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Producer & Consumer Prices Nexus: ARDL Bounds Testing Approach

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Abstract

The present endeavor explores relationship between producer and consumer price indices by employing new techniques. We have utilized the time series monthly (1992M1-2007M6) data while **ARDL Bounds Testing** and **Johanson Cointegration Approach** is used to determine the long run association and robustness of long run results. **Toda** & **Yamamato** (1995) and **Variance Decomposition** for causal rapport between producer and consumer prices are applied. **DF-GLS** & **Ng-Perron** Tests are also applied to inquire the order of integration for running variables.

Results have verified the existence of long run relationship between producer and consumer prices, and their association is robust in long span of time in the case of small developing economy like Pakistan. Causal results through Toda and Yamamato's (1995) technique asserts that there is two-way causality but it is stronger from producer to consumer prices and same with Variance Decomposition Method. Finally Feed back impacts show that feedback influence from PPI to CPI is stronger or dominating as compared to feedback from CPI to PPI, which support "Cushing and McGarvey (1990) hypothesis".

Keywords: D24, D12, C20

Introduction

The relevant literature reveals that consumer and producer price indices are considered as indicators of inflation and current producer prices lead consumer prices in future [Caporale, (2002) & Darestani and Arjomand, (2006)]. Researchers found causal relationship between producer price and consumer price from both sides simultaneously [Engle, (1978); Sims, (1972); Silver and Wallace, (1980); and Guthrice, (1981)] (Note 1). But Colclough and Langee (1982) argued that causality between the said variables can run from producer prices to consumer prices or might be bidirectional after applying the Granger & Sims tests and theoretically causality expects to run from consumer to producer prices. Over a long span of time, Mehra (1991) & Huh and Trehan (1995) concluded that consumer price index leads labor cost, which is major part of produce price index and this mechanism contradicts the chain view. In contrary, Emery and Chang (1996) summed up "*workers compensation growth adjusted for productivity has no power to anticipate the inflation*".

Further more Cushing and McGarvey (1990) indicated that feedback from producer prices to consumer prices is greater than that from consumer to producer prices that can be concluded as "consumer prices have very light incremental power". Further more, they argued that addition of money supply does not affect prevailing feedback from producer to consumer and causal link is consistent with the supple price model showing strong demand effects. Contrarily, Clark (1995) concluded that pass-through effect from producer prices to consumer prices may be weak and found "causality is unidirectional that runs from producer prices to consumer prices".

1. Theoretical Background

In literature producer price index is utilized frequently as an important indicator for consumer price index. Mostly causal relationship is related to supply-side that is an indication from production timing while retail sector also adds value in existing production after a lag period. According to standard open macro economy model, retail sector uses running domestic production as an input. Literature indicates that consumer prices depend upon producer prices of goods, imported goods' prices, exchange rate, rate of indirect taxes implementation, marginal cost of retail production and markup possibly. Theoretical basis for causal relationship running from wholesale price has been developed by Cushing and McGarvey (1990). 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 influence wholesale and consumer prices in upcoming period. Cushing and McGarvey (1990) find that primary goods are used as input with lag period in production process of consumption goods that's why wholesale prices will lead consumer prices independently.

Contrarily, Colclough and Langee (1982) argued that causal relationship from consumer prices to producer prices did not receive much attention to be investigated in the literature. Their theoretical argument stems from derived demand and was developed by Marshall (1961). Demand for inputs determined by demand for final goods and services between competing utility items and this framework indicates that opportunity cost of resources and intermediate materials is reflected by the production cost that influences the demand of final goods and services in response. This shows that consumer prices should affect producer prices. Cushing and McGarvey (1990) examined said link by allowing for demand side effects, while demand for primary goods determines expected future prices of consumer goods. Under this assumption, current demand and past expectations of current demand determine consumer price while wholesale price depends on expected future demand (Cushing and McGarvey, 1990). So causality running from consumer prices to wholesale prices would exist only for certain values of disturbance parameters (Cushing and McGarvey, 1990).

Caporale, et al. (2002) explain this link through labor supply channel, consumer prices also affect producer prices through supply shocks in labor market, if wage earners in the wholesale sector want to preserve the purchasing power of their incomes. This effect occurs with lag-period, it probably depends on the nature of wage-setting process along with expectations of machinery formation. Finally, Yee and Mummad (2008) find unidirectional causal relation running from producer price index to consumer price index in Malaysia.

Insert Figure 1 here

Figure-1 shows the behavior of Consumer Prices and Producer Prices and for this, Monthly Consumer Price and Producer Price Indices are utilized. Data set has been obtained from International Financial Statistics (IFS, 2007) and State Bank Monthly Bulletins (Various issues). Remaining part of the study is designed as follows: part **B** explains the methodological framework; Interpretations are in part **C** of the study and conclusions are drawn in part **D**.

2. Methodological Framework

To investigate the long run association between Producer Price and Consumer prices indices, ARDL bounds testing approach for cointegration by Pesaran, (2001) has been applied. This technique is advantageous over traditional econometric procedures and has been utilized to study the Producer and Consumer prices relationship in the available literature. This is the study of two vectors namely Z_t where $Z_t = (LPPI, LCPI)$. LPPI and LCPI are used as dependent and independent variables one by one. The ARDL bounds testing in the form of conditional error correction models are given below:

$$lppi = \gamma_1 + \gamma_2 lppi_{t-1} + \gamma_3 lcpi_{t-1} + \sum_{i=1}^{p} \varphi_1 \Delta lppi_{t-i} + \sum_{j=0}^{p} \varphi_2 \Delta lcpi_{t-j} + \eta_i \quad (1)$$

$$lcpi = \lambda_1 + \lambda_2 lppi_{t-1} + \lambda_3 lcpi_{t-1} + \sum_{j=1}^{p} \phi_1 \Delta lcpi_{t-j} + \sum_{i=0}^{p} \phi_2 \Delta lppi_{t-i} + \mu_i \quad (2)$$

Where, Δ is the difference operator while LCPI is the log of consumer price index (proxy for consumer prices) and LPPI is indicating log of producer price index (representing producer price) $\gamma_2 = \lambda_2$, $\gamma_3 = \lambda_3$ are showing the long run coefficients and $\gamma_1 = \lambda_1$ indicating drifts of both equations of the study. One may be noted that LPPI and LCPI are dependent variables simultaneously in both equations. Current and lagged values of differences for LPPI & LCPI are utilized in the model for short run dynamic structure. Lag length selection namely '*p*' Pesaran, et al. (2001, page-308) described that "there is delicate balance between choosing '*p*' sufficiently large to mitigate the residual serial correlation problem and, at the same time, sufficiently small so that the conditional ECM is not unduly over-parameterized, particularly in the view of limited time series data". In this study, time series data set is monthly ranging from 1992M1 to 2007M6 (186 observations). The bounds testing approach for the absence of any level association between PPI and CPI is through the exclusion of lagged levels of running actors like $LPPI_{t-1}$ and $LCPI_{t-1}$. This lends support for following not only for null hypothesis but also for the alternative hypothesis:

$$H_{\circ} : \gamma_2 = \lambda_2 = 0, \gamma_3 = \lambda_3 = 0 \quad \ldots (3)$$

$$H_a : \gamma_2 = \lambda_2 \neq 0, \gamma_3 = \lambda_3 \neq 0 \quad \ldots (4)$$

The F-statistics, which has been a non-standard distribution, depends not only on non-stationarity of the data and number of independent actors but also on the sample period and sample size. The asymptotic distributions of the F-statistics are non-standard under the null hypothesis of no co-integration relationship between the examined variables, irrespective of whether the variables are purely *I*(0) or *I*(1), or mutually co-integrated. Two sets of asymptotic critical values provided by Pesaran and Pesaran, (1997). The first set assumes that all variables are *I*(0) while the second set assumes that all variables are *I*(1). If the computed F-statistics is greater than the upper bound critical value then we reject the null hypothesis of no co-integration and conclude that there exists steady state equilibrium between the variables. If the computed F-statistics is less than the lower bound critical value, then we cannot reject the null of no co-integration. If the computed F-statistics falls within the lower and upper bound critical values, then the result is inconclusive; in this case, following Kremers*,* (1992) and Bannerjee, (1998), the error correction term will be a useful way of establishing co-integration(Note 2).

For granger causality, Rambaldi and Doran (1996) formulating for Toda-Yamamato's (1995) is employed. *dmax* is indicating the maximum order of integration in the system (in this study, it is 1) and a VAR(*k* + *dmax*) has to be estimated to use the Wald test for linear restrictions on the parameters of a VAR(*k*) which has an asymptotic χ2 distribution. In our case, *k* is determined to be by using the Akaike Information Criterion (AIC). *LPPI & LCPI* can be represented by X and Y respectively and for a VAR following system of equations can be applied:

$$LPPI = \gamma_1 + \sum_{i=1}^{p} \alpha_1 LPPI_{t-i} + \sum_{j=1}^{p} \alpha_2 LCPI_{t-j} + \eta_i \qquad \ldots(5)$$

$$LCPI = \lambda_1 + \sum_{j=1}^{p} \beta_1 LCPI_{t-j} + \sum_{i=1}^{p} \beta_2 LPPI_{t-i} + \mu_i \qquad \ldots(6)$$

For the above described system, F-statistics and Wald tests applied to examine the causality relation between said variables. If one wants to test that LCPI does not Granger-cause LPPI, null hypothesis will be as $H_\circ : \alpha_2 = 0$ and alternative $H_\alpha : \alpha_2 \neq 0$ while null hypothesis will be as $H_\circ : \beta_2 = 0$ and alternative $H_\alpha : \beta_2 \neq 0$ for second equation.

3. Interpreting Style

At the previous step standard tests are employed like DF-GLS and Ng-Perron in order to investigate the order of integration for said variables in the concerned models. Mostly in available literature to find out the order of integration ADF (Dicky & Fuller, 1979) and P-P (Philip & Perron, 1988) tests are often used respectively. Due to their poor size and power properties, both tests are not reliable (Dejong et al, 1992 and Harris, 2003). As earlier mentioned they conclude that these tests seem to over-reject the null hypotheses when it is true and accept it when it is false. While, these newly proposed tests seem to solve this arising problem: the Dicky-Fuller generalized least square (**DF-GLS**) de-trending test developed by Elliot (1996) and **Ng-Perron** test following Ng-Perron (2001). The results of Table-1 indicate that PPI & CPI are *I(1)* variables. Lag selection criteria does not allow to take lag more and less than 8 because at lag-8 AIC values is minimum.

Insert Table 1 here

Insert Table 2 here

Insert Table 3 here

The first step is to select the lag length of ARDL model with 8 on the basis of AIC (Akaike Information Criteria). The total number of regressions estimated following the ARDL method in the equation 6 is $(8+1)^2 = 81$. As results reported in Table 3 of F-Statistics, exceeds the critical bounds, 2.79 is lower bounds and 4.10 is upper bounds respectively at 1% level of significance and values of parsimonious model (**Wald-Statistics**) are given with their stability power in parenthesis. ARDL F-statistics and Wald-statistics push to accept the hypothesis of Cointegration between PPI and CPI. So, one may conclude that Consumer and Producer price indices are tied together in long run relationship. To investigate the robustness of long run relationship between PPI & CPI, Table-4 shows the output of Johansen Likelihood test and indicates the existence of long run association between Producer price index and Consumer price index in the long run.

Insert Table 4 here

Insert Table 5 here

Table 5 reports the regression results both by OLS and Johansen Normalized equation. One percent increase in producer prices lead to raise consumer prices in current period by more than 90 % in future while there is 88 percent increase in Consumer prices due to one percent increase in producer prices according to the Johanson normalized equation. From opposite side, one may conclude that producer prices are influenced more than 100 percent due to rise in consumer prices in the country. This proves the "existence of **derived demand hypothesis** in Pakistan" which was developed by Marshall (1961).

For Causal relationship between PPI and CPI Toda and Yamamato (1995) has applied and results in Table-6 reveal that there is bidirectional causality between Producer and consumer prices.

Insert Table 6 here

Insert Table 7 here

In table-7, Variance decomposition is an alternative method to impulse response function for investigating the response of dependent variable due to the effects of shocks by explanatory actors. This method explains that how much of predicted error variance for any variable is described by innovations through each independent variable in a system over the horizons. The shocks also affect other variables in the system due to shocks explained by error variance. From the above test it can be concluded that each time series describes the prevalence of its own values. Consumer price explains over 76.858 % of its forecast error variances or explain through its own innovative shocks. Whereas, producer price shows innovative impact through its own shocks nearly 77.558 %. This shows that consumer price predominately explains by its past values or innovative shocks and 23.141 percent through Producer price. This can also be concluded that current consumer price influences future consumer price. PPI lead CPI not more than 22.44 % through its innovative shocks while PPI leads CPI more than 23 % through their innovative shocks on each. The results of VDC have also proved that there prevails bidirectional causality between PPI & CPI.

Insert Table 8 here

For short term behavior, Error Correction Model (ECM) is applied. Table-8 shows that more than 11 percent CPI is raised by lag and PPI pushes the CPI to raise almost 39 percent but lag impact of **ΔPPI** is positive with insignificance. Lag impact **ΔCPI** is negative but in future it converts into positive and impacts **PPI** positively and significantly. Further more, lag of **ΔPPI** raises **PPI** by more than 23 percent with high level of significance. Feed back impacts show that feedback influence from PPI to CPI is stronger or dominating as compared to feedback from CPI to PPI supporting "Cushing and McGarvey (1990) hypothesis".

According to Pesaran and Shin (1999) the stability of the estimated coefficient of the error correction model should also be empirically investigated. Graphical representations of **CUSUMsq** are shown in figure1 and 2 for both models. Following Bahmani-Oskooee (2004) the null hypothesis (i.e. that the regression equation is correctly specified) cannot be rejected if the plot of these statistics remains within the critical bounds of the 5% significance level (see figure given in appendix-A). As it is clear from Fig. 1 and 2, the plots of both the **CUSUMsq** are with in the boundaries and hence these statistics confirm the stability of the long run coefficients of regressors.

4. Conclusion

The present endeavor analyzed the link between producer and consumer prices in Pakistan. For this purpose, we applied ARDL (Auto Regressive Distributive Model) and Johansson for its robustness. Time series data ranging for the period of 1992M1-2007M6 was utilized. DF-GLS and Ng-Perron tests were applied for the existence of a unit root in the level and first difference of both variables. Stationarity was found at the level ***1(1)***.

Results of particular study verified that there exists a long run relationship between producer and consumer price indices and their association is robust in long run in the case of small developing economy like Pakistan. Causal results through Toda and Yamamato's (1995) technique assert that there is two-way causality but stronger from producer to consumer prices while same by Variance Decomposition Method. Finally, Feed back impacts show that feedback influence from PPI to CPI is stronger or dominating as compared to feedback from CPI to PPI supporting "Cushing and McGarvey (1990) hypothesis".

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Notes

Note 1. On contrary, Gordon, (1988) found relationship between consumer and producer prices insignificantly

Note 2. To ascertain the goodness of fit of the ARDL model, the diagnostic and the stability tests are conducted. The diagnostic tests examine the serial correlation, functional form, normality of error term, autoregressive conditional heteroscedisticity and heteroscedisticity associated with the model. The stability test is conducted by employing the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMsq). Examining the prediction error of the model is another way of ascertaining the reliability of the ARDL model.

Note 3. Represents the significance at 1% level of significance.

Table 1. DF-GLS & Ng-Perron Unit Root Test

Variables	**DF-GLS at Level**		**DF-GLS at 1st Difference**	
PPI	-0.8473		-5.2023*	
CPI	-0.4897		-5.6994*	
Ng-Perron at Level				
Variables	MZa	MZt	MSB	MPT
CPI	-0.803	-0.528	0.658	83.347
PPI	-1.488	-0.827	0.555	57.486
Ng-Perron At 1st Difference				
CPI	-39.806*	-4.461	0.112	2.289
PPI	-23.181*	-3.388	0.146	1.111(Note 3)

Note: *Ng-Perron (2001, Table 1) & *Elliott-Rothenberg-Stock (1996, Table 1)

Table 2. Lag selection criteria

Lag order	**AIC**	**SBC**	**Log likelihood**
6	-14.322	-13.861	1315.060
7	-14.280	-13.745	1308.065
8	-14.338*	-13.7311	1310.165
9	-14.290	-13.609	1302.744

Table 3. ARDL Estimation

ARDL with Constant & Trend			
Dependent Variable	**F-Statistics**	**Wald-Statistics**	**Chi-square**
PPI	**6.623**	6.221 (**0.0025**)	12.443 (**0.0020**)
CPI	**5.294**	4.973 **(0.0081)**	9.945 **(0.0069)**
Critical Bounds	**Instability Level**	*Lower Bound*	*Upper Bound*
Pesaran, et, al (2001)	**1%**	2.79	4.10
	5%	2.22	3.39
	10%	1.95	3.06

Table 4. Johansen First Information Maximum Likelihood Test for Co-integration

Hypotheses	Likelihood ratio	5 Percent critical value	Prob-value*	Maximum Eigen values	5 Percent critical value	Prob-value**
$R = 0$	26.6131	20.2618	0.0058	19.0063	15.8921	0.0157
$R \le 1$	7.6067	9.1645	0.0979	7.6067	9.1645	0.0979

Note: * & ** shows rejection at 5 percent level & **MacKinnon-Haug-Michelis (1999) p-values.

Table 5. Regression Results

Dependent variable	**OLS Regression**		**Normalized Cointegration Coefficients (Johanson OLS)**	
	Constant	Coefficient	Constant	Coefficient
CPI	0.4275 **(22.982)**	0.9045 **(220.128)**	0.5585 **(8.698)**	0.8828 **(67.083)**
PPI	-0.3821 **(-15.228)**	1.0883 **(195.941)**	-0.6326 **(-7.812)**	1.1327 **(67.829)**

Table 6. Toda and Yamama (1995) Wald Test

Lags	**Wald Test Statistics**	**Instability Value**	**Chi-Square**	**Instability Value**
Running from PPI to CPI				
6	2.756	0.0140	16.538	0.0111
7	2.464	0.0198	17.248	0.0159
8	***2.824***	***0.0059***	***22.591***	***0.0039***
9	2.407	0.0138	21.664	0.0100
Running from CPI to PPI				
6	1.893	0.0848	11.357	0.0780
7	1.769	0.0968	12.379	0.0887
8	***2.256***	***0.0260***	***18.050***	***0.0209***
9	2.027	0.0395	18.243	0.0325

Table 7. VDC by Cholesky Ordering

Variance Decomposition of CPI

Period	**CPI**	**PPI**
1	100.000	0.000
3	97.886	2.113
5	93.353	6.646
6	90.147	9.852
9	80.003	19.996
10	76.858	23.141

Variance Decomposition of PPI

Period	**CPI**	**PPI**
1	37.568	62.432
3	25.477	74.522
5	22.364	77.635
6	22.027	77.972
9	22.191	77.808
10	22.441	77.558

Table 8. Short Run Dynamics

Dependent Variable: ΔCPI			Dependent Variable: ΔPPI	
Variables	Coefficient	T.values	Coefficient	T.values
Constant	0.0027	5.072*	0.0007	0.799
ΔCPI	-	-	0.9533	10.293*
ΔCPI_{t-1}	0.1115	1.566***	-0.2504	-2.245**
ΔPPI	0.3856	10.271*	-	-
ΔPPI_{t-1}	0.0076	0.162	0.2386	3.237*
Ecm_{t-1}	-0.0809	-4.133*	-0.0793	-2.793*
R-squared = 0.4179 F- Statistics = 32.125 (0.000) Durban Watson = 2.004			R-squared = 0.4039 F- Statistics = 30.3237(0.000) Durban Watson = 2.012	

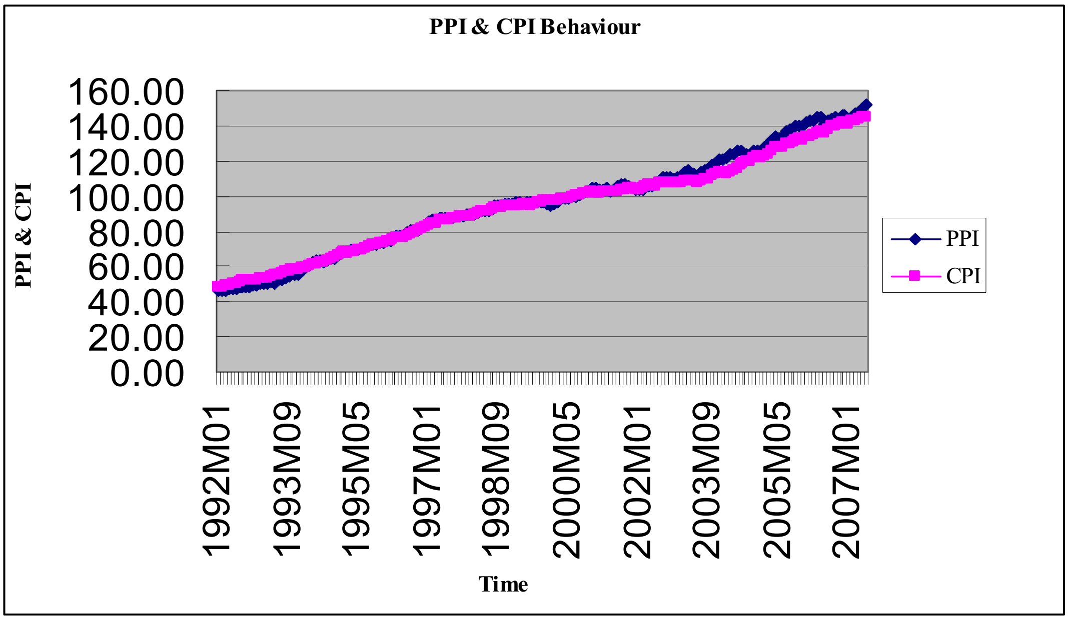

Figure 1. Behavior of Producer and Consumer price Indices in Pakistan

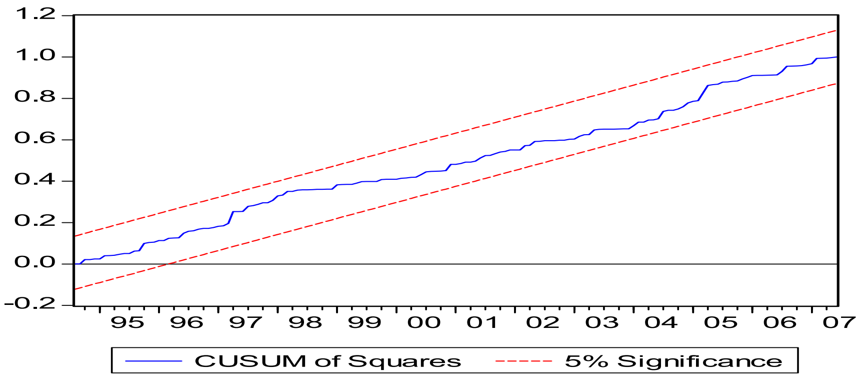

Figure 2. CPI is Dependent Variable

Plot of Cumulative Sum of Squares of Recursive Residuals

The straight lines represent critical bounds at 5% significance level.

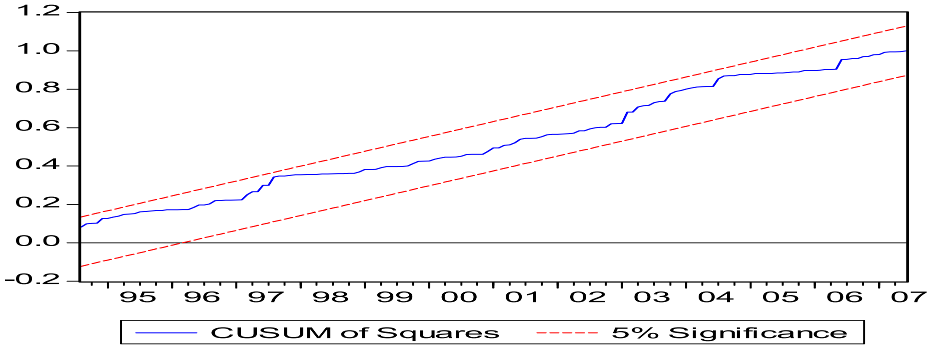

Figure 3. PPI is Dependent Variable

Plot of Cumulative Sum of Squares of Recursive Residuals

The straight lines represent critical bounds at 5% significance level.