STOCHASTIC PRODUCER PRICES AND SHOCK PERSISTENCE IN AGRICULTURE: IMPLICATIONS FOR FOOD POLICY AND PRICE INFORMATION[1]

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Abstract

Unstable product prices arising from shocks increase the uncertainties of producers and bias their subsequent price expectations and production decisions. This problem is known to be at the back of declining use of improved techniques by food crop producers. This paper investigates the time series properties of producer price data observed during the post-liberalization period for two major food crops in Ethiopia in order to understand whether prices are stochastic and shocks are persistent. The results obtained suggest non-stationary stochastic price dynamics and shock persistence in which price uncertainty is inherent, with a possible impact of negative bias in the expectation and production decisions of generally risk averting farmers. From a food policy point of view, negative bias in farmers' price expectations and production decisions, whenever prices follow a downward scenario, implies that agricultural market policy instruments meant for the promotion of food crop production might have very few chance of success unless accompanied by a strong market information service on prices. Moreover, policy interventions are recommended only to the extent that their impacts are predictable under a condition of non-stationary stochastic product prices and they do not result in negative shocks.

JEL: Q11, Q13, Q18
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1. Introduction

The premise of the agricultural market reform process in place in the developing countries since the early 1980s is that positive price signals will prompt producers to respond positively and rationally (Kherallah *et al*., 2000). Though the results are mixed, evaluation studies well addressed the impacts of the reform process in terms of market integration, price level, and supply response (e.g. Goletti and Babu, 1994; Alderman and Shively, 1996; Jayne and Jones, 1997; Badiane and Shively, 1998; Chilowa, 1998). In terms of food crop production, it has become clear from the evaluation results that the reform process had only a limited impact. Lack of market information is mentioned as one of the problems contributing to this limited success.

One of the necessary conditions for the reform process to prompt positive and rational production response in the developing countries is that producers have access to appropriate market information, including information on the true dynamics of the prices for their products. A failure could potentially lead toward bias in expectation formation and production decision. Unbiased production decision-making depends on understanding the true dynamics of prices to guide expectation formation in a way that is consistent with informationally efficient practice. The focus of the evaluation literature on market reform in the developing countries was thus far mainly on the final impacts of the reform process, leaving a knowledge gap with regard to farmers' awareness and perception of the true dynamics of prices during the liberalization period. A relevant question is therefore how smallholder farmers in the developing countries perceive the true dynamics of the prices for their products so that there is no bias in their production decisions arising from discrepancy between their expectations and the true price dynamics.

Generally, biased production decisions in association with product prices may arise from two possible sources. First, from a discrepancy between the true price dynamics and the farmers' expectation formations or, second, from expectation formation consistent to price dynamics, but with inherent bias. Therefore, as a part of the evaluation process and as information source to the process of food policy making in the developing countries, it is important to investigate what the true dynamics of product prices are and how farmers perceive and incorporate these dynamics into their price expectations and production decisions. This paper addresses the first of these issues in the context of smallholder food crop farmers in Ethiopia by investigating the true dynamics of the producer price time series of two major staples (white teff and white wheat).

Farmers are responsive to price signals (Stevens and Jabara, 1988) and, consequently, base their production decisions on price expectations. Errors from price expectations will generally be high and systematic when the expectations are uninformed (Ravallion, 1987). Therefore, taking the general lack of market information in the developing countries into consideration, it could be hypothesized that producers' price expectation formation is not rational and can be improved through providing them with appropriate market information. By doing so, producers can be led towards making informationally efficient and unbiased production decisions. This is important especially in circumstances of price volatility without any predictive structure. The idea was yet introduced by Dahl and Hammond (1977) who acknowledged that agricultural producers become able to make profitable production and marketing decisions only if they well understand the price movements for their products.

Price volatility and consequent financial risks have been reported as major obstacles for high yield input use in agricultural production (Crawford *et al*., 2003; Snapp *et al*., 2003). In a liberalized agricultural market where product prices are discovered by the market forces instead of price setting, prices become generally unpredictable and it remains uncertain for the farmers to have reliable expectations about the likely price scenarios that will turn out. Such phenomena would lead to large and systematic forecast errors and, as manifestations of biased decisions on the part of farmers, to boycotting the use of improved production techniques and, eventually, to a substantial reduction in the amount of food crop production. The latter is contrary to the food self-sufficiency and food security objectives of a typical developing country.

Ethiopia is a good example where agricultural prices are deregulated following the market liberalization policy in 1990, as a result of which food crop prices became volatile and adoption of improved agricultural technologies slowed down (ADE, 1999). The effect was devastating in the food production sub-sector of the country in 1997 and 2000 when farmers became discouraged to use improved techniques such as fertilizer for food crop production following the low level of producer prices in the previous years (e.g. DOA, 2000a; DOA, 2000b). Because they refer only to the negative past price scenarios, most smallholder farmers since then tended toward biased food crop production decisions (reduction of fertilizer use) in order to avoid risk of failure to pay fertilizer debt in case product prices remain low. This phenomenon was a major set back against maintaining the momentum of rising food crop production in the country in most of the 1990s. One of the possible explanations is probably lack of appropriate information to farmers on how prices actually behave as policy markers and public agricultural extension programs fail to design and enforce effective market information delivery in Ethiopia (Tschirley *et al*., 1995). Market information service, together with efforts aimed at raising the educational level of farmers (Knight *et al*., 2003), could make a positive contribution towards promoting farmers to adopt modern production techniques.

In the theoretical context, it has nowadays become clear that forecasts and specifications of relationships among economic variables are successful only to the extent that the time series properties of the variables under consideration are known *a priori* and can be taken into consideration for policy and business decisions. Like other areas of business forecast, it is indispensable to understand the time series properties of agricultural prices to make successful price forecasts (Jin and Frechette, 2002). An important distinction is between stationary and non-stationary stochastic time series processes. The former are processes in which basic characteristics such as the mean and variance are constant, while they are not and even difficult to calculate in the latter (Enders, 1995; Patterson, 2000). In the world of economic fluctuations (non-stationarity), expectations simply based on previously observed value lead to a systematic forecast error with the forecast results suffering from bias and loss of optimality.

Consequently, assessing the salient features of a time series is taken as a pre-requisite standard approach in recent empirical works involving economic time series. The information obtained could be applied to agricultural market analysis and, most importantly, to food policy decision-making. Policy makers can make use of such information to know how effective price stabilization interventions and other pro-agricultural production strategies would be and whether shocks from their policies or from other sources will have a transitory or permanent effect on agricultural prices. Moreover, it would be helpful to have insight into whether policy instruments meant for the promotion of food crop production should be accompanied with additional market information to avoid potential failure due to inherent bias on the part of producers about prices.

Studying agricultural prices is not a new phenomenon despite the little attention given to studying time series properties of agricultural prices (Jin and Frechette, 2002). Though there are a number of studies conducted for agricultural products using time series price data during the post-liberalization period, most of them are devoted to studying market integration, with less coverage of the time series properties of product prices to understand the true price dynamics on their own right and in association with the farmers' expectation formation. In the agricultural price literature, time series properties of product prices are addressed for other study purposes rather than to be studied and interpreted on their own as determinants of price expectations and production decisions. Because of this, it remains unclear whether farmers and policy makers always know the true dynamics of product prices and decide accordingly.

In view of these gaps, this paper tries to investigate the time series properties of the producer prices of selected food crops observed during the post-liberalization period in Ethiopia, through testing unit root hypothesis, with the aim of generating useful information on the price behaviors for expectation formation, production, and food policy decision-making purposes. Concerning the hypothesis testing, we describe in detail how the appropriate testing framework is specified and we discuss the successive steps followed to ensure robust results. Particular attention is paid to minimize the type II error, which is common in unit root tests[4].

The remaining part of the paper is organized as follows. First, a description is provided about models helpful in testing hypothesis about price dynamics, followed by the development of the empirical models and by the explanation of the data used in this study. Second, the testing strategies and the test results of the study are discussed. Finally, a conclusion is set forth in which the main results of the study and their implications are outlined.

2. Analysis of producer price dynamics

A class of univariate economic time series models is used in this study to understand the time series properties of producer prices through autoregressive representation. In a first order autoregressive process $AR(1)$, the current producer price P_t can be represented as the sum of a one period lagged value P_{t-1} and of an independent random error term ξ_t:

$$P_t = \varphi_1 P_{t-1} + \xi_t \tag{2.1}$$

where φ_1 is the lag coefficient. In an autoregressive process of order k, i.e., $AR(k)$, (2,1) can be rewritten as

$$P_t = \varphi_1 P_{t-1} + \varphi_2 P_{t-2} + ... + \varphi_k P_{t-k} + \xi_t \quad t = 1, 2, \ldots, k \tag{2.2}$$

The general first difference form of (2.2) can be specified as follows[5]:

$$\Delta P_t = \mu + \lambda P_{t-1} + \sum_{i=1}^{k} \eta_i \Delta P_{t-i} + \xi_t \tag{2.3}$$

4 In statistical inference, type II error is referred to as the failure of the test result to reject an incorrect null hypothesis. Unit root test statistics are found less powerful to reject the null hypothesis of unit root when the alternative hypothesis is nearly unit root though not exactly unit root.

5 See Appendix 1 for the derivation.

where Δ is the difference operator, μ is constant, $\lambda = (\varphi_1 + \varphi_2 + ... + \varphi_K) - 1$, and η_i are coefficients of lagged differences.

In a typical economic time series, φ_1 in (2.1) takes a theoretical value bound between 0 and 1. When φ = 1, the value of P_t becomes just identical to the lagged value P_{t-1}, with the only difference accounted for by the random error term ξ_t. In that case the time series properties of the economic variable resemble that of the random error term and magnitudes of the differences between successive prices, denoted as ΔP_t, become equal to the magnitudes of respective current random error terms, hence the series is considered as a *random walk* process. Being random, these changes are independent of each other and have zero autocorrelation. If agricultural price movements exhibit such time series properties, they might be considered as non-stationary stochastic processes. Under such circumstances neither the autoregressive process $P_{t-1} + \xi_t$ nor the random error term ξ_t in (1) provides a mechanism to speculate about future price levels (P_{t+1}) and the effect of shocks never dies out as it cumulates over time (shock persistence)6. Hence, the best estimate for the producer price at time *t* is the price at time $t-1$ and the best estimate for the producer price that will prevail at time $t+1$ is the price at time t, rather than the prices in the remote past. Literally, assessing whether producer prices follow a non-stationary stochastic process and whether there is shock persistence becomes equivalent to testing a hypothesis whether the magnitude of the lag coefficient φ in autoregressive models such as (2.1) specified for the time series under investigation is equal to or less than unity, or whether λ in (2.3), a model specified in difference forms, is equal to zero in statistical terms. The importance of these unit root tests attracted a considerable amount of empirical research to evaluate the nature of economic time series (Xiao and Phillips, 1998; Patterson, 2000; Sarris, 2000).

3. Price data and models

The analysis of the time series properties of the producer prices of the two food crops is made using real price data observed on monthly basis from 1996M1 to 2000M12. The data are obtained from the Ethiopian Grain Trading Enterprise. The sample

[6] A random walk process is a non-stationary stochastic process resulting from the accumulation of shocks. For a process started at time *t* = 0, $P_1 = P_0 + \xi_1$, and $P_2 = P_1 + \xi_2 = P_0 + \xi_1 + \xi_2$. Consequently, the current observation of P_t in a random walk process becomes $P_0 + \sum_{i=1}^{t} \xi_i$ in which the effect of each shock is accumulated.

period is chosen in such a way that it represents the post agricultural market liberalization period in Ethiopia and that availability of continuous price data and deflator indices is ensured.

First order lag models were fitted for the producer prices of each food crop in their difference forms for testing the unit root hypotheses. The Akaike Information Criterion (AIC) is used as decision criterion on lag order selection. Unrestricted versions of the inferential models are specified as follows, with a constant and with a deterministic time trend variable, in addition to the lagged prices:

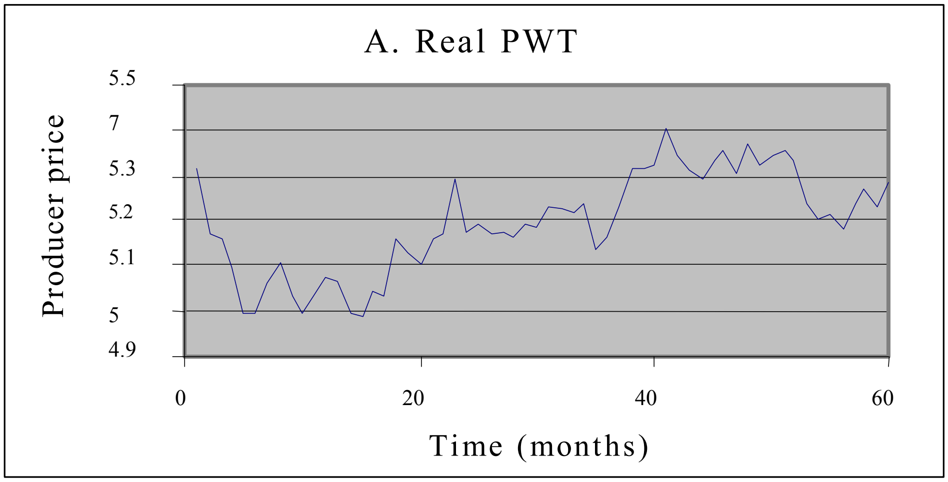
$$\Delta \ln PWT_t = \mu_1 + \lambda_1 \ln PWT_{t-1} + \eta_1 \Delta \ln PWT_{t-1} + \beta_1 T_1 + \xi_t \qquad \textbf{(3.4)}$$

$$\Delta \ln PWW_t = \mu_2 + \lambda_2 \ln PWW_{t-1} + \eta_2 \Delta \ln PWW_{t-1} + \beta_2 T_2 + \xi_t \qquad \textbf{(3.5)}$$

where PWT denotes the real producer price of white teff, PWW denotes the real producer price of white wheat, μ_1 and μ_2 are constants, λ_1, λ_2, η_1, η_2, β_1 and β_2 are coefficients, T_1 and T_2 represent deterministic time trends, and *ln* refers to natural logarithm.

The decision to include a constant and a deterministic time trend variable in each model and to hypothesize that each price series follows a non-stationary stochastic process is based on visual evidence from graphical representations of the respective time series. It can be observed from Figure 1.A that real PWT seems to have a sustained positive deterministic time trend, though not strong. On the other hand, there is a tendency for the successive values to follow the pattern of their immediate past values, which is an indicator of the presence of a unit root (stochastic trend). Slow decay in the autocorrelations of real PWT (Figure 1.B) is in support of the presence of a unit root in the series. This slow decay in the autocorrelations is an indicator of a long lasting impact of shocks on real PWT, which is a property of a series with non-stationary stochastic processes. The observation from Figure 2.A also indicates the presence of a positive, albeit weak, deterministic time trend in the real PWW. However, negatively ragged observations at the center and at the very end of the curve provide evidence for the view that the series is stochastic rather than deterministic. This is further supported by the nature of the autocorrelations observed in Figure 2.B, which decline slowly indicating presence of a unit root in the series.

Figure 1. A and B



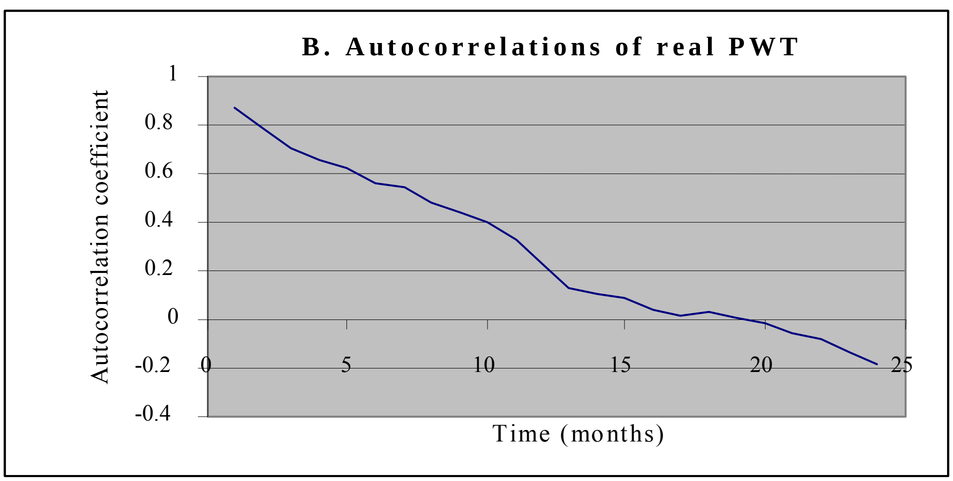
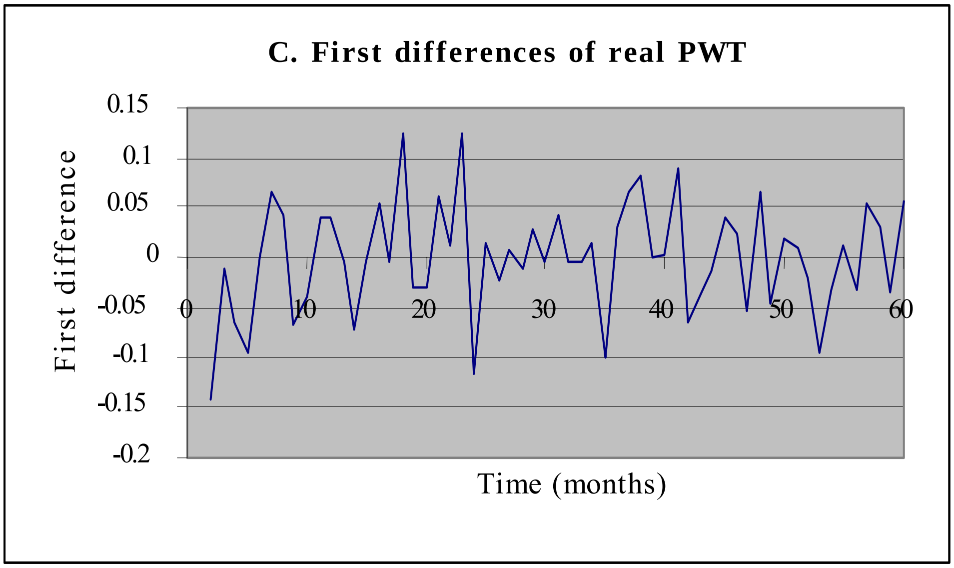


Figure 1. C and D



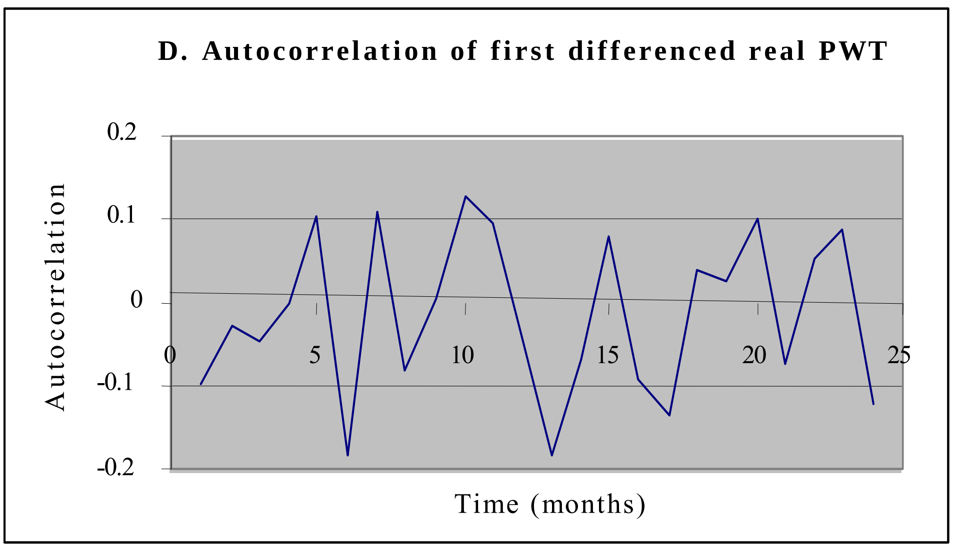
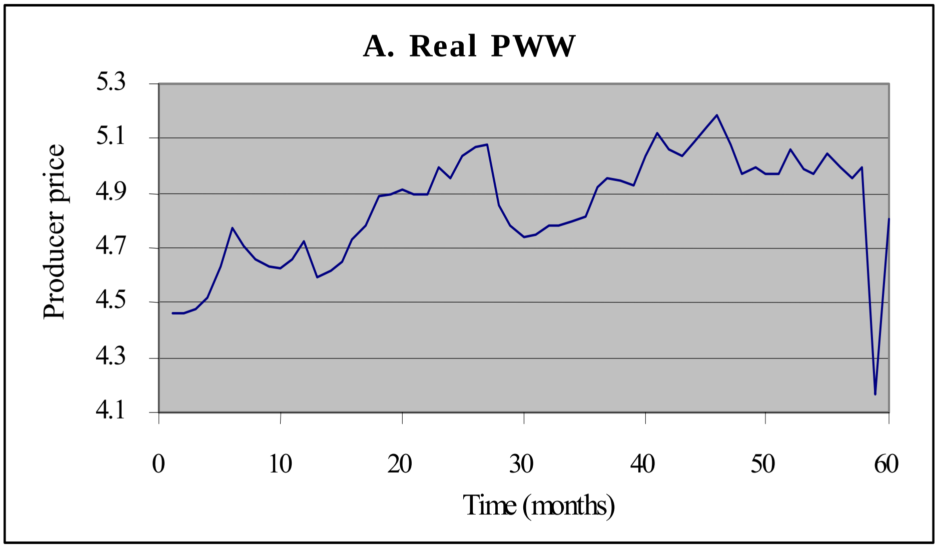


Figure 1

Real Price of White Teff (A), autocorrelations (B and D) and first differences (C) (1996M1 to 2000M12) (Figures in the graphs are natural logarithmic values)

Figure 2. A and B



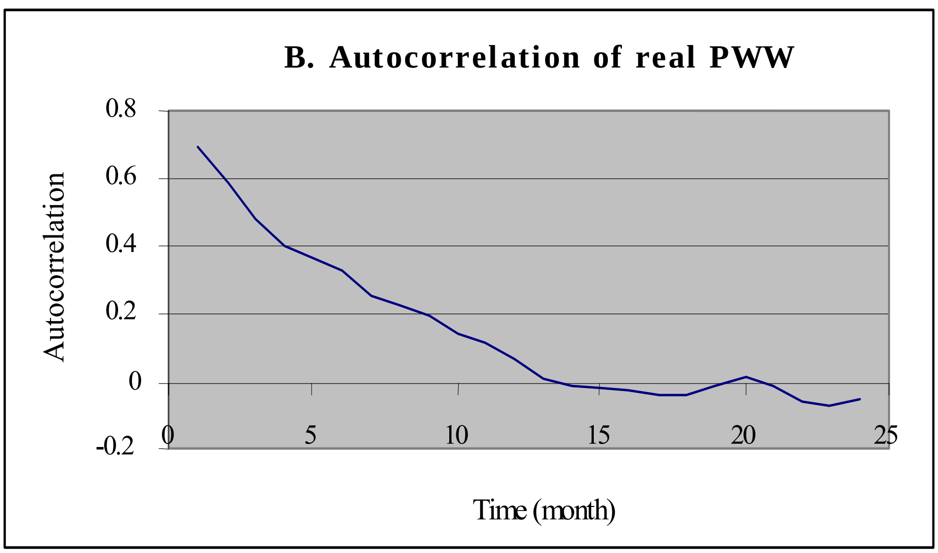
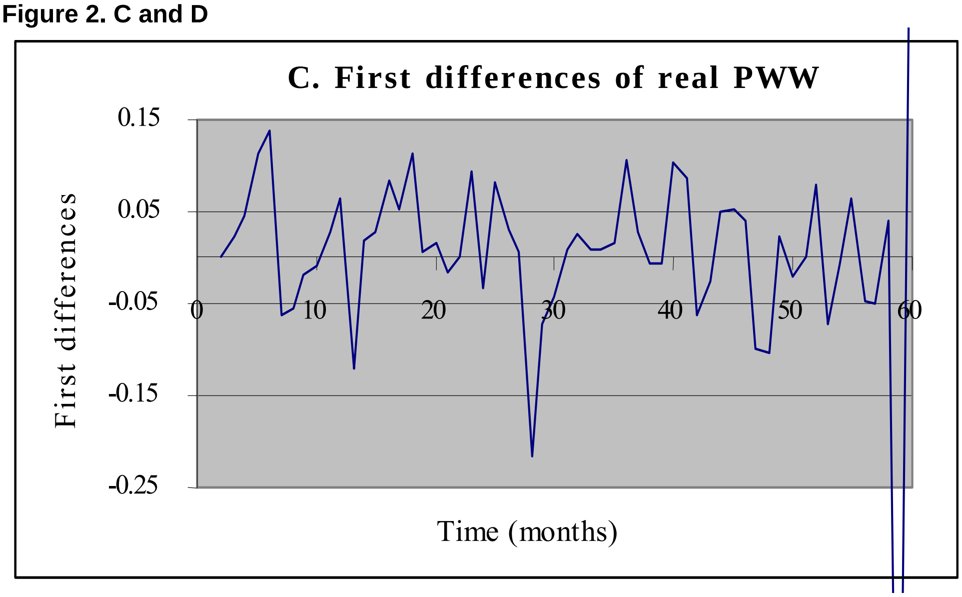


Figure 2. C and D



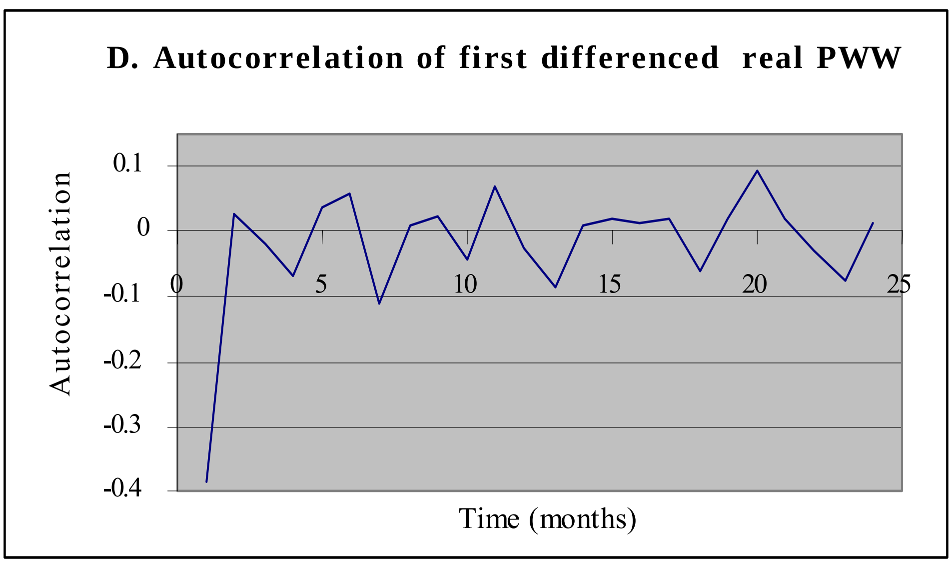


Figure 2
Real Price of White Wheat (A), autocorrelations (B and D) and first differences (C) (1996M1 to 2000M12) (Figures in the graphs are natural logarithmic values).

Generally, the visual evidence from Figure 1.A and Figure 2.A, in support of either a deterministic or a stochastic trend, is inconclusive. The respective autocorrelation figures (Figure 1.B and Figure 2.B), however, indicate presence of unit root in the series in the sense that the autocorrelations decay slowly. On the contrary, graphs for the first differences of real PWT and real PWW seem to have a zero mean, indicating absence of unit root. Relatively speaking, however, it can be seen that the curve in Figure 1.C lacks successive crossing of the expected mean value (zero), because of some positive and some negative accumulations, successively. Though this could cast a doubt about the presence of a unit root in the first differences of real PWT, fast decline in the autocorrelation coefficients of first differences of both series to magnitudes near zero even for the most recent lags (Figure 1.D and Figure 2.D) indicates that first differences do not have unit root.

As discussed above, visual impressions from the graphical representations give indications only about the dominant properties of a time series, without leading to inferential conclusions. As such, the above discussed visual impressions could not replace formal tests for a unit root since they are unable to unambiguously distinguish between near unit root and unit root processes. Formal test procedures for a unit root proceed by specifying and estimating appropriate time series models from which statistical inference is made. For this purpose, three autoregressive models are specified for each producer price series, depending on whether a constant and a deterministic time trend are included. The models are estimated from average monthly real producer price data observed for five successive years (1996M1 to 2000M12), using ordinary least squares estimation techniques. The estimated models are shown in equation (3.6) to (3.11). The marginal significance levels (msl) values show that there is no indication for serial correlation in the error terms at the conventional levels of significance; hence, the models are robust and tentatively adequate for statistical inference. Figures in parenthesis are *t*-ratios and RSS stands for the residual sum of squares. Figures in square brackets are marginal significance levels for serial correlation in the error terms.

Models with a constant and with a deterministic time trend:

$$\Delta \ln PWT_t = 1.50 - 0.30 \ln PWT_{(t-1)} - 0.03 \Delta \ln PWT_{(t-1)} + 0.002T + \xi_t \quad \text{[msl = 0.41]} \quad \textbf{(3.6)}$$

(3.11) (-3.12) (-0.02) (2.68) RSS = 0.13259

$$\Delta \ln PWW_t = 0.89 - 0.18 \ln PWW_{(t-1)} - 0.46 \Delta \ln PWW_{(t-1)} - 0.52T + \xi_t$$ [msl=0.37] **(3.7)**

(1.21) (-1.12) (-2.17) (-0.52) RSS = 0.96681

Models with a constant but without a deterministic time trend:

$$\Delta \ln PWT_t = 0.52 - 0.10 \ln PWT_{(t-1)} - 0.05 \Delta \ln PWT_{(t-1)} + \xi_t$$ [msl = 0.56] **(3.8)**

(1.57) (-1.56) (-0.49) RSS = 0.15023

$$\Delta \ln PWW_t = 1.05 - 0.21 \ln PWW_{(t-1)} - 0.42 \Delta \ln PWW_{(t-1)} + \xi_t$$ [msl = 0.37] **(3.9)**

(2.22) (-2.21) (-2.74) RSS = 0.96832

Models without a constant and without a deterministic time trend:

$$\Delta \ln PWT_t = 0.32 \ln PWT_{(t-1)} - 0.10 \Delta \ln PWT_{(t-1)} + \xi_t$$ [msl=0.51] **(3.10)**

(0.24) (-0.78) RSS = 0.15692

$$\Delta \ln PWW_t = 0.36 \ln PWW_{(t-1)} - 0.56 \Delta \ln PWW_{(t-1)} + \xi_t$$ [msl = 0.46] **(3.11)**

(0.10) (-0.34) RSS = 1.0547

4. Testing strategy

For the unit root hypothesis testing, we used a stepwise movement from the most unrestricted versions of the models to the restricted ones. The test statistics used are the augmented Dickey-Fuller unit root test statistics (Dickey and Fuller, 1981), as these are the most commonly used in empirical work (Xiao and Phillips, 1998; Patterson, 2000; Sarris, 2000).

The standard procedure for a unit root test in empirical economic analysis is to start with the most unrestricted model, i.e., the model with a constant and with a deterministic time trend (if the nature of the time series suggests so). Figure 1.A and Figure 2.A indicate presence of a sustained positive deterministic time trend in each of the price series, though not strong. Based on this observation we started our test using the strategy that tests for the null hypothesis of a stochastic trend $(\lambda = 0)$ against the alternative hypothesis of a deterministic time trend $(\beta \neq 0)$ in the unrestricted model of each price series. The constant term is not restricted while testing this hypothesis because it should be there for the trend to be sustained in the direction of the sign of the constant. Therefore, a joint null hypothesis is formulated to test only for ($\lambda = \beta = 0$) against the alternative (λ and/or $\beta \neq 0$) in (3.6) for real PWT and in (3.7) for real PWW. The null hypothesis is that of a stochastic process with a constant and without a deterministic time trend. The alternative hypothesis can take different forms provided that the null hypothesis is rejected.

At this step of the test procedure we made sure that both the null and the alternative hypotheses are nested in the estimated models (3.6) to (3.9). The joint null hypothesis of a stochastic process ($\lambda = \beta = 0$) in real PWT is nested by (3.6) and the alternative by (3.8). Accordingly, the null hypothesis claims that (3.6) generates producer prices of white teff while the alternative claims that (3.8) generates them. The joint null hypothesis of a stochastic process ($\lambda = \beta = 0$) in real PWW is nested by (3.7) and the alternative by (3.9). The null hypothesis here claims that (3.7) generates producer prices of white wheat and the alternative claims that it is (3.9) that generates producer prices of white wheat. The type of test statistic used to test the above null hypothesis, in each series, is Φ_3, which is a type of F-statistic[7].

Table 1: Autoregressive models, hypotheses, and associated test statistics for unit root test

Model type	Null hypothesis	Alternative hypothesis	Test statistic: Type	Test statistic: Calculated value
$\begin{bmatrix} \Delta P_t = \mu + \lambda P_{t-1} + \eta \Delta P_{t-1} + \\ \beta T + \xi_t \end{bmatrix}$	$\lambda = 0$, $\beta = 0$ Stochastic process without a deterministic time trend.	$\lambda \neq 0$ and/or $\beta \neq 0$	Φ_3	4.95[f] 2.45[w]
	To confirm the test result (i.e., whether the null is truly rejected by Φ_3), test directly for a unit root ($\lambda = 0$ as a null).	$\lambda < 0$	$\hat{\tau}_{\beta}$	-3.12[f] -1.11[w]
$\Delta P_t = \mu + \lambda P_{t-1} + \eta \Delta P_{t-1} + \xi_t$	$\mu = 0$, $\lambda = 0$ Stochastic process without a constant.	$\mu \neq 0$ and/or $\lambda \neq 0$	Φ_1	2.45[f] 4.91[w]
	To confirm the test result (i.e., whether the null is truly rejected by Φ_1), test directly for a unit root ($\lambda = 0$ as a null).	$\lambda < 0$	$\hat{\tau}_{\mu}$	-1.56[f] -2.21[w]

3 $\Phi_i = [(RRSS - URSS)/r] / [(URSS/T-K)]$, where *RRSS* = Restricted Residual Sum of Squares, *URSS* = Unrestricted Residual Sum of Squares, *r* = number of parametric restrictions, *T* = number of observations used in estimation, and *K* = number of parameters in the unrestricted model.

$\Delta P_t = \lambda P_{t-1} + \eta \Delta P_{t-1} + \xi_t$	$\lambda = 0$	$\lambda < 0$	$\hat{\tau}$	0.24^{f} 0.10^{w}

Note: *f* stands for the values calculated on real producer prices of white teff and *w* stands for the values calculated on real producer prices of white wheat.

5. Results and discussion

The calculated value of Φ_3 is 4.95 for real PWT and 2.45 for real PWW. These values are compared with the Dickey-Fuller (1981) critical values (6.78 and 9.84) at 5% and 1% significance levels, respectively, for a sample size of 50 (the nearest entry to our sample size of 60). Since the calculated values are below the critical values, the null hypothesis of a stochastic process with a constant and without a deterministic time trend is not rejected for real PWT and real PWW.

While this result could lead us to conclude that the two series are consistent with stochastic processes, two facts make it necessary to further proceed with the test in search of further evidence to support the result. One is that the Φ_3 test has a two-sided alternative hypothesis, hence loss of power against the likely departure of the alternative hypothesis from the null. Therefore, it is necessary to use a test statistic with a one-sided alternative hypothesis, in order to seek additional confirmation about the reliability of the results from the Φ_3 test. The other fact is that generally unit root tests in unrestricted models are weak against the alternative hypothesis, possibly because of the inclusion of unnecessary regressors such as a constant and a deterministic time trend. To minimize the chance of type II errors from the Φ_3 test results, we used a test statistic τ_β that tests for a single null hypothesis of a unit root ($\lambda = 0$) against a one-sided alternative hypothesis of a deterministic process ($\lambda < 0$). This test is conducted directly in (3.6) for real PWT and in (3.7) for real PWW. The calculated τ_β test statistic is -3.12 for real PWT and -1.11 for real PWW. These calculated values for the τ_β test statistic are compared with the critical values (-3.49 and -4.14) at 5% and 1% significance levels, respectively, for a sample size of 50. Because the calculated values of τ_β test statistic are lower in absolute value than the critical values, the null hypothesis of a unit root is not rejected for both series. This result gives an additional confirmation to the Φ_3 test result.

To see whether the failure of the first test (Φ_3 test) to reject the null hypothesis of a unit root is because of inclusion of unnecessary deterministic regressors (i.e., deterministic time trend variable), we re-estimated (3.6) and (3.7) without a deterministic time trend variable as a regressor and obtained (3.8) and (3.9), respectively. The necessity of exclusion of the deterministic time trend variables from the models is also suggested by the fact that the hypothesis ($\beta = 0$) in the joint null of the Φ_3 tests is not rejected. Model (3.8) and model (3.9), specified with a constant but without a time trend variable, are then used to test for a unit root with the joint null hypothesis ($\mu = \lambda = 0$) using the Φ_1 test statistic. This null is adopted in order to see whether the role of the constant term μ is significant in the series. The calculated values of Φ_1 are 2.45 for real PWT and 4.91 for real PWW. These values are compared with the critical values (4.81 and 6.96) at the 5% and 1% significance levels, respectively, for a sample size of 50. While the calculated Φ_1 statistic for real PWW is insignificant only at the 1% significance level, it is insignificant both at the 5% and 1% significance level for real PWT. Hence, the major evidence from the Φ_1 test leads to non-rejection of the null hypothesis of a unit root without a constant for each price series. According to this null hypothesis, each price series is generated by a non-stationary stochastic process without a constant. The finding that the processes are stochastic and have no constant implies that it is equally likely for each of the two series to move downward from the current direction that seems moving upward, as depicted in Figure 1.A and 2.A. This is because there is no minimum (constant) price level that regulates the series from moving into one or the other direction.

For the same reason that the Φ_1 test looses power against the alternative hypothesis (because it has a two-sided alternative), a test statistic τ_μ with a one-sided alternative hypothesis is applied. This test statistic tests directly for a unit root in the models with a constant but without a deterministic time trend ((3.8) and (3.9)). The null hypothesis under this test statistic is of a unit root ($\lambda = 0$) against the alternative hypothesis of a deterministic series ($\lambda < 0$). The calculated values of τ_μ are -1.56 for real PWT and -2.21 for real PWW. When compared with the critical values (-2.92 and -3.57) at the 5% and 1% significance levels, respectively, for a sample size of 50 observations, these values are lower in absolute value and lead to non-rejection of the null hypothesis that each series is consistent with a stochastic process without a constant.

These findings in favor of the null hypotheses under the Φ_1 and τ_μ tests bring the test sequence to its end. However, to see whether the constant term (as unnecessarily included regressor) might have minimized the power of Φ_1 and τ_μ

tests, and because the exclusion of the constant μ is not rejected in the joint null hypothesis ($\mu = \lambda = 0$) under the Φ_1 test, (3.10) and (3.11) are estimated without a constant and without a deterministic time trend. These models could be used to test for the null hypothesis of a unit root ($\lambda = 0$) using the τ test statistic. However, the alternative hypothesis of this null is a deterministic series with zero mean, which does not represent the characteristics of the two price series as there could be no zero mean for producer prices. Therefore, this test is not proceeded with and the entire test procedure ends here with the main finding that each of the two price series follows a non-stationary stochastic process8. According to the test results, (3.10) and (3.11) are the appropriate models for real PWT and real PWW , respectively. These models without a constant and without a deterministic time trend are chosen as suggested by the non-rejection of the null hypotheses under Φ_3 and Φ_1 tests in that the Φ_3 test results suggest exclusion of the deterministic time trend term and the Φ_1 test results suggest exclusion of the constant term.

6. Conclusions and implications

Occasionally low and unstable producer prices increase farmers' uncertainties. Through biasing farmers' expectations and production decisions, such phenomena are known to be at the back of the declining use of improved techniques for food crop production in Ethiopia in recent years. Price expectations based only on the past price scenarios of a series lead to biased and non-optimal production decisions. If producers are preoccupied with occasionally low prices observed in the past, their successive production decisions are at risk of being unnecessarily adaptive to these price signals, with negative consequences on the food self-sufficiency and food security status of the farm households and the country.

This study tried to investigate the true price dynamics of two staples in Ethiopia in order to know if actual price behaviors could explain the declining use of improved production techniques for food crop production in the smallholder agriculture of Ethiopia. This is approached in terms of testing unit root hypotheses for producer price data observed from 1996M1 to 2000M12. Different univariate autoregressive models were specified and estimated for each price time series depending on

8 Each producer price series is also tested for a possible single structural break due to the Ethio-Eritrea border conflict during the sample period (T_b = May 1998), using the Innovative Outlier Augmented Dickey-Fuller (IOADF) test of Perron (1989). The test results for each series do not reject the null hypothesis of unit root against the alternative of trend stationary series with a single structural break. The $\tilde{\tau}_A$ statistics for producer price of white teff and white wheat are -3.26 and 0.91, respectively, while the critical values are -3.76 at the 5% and -3.46 at 10% significance level for $\lambda =$ 0.50.

whether or not a constant and a deterministic time trend are included. Consistency of the results from these different tests, in the direction of the null hypotheses of a unit root, reinforced the prior impression from the visual evidences that the two series are consistent with non-stationary stochastic processes. This view was typically evident from the slow decays in the autocorrelations of levels (Figure 1.B and Figure 2.B) and from the frequent crossings of the autocorrelations of differences on the zero mean (Figure 1.D and Figure 2.D).

When product prices follow a non-stationary stochastic process, it is most likely that the direction of their movement through time persists, yet with variations due to unpredictable random factors. As a consequence of such unpredictable random factors in such series, the best expectation farmers could have about the future price level is the immediate past price level. This is because, through exhibiting a random walk behavior, the price level is known to have a high probability of persistence in a particular direction. Hence, farmers tend to adapt their price expectations to the immediate past price levels, the scenario which they know to persist and are able to predict. Nevertheless, the resulting production decisions that depend only on the past price levels are most likely to be biased and not fully informed for they lack information on the current and future phenomena (informationally inefficient practice). In this regard, the results show the need for market information provision to farmers if the policies meant for increasing food production are to be successful. This is because the bias from the stochastic properties of their prices could cause the farmers to overlook the importance of incorporating recent developments and information in their production decisions. Partly, farmers may opt for adaptive choices in making production decisions simply because they lack appropriate information about the recent and prospective market situations to make rational instead of adaptive choices. Therefore, we suggest government commitment to provide timely information on the price movements and other market phenomena like weather and the evolution of input prices that are known to influence producer prices. By doing so, it is possible to help farmers making optimal and informationally efficient production decisions that incorporate the past, current, and future market outlook.

The finding of a non-stationary stochastic process in producer prices provides useful information that needs to be considered in making production and policy decisions. First, the stochastic behavior of producer prices implies that the seemingly increasing tendencies in the prices have random behavior, with the possibility of direction reversal at any time. This suggests that the sequential changes (positive or negative) are not with fixed but random magnitude and direction, though the chance to persist in the particular direction is high. As a result, there is the problem of price unpredictability based on previous observations. In their autoregressive form, (10) and (11) allow back reference that is limited only to the prices of the last two months.

This very limited predictive structure informs that the occasionally low prices like those that occurred in 1997 and 2000 should not influence farmers' production decisions without time limit. Instead, given appropriate market information, the only best estimate of a future price level of each food crop is the price level prevailing during the time of such decision-making. After all, considerable advantages could have been taken from the rising moments of producer prices during most of the periods from 1996M1 to 2000M12 as seen from Figure 1.A and 2.A had the bias and reference of farmers back to the preceding few bad price scenarios been avoided. It is difficult to know the movement of each price series *a priori* and to extrapolate them into the future. As such, decision-making based on the bad experience of the situation of 1997 and 2000 and derailing from optimal investment in crop production are irrational. This is evident from the experiences that farmers faced since the harvesting season of the 2005/2006 production year during which food crop prices spike and persist at historically high levels.

Second, for agricultural and food policy makers the results from this study inform that particular events of price increase or decrease should not be regarded as bases for a long-term policy and strategy making purpose, such as for devising long-term price stabilization intervention schemes. This is because such price phenomena are subject to stochastic processes to be firmly relied upon. Instead, we suggest an approach that is responsive to price shocks only when deemed necessary.

Third, the finding of a stochastic process is also an indicator of persistence of price shocks unless offset by another counteractive phenomenon. Price movements due to shocks are sustained in the direction of the departure from the long-run average, with no tendency to return to their previous level in the near future (for example, the positive price trend since the harvest period of the 2005/2006 production year). As these shocks may also arise from economic policies that are not intentionally directed to prices, but with implications on prices, policy makers should assess their policy decisions *ex-ante* in a far-sighted and wider perspective. In this regard the result obtained corroborates that of Dercon (2004) that concludes about the persistent effect of shock factors such as rainfall and famine in Ethiopia.

References

ADE (Aide a la Decision Economique) (1999). *An Analysis of Grain Market Integration in Ethiopia*. Louvain-la-Neuve, Belgium.

Alderman, H. and Shively, G. (1996). Economic reform and food prices: Evidence from markets in Ghana. *World Development* (24), 521-534.

Badiane, O. and Shively, G. E. (1998). Spatial Integration, Transport Costs, and the Response of Local Prices to Policy Changes in Ghana. *Journal of Development Economics* (56), 411-431.

Crawford, E., Kelly, V., Jayne, T. S. and Howard, J. (2003). Input use and market development in Sub-Saharan Africa: an overview. *Food Policy* (28), 277-292.

Dahl, D. C. and Hammond, J. W. (1977). *Market and Policy Analysis: The Agricultural Industries*. McGraw-Hill, Inc., USA.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia, *Journal of Development Economics* (74), 309-329.

Dickey, D. A. and Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica* (49), 1057-1072.

DoA (Department of Agriculture) (2000a). First Quarter Performance Report. Department of Agriculture, West Shoa Zone, Ambo, Ethiopia.

______. (2000b). Second Quarter Performance Report. Department of Agriculture, West Shoa Zone, Ambo, Ethiopia.

Enders, W. (1995). *Applied Econometric Time Series*. John Wiley & Sons, Inc., USA.

Fuller, W. A. (1976). *Introduction to Statistical Time Series*, John Wiley, New York.

Goletti, F. and Babu, S. (1994). Market liberalization and integration of maize markets in Malawi. *Agricultural Economics* (11), 311-324.

Jayne, T. S. and Jones, S. (1997). Food marketing and pricing policy in Eastern and Southern Africa: a survey. *World Development* (25), 1505-1527.

Jin, H. J. and Frechette, D. L. (2002). Forecasting Agricultural Cash Price Movements in the Presence of Long-Term Memory.

(http://www.lucid.aers.psu.edu/Frechette/Working/FracCash).

Kherallah, M., Delgado, C., Gabre-Madhin, E., Minton, N. and Johnson, M. (2000). *Agricultural Market Reforms in Sub-Saharan Africa: A Survey of Research Findings*. Revised Draft, IFPRI, Washington, D.C.

Knight, J., Weir, S. and Woldehanna, T. (2003). The role of education in facilitating risk-taking and innovation in agriculture. *The Journal of Development Studies* (39), 1-22.

Patterson, K. (2000). *An Introduction to Applied Econometrics: a time series approach*. Palgrave, New York.

Perron, P. P. (1989). The Great Crash, the Oil Price Shock and the Unit Root Hypothesis. *Econometrica* (57), 1361-1401.

Ravallion, M. (1987). *Markets and Famines*. Oxford University Press, New York.

Sarris, A. H. (2000). Has world cereal market instability increased? *Food Policy* (25), 337-350.

Snapp, S. S., Blackie, M. J. and Donovan, C. (2003). Realigning research and extension to focus on farmers' constraints and opportunities. *Food Policy* (28), 349-363.

Stevens, R. D. and Jabara, C. L. (1988). *Agricultural Development Principles: Economic Theory* *and Empirical Evidence*. The John Hopkins University Press, Baltimore.

Tschirley, D., Diskin, P., Daniel, M. and Clay, D. (1995). Improving Information and Performance in Grain Marketing: An Assessment of Current Market Information Systems, and Recommendations for Developing Public Grain MIS. Food Security Research Project, Working Paper No. 1, Addis Ababa, Ethiopia.

Xiao, Z., and Phillips, C. B. P. (1998). An ADF coefficient test for a unit root in ARMA models of unknown order with empirical applications to the US economy. *Econometrics Journal* (1), 27-43.

Appendix 1: Derivation of augmented Dickey-Fuller model

According to Fuller (1976), a second order autoregressive process such as $P_t = \mu + \varphi_1 P_{t-1} + \varphi_2 P_{t-2} + \xi_t$ can also be written as

$$P_t = \mu + (\varphi_1 + \varphi 2)P_{t-1} - (\varphi_2)(P_{t-1} - P_{t-2}) + \xi_t \qquad (1.1)$$

By subtracting P_{t-1} from both sides, the autoregressive process in (1.1) can be specified in a first difference form as follows:

$$\Delta P_t = \mu + \lambda P_{t-1} + \eta_1 \Delta P_{t-1} + \xi_t \qquad (1.2)$$

where $\lambda = (\varphi_1 + \varphi_2)$ and $\eta_1 = -\varphi_2$. Accordingly, the general first difference form for a *k* order autoregressive process takes the form of

$$\Delta P_t = \mu + \lambda P_{t-1} + \sum_{i=1}^{k} \eta_i \Delta P_{t-i} + \xi_t \qquad (1.3)$$

where Δ is the difference operator, $\lambda = (\varphi_1 + \varphi_2 + ... + \varphi_K) - 1$, η_i are coefficients of lagged differences $(\eta_1 = -(\varphi_2 + \varphi_3 + ... + \varphi_k)$, $\eta_2 = -(\varphi_3 + ... + \varphi_k)$, …, and $\eta_{k-1} = -(\varphi_k))$.