}$. We assume that the error vector ε_t is white noise with $E(\varepsilon_t)=0$ and $E(\varepsilon_t\varepsilon_t')=\Sigma$; where Σ is positive definite. For ease of exposition, any deterministic terms in Eq. (3) is neglected.

Let G be the lower triangular matrix of the Cholesky decomposition $G'G=\Sigma^{-1}$, such that $E(\eta_t\eta_t')=I$ and $\eta_t=G\varepsilon_t$. If the system is assumed to be stationary, the Moving Average (MA) representation of the system is

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix}\Phi_{11}(L) & \Phi_{12}(L)\\ \Phi_{21}(L) & \Phi_{22}(L)\end{bmatrix}\begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix} \tag{4}$$

$$= \psi(L)\eta_t = \begin{bmatrix}\psi_{11}(L) & \psi_{12}(L)\\ \psi_{21}(L) & \psi_{22}(L)\end{bmatrix}\begin{bmatrix}\eta_{1t}\\ \eta_{2t}\end{bmatrix} \tag{5}$$

where, $\Phi(L)=\Theta(L)^{-1}$ and $\psi(L)=\Phi(L)G^{-1}$. Using this representation, the spectral density of CPI_t can be expressed as:

$$f_{CPI}(\omega)=\frac{1}{2\pi}\left\{\left|\psi_{11}\left(e^{-i\omega}\right)\right|^2+\left|\psi_{12}\left(e^{-i\omega}\right)\right|^2\right\}. \tag{6}$$

[7] 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 Granger causality, 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.

The measure of causality suggested by Geweke (1982) and Hosoya (1991) is defined as:

$$M_{PPI\to CPI}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{\left|\psi_{11}\left(e^{-i\omega}\right)\right|^2}\right] \tag{7}$$

$$= \log\left|1+\frac{\left|\psi_{12}\left(e^{-i\omega}\right)\right|}{\left|\psi_{11}\left(e^{-i\omega}\right)\right|}\right|. \tag{8}$$

If $|\psi_{12}(e^{-i\omega})|^2=0$, then the Geweke's measure will be zero, then the *PPI* will not Granger-cause the *CPI* at frequency ω.

If the elements of z_t are $I(1)$ and cointegrated, in that case, in the frequency domain, the measure of causality can be defined by using the orthogonalized MA representation

$$\Delta z_t = \tilde{\Phi}(L)\varepsilon_t = \tilde{\psi}(L)\eta_t, \tag{9}$$

where, $\tilde{\psi}(L)=\tilde{\Phi}(L)G^{-1}, \eta_t = G\varepsilon_t$, and G is a lower triangular matrix, such that $E(\eta_t\eta_t')=I$. Note that in a bivariate cointegrated system $\beta'\tilde{\psi}(1)=0$, where β is a cointegration vector, such that $\beta'z_t$ is stationary (Engle and Granger, 1987). As in the stationary case, the resulting causality measure is

$$M_{PPI\to CPI}(\omega) = \log\left|1+\frac{\left|\tilde{\psi}_{12}\left(e^{-i\omega}\right)\right|}{\left|\tilde{\psi}_{11}\left(e^{-i\omega}\right)\right|}\right|. \tag{10}$$

To test the hypothesis that the *PPI* does not cause the *CPI* at frequency ω, we consider the null hypothesis:

$$M_{PPI\to CPI}(\omega)=0 \tag{11}$$

within a bivariate framework. Following Breitung and Candelon (2006), we can present this test by reformulating the relationship between *CPI* and *PPI* in VAR (p) equation:

$$CPI_t = a_1CPI_{t-1}+\ldots+a_pCPI_{t-p}+\beta_1PPI_{t-1}+\ldots+\beta_pPPI_{t-p}+\varepsilon_{1t} \tag{12}$$

The null hypothesis tested by Geweke, $M_{PPI\to CPI}(\omega)=0$, corresponds to the null hypothesis of

$$H_0: R(\omega)\beta=0 \tag{13}$$

where, β is the vector of the coefficients of *PPI* and

$$R(\omega)=\begin{bmatrix}\cos(\omega)\cos(2\omega)\ldots..\cos(p\omega)\\ \sin(\omega)\sin(2\omega)\ldots\ldots\sin(p\omega)\end{bmatrix}. \tag{14}$$

The ordinary F statistic for Eq. (13) is approximately distributed as $F(2,T-2p)$ for $\omega\in(0,\pi)$. It is interesting to consider the frequency domain GC test within a cointegrating framework. To this end, Breitung and Candelon (2006) suggested to replace CPI_t in regression (12) by ΔCPI_t, with the right-hand side of the equation remaining the same (see Breitung and Candelon, 2006, for more detailed discussion on this and also for the case when one variable is $I(1)$ and other is $I(0)$). Further, it is important to mention that in cointegrated systems the definition of causality at frequency zero is equivalent to the concept of "long-run causality" and in stationary framework there exists no long-run relationship between the time series, a series may nevertheless explain future low frequency variation of another time series. Hence, in a stationary system, causality at low frequencies implies that the additional variable is able to forecast the low frequency component of the variable of interest, one period ahead.

Analyzing 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). The study reconsidered the original framework proposed by Pierce (1979), and proposed a testing procedure for Pierce's (1979) spectral GC measure. This GC test in the frequency domain relies on a modified version of the coefficient of coherence, which the study estimates in a nonparametric fashion, and for which the study derives the distributional properties.

Let CPI_t and PPI_t be two stationary (after seasonal adjustments) time series of length T (here $T=166$). In this section, we review the Lemmens et al. (2008) approach to measure and test whether CPI_t Granger causes PPI_t at a given frequency λ. However, it is worthy to mention that the GC approaches, in the present approach, measure the predictive content a variable conveys regarding the value of another variable one period ahead. In the study, we have performed the Pierce (1979) measure for GC in the frequency domain on the univariate innovations series, u_t and v_t, derived from CPI_t and PPI_t. The latter are modeled as univariate Autoregressive Moving Average (ARMA) processes, i.e.,

$$\Theta^{CPI}(L)CPI_t = C^{CPI} + \Phi^{CPI}(L)u_t \tag{15}$$

$$\Theta^{PPI}(L)PPI_t = C^{PPI} + \Phi^{PPI}(L)v_t \tag{16}$$

where, $\Theta^{CPI}(L)$ and $\Theta^{PPI}(L)$ are autoregressive polynomials, $\Phi^{CPI}(L)$ and $\Phi^{PPI}(L)$ are moving average polynomials and C^{CPI} and C^{WPI} potential deterministic components. After filtering the series with the above ARMA models, we 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

$$S_u(\lambda) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_u(k)e^{-i\lambda k} \tag{17}$$

$$S_v(\lambda) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_v(k)e^{-i\lambda k} \tag{18}$$

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. In the spectral representation, each time series may be decomposed into a sum (or integral) of uncorrelated components, each related to a particular frequency λ.[8] 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 $(\lambda, \lambda + d\lambda)$. To investigate the relationship between the two stochastic processes under consideration, we consider the cross-spectrum, $S_{uv}(\lambda)$, between u_t and v_t. 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. This is a complex number, which is defined as

$$\begin{aligned} S_{uv}(\lambda) &= C_{uv}(\lambda) + iQ_{uv}(\lambda) \\ &= \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_{uv}(k)e^{-i\lambda k} \end{aligned} \tag{19}$$

where, $C_{uv}(\lambda)$ and $Q_{uv}(\lambda)$ are cospectrum and quadrature spectrum, respectively, representing 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 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, pp. 274). The cross-spectrum can be estimated non-parametrically by,

$$\hat{S}_{uv}(\lambda) = \frac{1}{2\pi}\left\{\sum_{k=-M}^{M} w_k\hat{\gamma}_{uv}(k)e^{-i\lambda k}\right\} \tag{20}$$

with $\hat{\gamma}_{uv}(k) = C\hat{O}V(u_t, v_{t-k})$ the empirical cross-covariances, and with window weights w_k, for $k=-M,..,M$. Eq. (10) is called the *weighted covariance estimator*, and the weights w_k are selected on the basis of Bartlett weighting scheme i.e., $1-|k|/M$. The constant M determines the maximum lag order considered and if the length of the time series, T tends to be infinity i.e., $T\to\infty$, then, M also tends to be infinity, i.e., $M\to\infty$, but at a much slower rate, such that $M/T\to 0.1$. The spectra of Eqs. (17) and (18) are estimated in a similar way. This cross-spectrum allows us to compute the coefficient of coherence, $h_{uv}(\lambda)$, defined as,

$$h_{uv}(\lambda) = \frac{|S_{uv}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}}. \tag{21}$$

It is interesting to note that, this coefficient measures the strength of the linear association between two time series, frequency by frequency. However, it fails to provide any information on the direction of the relationship between the two processes. The interpretation of the squared coefficient of coherence is similar to the R-squared in a regression context. According to Pierce (1979), the R-squared of a regression of v_t on all past, present, and future values of u_t is the integral, across frequencies, of the squared coefficient of coherence. Hence, coherence takes values between 0 and 1. Lemmens et al. (2008) have shown that under the null hypothesis, that $h_{uv}(\lambda)=0$, the estimated squared coefficient of coherence at frequency λ, with $0<\lambda<\pi$ when appropriately rescaled, converges to a chi-squared distribution with 2 degrees of freedom,[9] denoted by χ^2_2.

$$2(n-1)\,\hat{h}^2_{uv}(\lambda) \xrightarrow{d} \chi^2_2 \tag{22}$$

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

$$\hat{h}_{uv}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n-1)}} \tag{23}$$

with $\chi^2_{2,1-\alpha}$ being the $1-\alpha$ quantile of the chi-squared distribution with 2 degrees of freedom. The coefficient of coherence in Eq. (21)

[8] We can model the frequencies $\lambda_1, \lambda_2, \ldots, \lambda_N$ as follows:

$$\begin{aligned} \lambda_1 &= 2\pi/T \\ \lambda_2 &= 4\pi/T \\ &\cdot \\ &\cdot \end{aligned}$$

The highest frequency considered is $\lambda_N = 2N\pi/T$; where, if T is an even number $N\equiv T/2$ and if T is an odd number $N\equiv(T-1)/2$ (see Hamilton, 1994, pp. 159 for elaborations).

[9] 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.

gives a measure of the strength of the linear association between the two time series, frequency by frequency, but does not provide any information on the direction of the relationship between the two processes. Following Pierce (1979), Lemmens et al. (2008) have decomposed the cross-spectrum (Eq. (19)) into three parts: (i) $S_{u \Leftrightarrow v}$, the instantaneous relationship between u_t and v_t; (ii) $S_{u \Rightarrow v}$, the directional relationship between v_t and lagged values of u_t; and (iii) $S_{v \Rightarrow u}$, the directional relationship between u_t and lagged values of v_t, i.e.,

$$S_{uv}(\lambda) = [S_{u\Leftrightarrow v} + S_{u\Rightarrow v} + S_{v\Rightarrow u}] = \frac{1}{2\pi}\left[\gamma_{uv}(0) + \sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k} + \sum_{k=1}^{\infty}\gamma_{uv}(k)e^{-i\lambda k}\right]. \tag{24}$$

The proposed spectral measure of GC is based on the key property that CPI_t does not Granger cause PPI_t if and only if $\gamma_{uv}(k)=0$ for all $k<0$. Hence, if one is to assess the predictive content of CPI_t relative to PPI_t, focus should be on the second part of Eq. (24), i.e.

$$S_{u\Rightarrow v}(\lambda) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{-1}\gamma_{uv}(k)e^{-i\lambda k}\right]. \tag{25}$$

The Granger coefficient of coherence is then, given by,

$$h_{u\Rightarrow v}(\lambda) = \frac{|S_{u\Rightarrow v}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}}. \tag{26}$$

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

$$\hat{h}_{u\Rightarrow v}(\lambda) = \frac{\left|\hat{S}_{u\Rightarrow v}(\lambda)\right|}{\sqrt{\hat{S}_u(\lambda)\hat{S}_v(\lambda)}}, \tag{27}$$

with $\hat{S}_{u\Rightarrow v}(\lambda)$, as in Eq. (18), but with all weights $w_k=0$ for $k\geq 0$. The distribution of the estimator of the Granger coefficient of coherence is derived from the distribution of the coefficient of coherence Eq. (20). 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

$$2(n'-1)\,\hat{h}^2_{u=>v}(\lambda) \xrightarrow{d} \chi^2_2 \tag{28}$$

where, n is now replaced with $n' = T/\left(\sum_{k=-M}^{-1} w_k^2\right)$. 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 is taken into account. The null hypothesis of no GC at frequency λ i.e., $\hat{h}_{u\Rightarrow v}(\lambda)=0$ versus $\hat{h}_{u\Rightarrow v}(\lambda)>0$ is then rejected if

$$\hat{h}_{u\Rightarrow v}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n'-1)}}. \tag{29}$$

Hence, $\hat{h}_{u\Rightarrow v}(\lambda)$ captures the contribution at frequency λ, and does not do it for the total of CPI_t–PPI_t relationship (as the usual coherence does), but does it for the Granger-causal relationship from CPI_t to PPI_t. This is relevant in the present context, wherein, we are interested in finding out the degree of Granger-causal relationship and not just the direction between CPI_t and PPI_t for Australia. Another advantage, in terms of the estimation, of this approach is that it does not require a bivariate VAR specification, but uses a non-parametric estimation of the cross-spectrum. Hence, in the estimation, we compute Granger coefficient of coherence given by Eq. (27) and test the significance of causality by making use of Eq. (29).

Table 1
Estimation of unit root tests.

Variables	PP test with constant		PP test with constant and trend	
	T-calculated	Prob-value	T-calculated	Prob-value
$\ln CPI_t$	−4.749352*(9)	0.0001	−0.722692(9)	0.9692
$\Delta \ln CPI_t$	−7.106802*(9)	0.0000	−9.327946*(9)	0.0000
$\ln PPI_t$	−4.168027*(7)	0.0010	−0.803250(7)	0.9624
$\Delta \ln PPI_t$	−7.212602*(7)	0.0000	−8.326269*(7)	0.0000

Note: The asterisk * denotes the significance at 1% level. The figure in the parenthesis is the bandwidth for the PP unit root test determined by the Schwert (1989) formula.

4. Data analysis and empirical findings

First of all descriptive statistics of variables[10] was 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.[11] We found a very high correlation and its value is 0.99. In the next step stationary property of the data series of all test variables has been tested through the PP test and results are reported in Table 1.

Table 1 reports that both variables are non-stationary at their level form while they are stationary at their first differenced form i.e., they are integrated of order one, $I(1)$. This unique order of integration allows us to proceed with cointegration analysis in the framework of Johansen and Juselius (1990). Results of cointegration analysis are presented in Table 2.

With application of the Pantula principle we found that both series do not have cointegration relationship, a surprising finding.[12] Therefore, in the next step to analyze Granger-causality (GC) between CPI and PPI in the frequency domain framework we adopted two approaches. In the first case, GC was analyzed by adopting the approach of Breitung and Candelon (2006) for the log differenced data of the variables so that series become stationary. In the second case, the log differenced variables have been filtered using ARMA models to obtain the innovation series and then the approach suggested by Lemmens et al. (2008) was utilized. We have used lag length[13] $M=\sqrt{T}$ for utilizing the approach of Lemmens et al. (2008) and lag length was decided on the basis of AIC in case of Breitung and Candelon (2006). The frequency (λ) on the horizontal axis can be translated into a cycle or periodicity of T by $T=2\pi/\lambda$; where T is the period (in our case T represents quarter).

Fig. 1, which presents the result for causality running from CPI to PPI, has two parts, Fig. 1a and Fig. 1b. Fig. 1a shows that at 5% level of significance, CPI Granger-causes PPI for all frequencies in the interval (1.2,2.6). However, Fig. 1b, which presents the result of Granger coefficient of coherence for causality running from CPI to PPI after

[10] Time series plot and descriptive statistics of the variables are presented in Fig. 1 and Table 1 respectively, in Appendix A. Table 1 in Appendix A indicates that all the two variables do not have log normal distribution and therefore, provides scope for nonlinear analysis.

[11] Results are reported in Table 1 in Appendix A.

[12] Following the 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.

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

Table 2
Cointegration rank and model selection: trace statistic.

Hypothesized (no. of CE(s))	Model 2	Model 3	Model 4s
Ln(PPI) and Ln(CPI)	VAR Lag Order Selection Criteria : AIC, HQIC, FPE (Lag 4)		
R = 0	26.3193 (20.2618)	22.4546 (15.4947)	23.9861 (25.8721)
R = 1	6.3049 (9.16454)	6.1069 (3.8414)	6.6394 (12.5179)

Note: (1) Figures in the parenthesis are the 5% critical values of the respective test statistics.

filtering the variables, shows that at 5% level of significance, CPI Granger-causes PPI at the intermediate frequencies (that is 1.2,1.6) reflecting medium-run cycles.

Similarly, Fig. 2, which presents the result of GC running from PPI to CPI, has two parts, Fig. 2a and Fig. 2b. Fig. 2a shows that at 5% level of significance, PPI Granger-causes CPI at very low level of frequencies (that is $\omega \in (0,1)$). However, Fig. 2b, which presents the result of Granger coefficient of coherence for causality running from PPI to CPI after filtering the variables, shows contrary results to that of Fig. 2a. Fig. 2b does not provide evidence of GC from PPI to CPI at 5% level of significance at all the levels of frequencies.

5. Conclusions and policy implications

This paper applies the frequency domain approach to the quarterly Australian data from 1969q3 to 2010q4 to examine the direction of Granger-causality between CPI and PPI which helps to capture the nonlinear effect and the cyclical nature of the cause and effect relationship. Our results lend support to the fact that the recent information on CPI has been useful in improving forecasts performance of PPI inflation for medium run cycles in Australia, reconfirming that PPI is not a useful predictor of CPI movements. Our results lend support to Colclough and Lange (1982) and Caporale et al. (2002) for Australia.

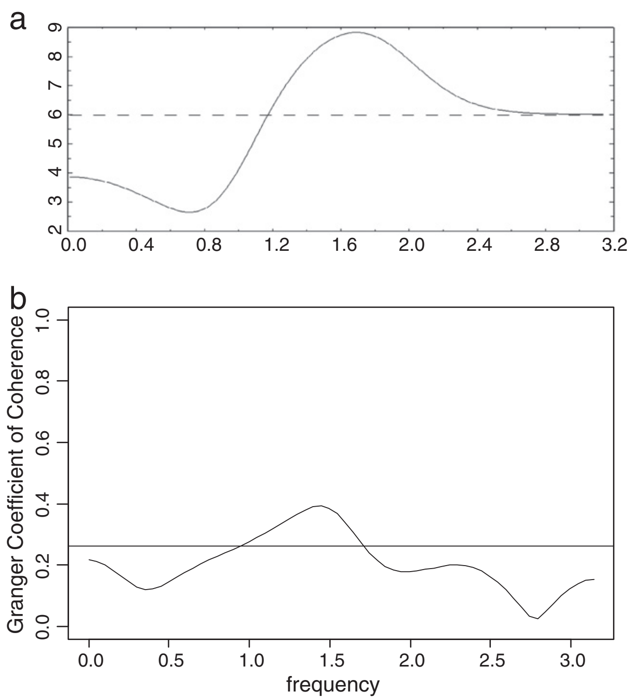

Fig. 1. The solid line shows the Granger-causality from CPI to PPI. The horizontal axis shows the frequency ordinates as fractions of π and vertical axis shows calculated value of *F* statistic in part a. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance.

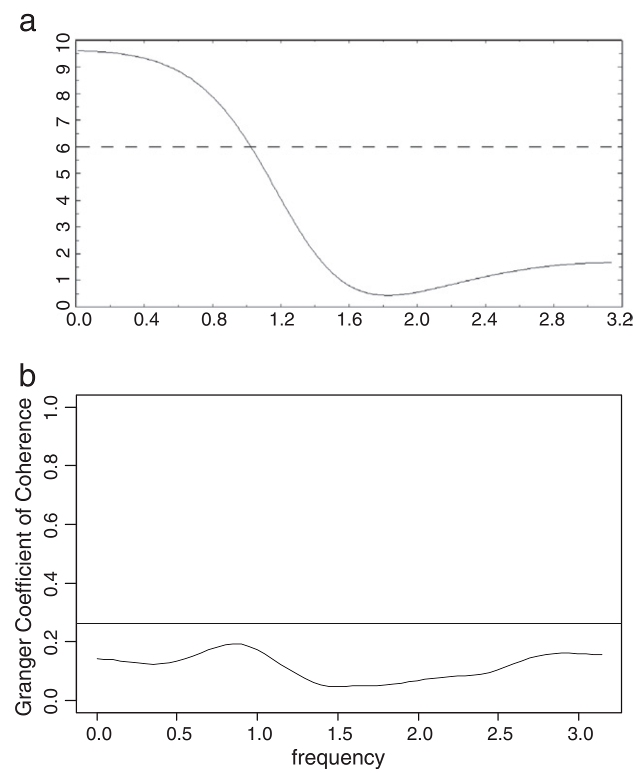

Fig. 2. The solid line shows the Granger-causality from PPI to CPI. The horizontal axis shows the frequency ordinates as fractions of π and vertical axis shows calculated value of *F* statistic in part a. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance.

Both the series were found nonstationary in log level form, but first difference stationary in log. The application of Johansen and Juselius's (1990) maximum likelihood approach failed to establish cointegration between the variables.

Our results suggest that for the Australian economy causality and reverse causality between CPI and PPI vary across frequencies. We found that CPI Granger-causes PPI at intermediate range reflecting medium-term cycles. We also found that PPI does not Granger-cause CPI at the 5% level of significance, at all the levels of frequencies.

We find that CPI Granger-causes PPI at intermediate frequencies. An implication for this is that CPI is the leading indicator here and thus is important in policy discussion involving intermediate macroeconomic targets pertaining to domestic policies such as monetary or fiscal. It also suggests that by looking at the link policy makers maybe better prepared to address the negative consequences of producers' inflation in the intermediate horizon.

The lack of robust evidence on causal link between the PPI and the CPI, along with the fact that most central banks define their inflation targets in terms of a certain measure of consumer prices, has led some central bankers to disregard the PPI as a relevant indicator in assessing inflation dynamics. Our findings lend support to this view for the Australian economy.

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Appendix A

Table A1
Descriptive statistics and correlation matrix.

Descriptive statistics									Correlation matrix	
Variables	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque–Bera	ln PPI_t	ln CPI_t
ln PPI_t	4.32	4.61	5.166	2.91	0.666	−0.798	2.375	20.31	1	0.9988
ln CPI_t	4.31	4.62	5.159	2.83	0.701	−0.758	2.29	19.38	0.9989	1

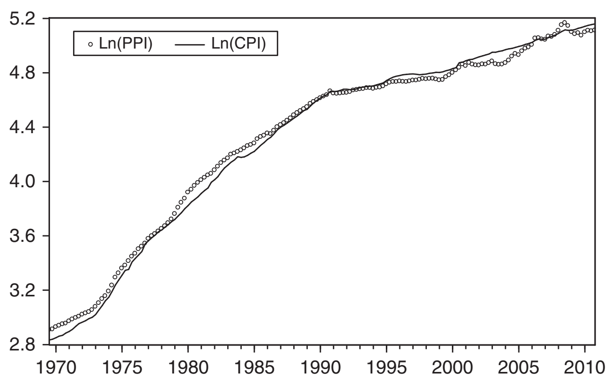

Fig. A1. Time series plots of the variables.

References

Assenmacher-Wesche, K., Gerlach, S., 2007. Money at low frequencies. Journal of the European Economic Association 5, 534–542.

Assenmacher-Wesche, K., Gerlach, S., 2008a. Interpreting euro area inflation at high and low frequencies. European Economic Review 52, 964–986.

Assenmacher-Wesche, K., Gerlach, S., 2008b. Money growth, output gaps and inflation at low and high frequency: spectral estimates for Switzerland. Journal of Economic Dynamics and Control 32, 411–435.

Assenmacher-Wesche, K., Gerlach, S., Sekine, T., 2008. Monetary factors and inflation in Japan. Journal of the Japanese and International Economies 22, 343–363.

Baek, E., Brock, W., 1992. A general test for nonlinear granger causality: bivariate model. Working paper. Iowa State University.

Blomberg, S.B., Harris, E.S., 1995. The commodity–consumer price connection: fact or fable? Federal Reserve Bank of New York Economic Policy Review, 1.

Breitung, J., Candelon, B., 2006. Testing for short and long-run causality: a frequency domain approach. Journal of Econometrics 132, 363–378.

Caporale, G.M., Katsimi, M., Pittis, N., 2002. Causality links between consumer and producer prices: some empirical evidences. Southern Economic Journal 68, 703–711.

Cheung, Y.W., Lai, K.S., 1993. Finite sample sizes of Johansen's likelihood ratio tests for cointegration. Oxford Bulletin of Economics and Statistics 55, 313–328.

Clark, T., 1995. Do producer prices lead consumer prices? Federal Reserve Bank of Kansas City Economic Review 80, 25–39.

Colclough, W.G., Lange, M.D., 1982. Empirical evidence of causality from consumer to wholesale prices. Journal of Econometrics 19, 379–384.

Cushing, M.J., McGarvey, M.G., 1990. Feedback between wholesale and consumer price inflation: a reexamination of the evidence. Southern Economic Journal 56, 1059–1072.

Dawson, P.J., 2006. The export–income relationship and trade liberalisation in Bangladesh. Journal of Policy Modeling 28, 889–896.

Diebold, F.X., 2001. Elements of Forecasting, 2nd ed. Cincinnati: South-Western College Publishing.

Dion, R., 1999. Indicator models of core inflation for Canada. Bank of Canada Working Paper 99-13.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction representation: estimation and testing. Econometrica 55, 251–276.

Geweke, J., 1982. Measurement of linear dependence and feedback between multiple time series. Journal of the American Statistical Association 77, 304–324.

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.

Granger, C.W.J., 1969. Investigation causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

Granger, C.W.J., Lin, J.L., 1995. Causality in the long run. Econometric Theory 11, 530–536.

Gronwald, M., 2009. Reconsidering the macroeconomics of the oil price in Germany: testing for causality in the frequency domain. Empirical Economics 36, 441–453.

Guthrie, R.S., 1981. The relationship between wholesale and consumer prices. Southern Economic Journal 47, 1046–1055.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton, NJ.

Hosoya, Y., 1991. The decomposition and measurement of the interdependence between second-order stationary process. Probability Theory and Related Fields 88, 429–444.

Johansen, S., 1988. Statistical analysis on cointegration vectors. Journal of Economic Dynamics and Control 12, 231–254.

Johansen, S., 1992. Determination of cointegration rank in the presence of a linear trend. Oxford Bulletin of Economics and Statistics 54, 383–397.

Johansen, S., 1995. Likelihood-based Inference in Cointegrated Autoregressive Models. Oxford University Press, Oxford.

Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration with applications to money demand. Oxford Bulletin of Economics and Statistics 52, 169–210.

Jones, J.D., 1986. Consumer prices, wholesale prices, and causality. Empirical Economics 11, 41–55.

Lemmens, A., Croux, C., 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.

Lim, S.Y., Chia, R.C.-J., Ho, C.M., 2010. Long-run validity of export-led growth: an empirical reinvestigation from linear and nonlinear cointegration test. Economics Bulletin 30, 1182–1190.

Love, J., Chandran, R., 2005. Testing export-led growth in Bangladesh in a multivariate VAR framework. Journal of Asian Economics 15, 1155–1168.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrical 75, 335–446.

Pierce, D.A., 1979. R-squared measures for time series. Journal of the American Statistical Association 74, 901–910.

Priestley, M.B., 1981. Spectral Analysis and Time Series. London Academic Press, London.

Samanta, G., Mitra, S., 1998. Recent divergence between wholesale and consumer prices in India—a statistical exploration. RBI Occasional Papers, p. 19.

Schwert, G.W., 1989. Tests for unit roots: a Monte Carlo investigation. Journal of Business and Economic Statistics 7, 147–160.

Shahbaz, M., Awan, U.R., Nasir, M.N., 2009. Producer and consumer prices nexus: ARDL bounds testing approach. International Journal of Marketing Studies 1, 78–86.

Shahbaz, M., Wahid, A.N.M., Haider, A., 2010. Empirical psychology between wholesale price and consumer price indices: the case of Pakistan. Singapore Economic Review 55, 537–551.

Shunmugam, V., 2009. Causality links between CPI and WPI—an econometric exploration. Mimeo.

Sidaoui, J., Capistran, C., Chiquiar, D., 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.

Tiwari, Aviral K., 2012. Tax burden and GDP: evidence from frequency domain approach for the USA. Economics Bulletin 32, 147–159.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated processes. Journal of Econometrics 66, 225–250.