Estimation of the aggregate agricultural supply response in Zimbabwe: The ARDL approach to cointegration

Edwin Muchapondwa[1]

Working Paper Number 90

[1] School of Economics, University of Cape Town

Estimation of the aggregate agricultural supply response in Zimbabwe: The ARDL approach to cointegration

Edwin Muchapondwa*

August 20, 2008

Abstract

This paper uses relatively recent time series techniques on data spanning over different pricing regimes to estimate the aggregate agricultural supply response to price and non-price factors in Zimbabwe. The ARDL approach to cointegration employed here gives consistent estimates of supply response in the presence of regressor endogeneity and also permits the estimation of distinct estimates of both long-run and short-run elasticities when variables are not integrated of the same order. The results confirm that agricultural prices in Zimbabwe are endogenous and the variables are not integrated of the same order hence use of the ARDL was worthwhile. The paper finds a long-run price elasticity of 0.18 confirming findings in the literature that aggregate agricultural supply response to price is inelastic. This result means that the agricultural price policy is rather a blunt instrument for effecting growth in aggregate agricultural supply. The provision of non-price incentives must play a key role in reviving the agricultural sector in Zimbabwe.

KEYWORDS: Aggregate agricultural supply response, ARDL approach to cointegration

1 Introduction

This paper seeks to provide empirical evidence on the supply responsiveness of Zimbabwe's agricultural sector from the econometric estimation of supply elasticities with respect to price and non-price factors. Estimates of supply responsiveness are useful guides to economic policy formulation especially in light of the astonishing collapse of the Zimbabwean economy after a controversial land reform. Traditionally, agriculture has been the second largest contributor to Gross Domestic Product, the largest employer of labour, the largest contributor to export earnings, a significant source of raw materials for the manufacturing sector and supplier of the nation's food requirements. Clearly, the agricultural sector is still of great importance to Zimbabwe and knowledge of its supply responsiveness may assist policy makers to utilise the sector to spearhead external and internal adjustment processes. In fact, any hopes to revive the economy will necessarily have to include strategies focused on the agricultural sector. If agriculture is highly responsive, then policy reform induced changes in relative prices could bring about increased exports to restore external balance. Also, agricultural response in the form of increased food production could assist in moderating inflation and thus contribute to the process of internal adjustment.

However, use of agricultural policy instruments to affect agricultural activity without empirical knowledge of the structural parameters of supply, leaves the possibility that the policy instruments may be inappropriately used and thus getting unintended results (Mumbengegwi 1990). There is a need to know the exact responses of agricultural supply if an effective overall agricultural policy is to be implemented. Thus this study is necessary in that it would assist policy makers to identify

*School of Economics, University of Cape Town

the key variables which are important in determining agricultural supply. Policies would then be formulated on the basis of empirical evidence on the significant variables. Once the quantitative impacts of the policy variables are established they can be used to achieve the desired objectives.

2 Statement of the problem

In Zimbabwe several constraints have been identified as hindering agricultural growth. These constraints include the land policy, the agricultural pricing policy, the trade and exchange rate policies and technology. At the same time that these constraints have been observed, the agricultural sector has never been able to maintain its position as the major contributor to the GDP. In 1999 the agricultural sector contributed 27.5 percent of GDP and this has been declining since 2000 (FAO 2006). Various other agricultural performance indicators provide further evidence of the relative deterioration of the agricultural sector since the start of the current millennium. For instance, the total agricultural production per capita has been declining as shown in the figure below.

The food production per capita index has also been falling particularly since 2000. This partly explains the rampant food shortages that Zimbabwe has witnessed, with consequent increases in domestic food prices and dramatic increases in agricultural imports which have been observed in the current millennium.

Controlling for the effects of the land policy, the pricing policy is at the heart of Zimbabwe's agricultural activity stagnation in terms of output. There has been a reduction in the real producer prices, which reduced farm profits and contributed to a reduction in the area planted for some crops. Thus, all things equal, failure to provide incentive prices constrains agricultural growth. In the hyperinflationary Zimbabwe, the officially controlled consumer prices have kept farm producer prices very low relative to inflation.

The factors affecting the agricultural sector thus also contributed to the poor performance of the national economy given that the national economy has traditionally heavily depended on agricultural growth and export earnings. For growth of the national economy, the agricultural sector should provide a surplus over and above the needs of the agricultural population. So agricultural activity should be stimulated to increase the purchasing power of farmers and hence the domestic market for non-agricultural products in the rural sector; to increase food supplies and agricultural raw materials; to facilitate transfers of labour and other resources from agriculture for industrial development; and to increase foreign exchange earnings from agricultural exports.

The contribution which the agricultural sector can make in these areas will depend on the responsiveness of domestic agricultural production to economic incentives and to price signals in particular. Any meaningful attempt to reform the structure of incentives provided by the land policy, the agricultural pricing policy, the trade and exchange rate policies in favour of the agricultural sector, and hence the national economy, would require a detailed knowledge of the supply response parameters of the agricultural sector, *inter alia*. The provision of these supply response estimates in order to create a basis for further policy reforms is the main motive of this study.

3 Methodological Framework

The modelling of the aggregate supply response has its foundations in the theory of the firm. Since our interest is just on the output supply function, and not on input demand functions, we will use the commonly used approach of expressing the firm's problem in an output perspective. Such an approach assumes that optimisation has already been achieved in the input space and that the firm uses the least cost combinations for the production of any output level. This least cost approach is conceptually plausible because producers would just want to produce a given output with the minimum cost outlay rather than try to directly optimise in the input space by equating marginal factor productivity to marginal factor cost. Producers are only aware of the costs they pay for inputs and do not generally have an idea of the input marginal productivities.

A profit maximizing firm produces output up to the point where it equates marginal revenue to its marginal cost. When producers are price takers, as the general case for farmers, profit maximisation behaviour equates the marginal cost to price. As such, the firm's supply function is simply its marginal cost function. The supply function is defined only in the range where price is greater or equal to the minimum of the average variable cost. So the quantity of a product produced and supplied depends on its own price, the prices of substitute and complementary products, and the prices of inputs. Supply can thus be expressed as the inverse of the marginal cost function and is increasing in the market price – the fundamental result from the theory of the firm is that price is the most important determinant of supply.

The analysis underlying the theory of the firm assumes instantaneous response between inputs and outputs, which is not applicable for agriculture. Firstly, the agricultural sector is characterised by biological lags between input application and output production. Secondly, for the agricultural firm the technical rules implied by the production function may actually change during the course of the production process. Thirdly, for agricultural firms, there exist technological and institutional factors which prevent intended production decisions from being fully realised during any one period. Fourthly, the assumption of perfect knowledge and foresight is not valid for the majority of agricultural firms – the agricultural sector is characterised by high imperfections in price and other information. Finally, the risk and uncertainty faced by agricultural firms is much higher than that faced by other standard firms – as a result the production behaviour of agricultural firms might be expected to divert from what the theory of the firm stipulates. For example, as a result of the presence of risk and uncertainty farmers might not have the profit maximisation goal but rather they might seek to minimise risks and maintain food security. Modifications and extensions to the theory of the firm would thus be needed to capture the realistic production processes of the agricultural firms, in any attempt to model aggregate agricultural supply response.

All the above problems have been dealt with in the literature in a number of ways. The generic solution for these problems has been the use of dynamic models in modelling aggregate agricultural supply response.

Most empirical estimations of agricultural supply response are based on the Nerlove (1958) model which captures the dynamics of agriculture by incorporating price expectations and/or adjustment costs. This model can be extended to include other expectational variables other than price to capture imperfect information on these variables. In the Nerlove price expectations model, the desired output X_t^* is a function of price expectations P_t^e so that the supply function can be represented as

$$X_t^* = a + bP_t^e \tag{1}$$

where b is the long-run elasticity of output with respect to price. Assuming that price expectations are adaptive then

$$P_t^e - P_{t-1}^e = \delta(P_{t-1} - P_{t-1}^e) \tag{2}$$

where $P_{t-1}$is the price in period $t-1$. Also assuming that $X_t^* = X_t$i.e. desired output is equal to realized output X_t in equilibrium and substituting for $X_t^*$and P_t^e from equation (2) into equation (1) gives (for manipulations, see Lim 1975 for example)

$$X_t = a\delta + b\delta P_{t-1} + (1-\delta)X_{t-1} \tag{3}$$

This implies that output supplied can be expressed as a function of its own lagged value and price as in equation (3) with the short-run elasticity $b\delta$.

Alternatively, the supply function can be derived from the partial adjustment perspective i.e. that the actual change in output in one period is a fraction α (such that $0 < \alpha < 1$) of the change required to achieve the desired output X_t^*. Thus

$$X_t = \alpha X_t^* + (1-\alpha)X_{t-1} \tag{4}$$

Assuming that $P_t^e = P_{t-1}$ and substituting equation (4) into equation (1) gives

$$X_t = a\alpha + b\alpha P_{t-1} + (1-\alpha)X_{t-1} \tag{5}$$

Thus the output supplied is expressed as a function of its lagged value and the lagged price just like in equation (3).

From both equations (3) and (5), the reduced form of the supply function in the Nerlove model is

$$X_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 X_{t-1} \tag{6}$$

As mentioned earlier, most empirical estimates have been based on the Nerlove model. Since only the actual output rather than the optimal output is observed in reality, only the reduced form equation (6) or its variation can be estimated. However, McKay *et al.* (1999) point out that estimating equation (6) makes it difficult to distinguish between δ and α when both adaptive expectations and partial adjustment are present. This implies that the long-run price elasticity cannot be estimated based on the Nerlove model unless assumptions are made on whether the model is a partial adjustment or price expectations model. Therefore, certain arbitrary restrictions often have to be made. Furthermore, the simple adjustment mechanism can be derived from the minimization of a single period quadratic loss function with static expectations. This assumes no forward looking behaviour by agriculture producers. In any case, output adjustment to annual price fluctuations is likely to be small since a strong response may come only if price changes are deemed permanent. Thus the Nerlove model is unlikely to capture the full dynamics of agricultural supply hence biasing the elasticity estimates downwards (Thiele, 2000).

An alternative to the Nerlove model will be needed. Indeed, a lot of work has been done on estimating the supply response of agriculture with the general finding that its response is inelastic (Bond 1983, Chibber 1989, McKay *et al.* 1999).

However, there has been controversy as to whether aggregate agricultural supply is really not responsive. Schiff and Montenegro (1997), argued that aggregate agricultural supply response to prices is in fact high but that there are other constraints such as financing that hinder this response such that a low elasticity is found. Other writers also assert that aggregate agricultural supply is highly responsive but that low elasticities have been observed because of factor prices adjusting in parallel to output prices. A lot of methodological questions have been raised on the previously used models and the estimation techniques applied. These questions range from the reliability of the estimates for forecasting supply response to the validity of the estimates. For instance, the major criticism of time series estimates of aggregate agricultural supply response has been that estimates are drawn for a given price regime hence they mainly reflect short run variations in prices. Given that agriculture heavily relies on a fixed input, land, it is unlikely that aggregate agricultural supply will respond to short run fluctuations hence time series estimates are biased downwards.

In response to these criticisms we note that for our study, we are not likely to have the financial-constraint-based criticism given the huge financial support that the Agricultural Financing Corporation of Zimbabwe extended to smallholder farmers (Muir-Leresche and Muchopa 2006) and that which the financial sector extended to the commercial farmers. With respect to the argument of input prices adjusting in parallel to output prices, indeed, the data for Zimbabwe shows that domestic fertilizer prices were below their import parity during the periods of agricultural price controls. Inclusion of input consumption in the estimated supply equation should isolate this bias. As for the time series nature of our study, we will use data which spans over different pricing regimes thereby lending credence to the validity of the elasticity estimates for forecasting effects of prices changes on aggregate agricultural supply.

4 Empirical Estimation

In light of the new developments of econometric techniques that are capable of estimating distinct short-run and long-run elasticities, it is worthwhile to answer some of the methodological questions raised in the early literature on aggregate agricultural supply response. This paper will estimate the responsiveness of aggregate agricultural supply response to price changes by applying recent time series techniques and using data spanning over different pricing regimes. The study uses cointegration analysis, which only requires a co-movement of agricultural supply and price in the long-run.

In any error correction model (ECM), cointegration analysis offers a method of obtaining distinct estimates of both the long-run and short-run elasticities. Nickell (1985) shows that the ECM can be derived from the minimization of inter-temporal quadratic loss function hence it incorporates forward looking behaviour by agricultural producers. This approach has been used to estimate the aggregate agricultural supply response for Tanzania (see McKay *et al.* 1999).

This paper improves upon the McKay *et al.* (1999) methodology by making use of a more recent cointegration technique and by further highlighting that estimation of the aggregate agricultural supply response to prices may produce biased estimates if the possibility of reverse causality is not taken into account as often is the case in single equation time series estimation.

The most widely known single equation approach to cointegration is the Engle-Granger two-step procedure. This approach has some limitations. Firstly it ignores short-run dynamics when estimating the cointegrating vector. When short-run dynamics are complex, this biases the estimate of the long-run relationship in finite samples.

To counter this, a test based on the coefficient of the lagged dependent variable in an autoregressive distributed lag framework has been proposed (Banerjee *et al.* 1998). However, the parameter estimates are only asymptotically efficient on the assumption of weak exogeneity of the regressors. McKay *et al.* (1999) adopts this approach but there is reason to believe that agricultural prices may not be weakly exogenous thus shading doubt on the asymptotic efficiency and consequently validity of their estimates. Secondly, the procedure only assumes that one cointegrating vector exists leading to inefficiency in estimation in the event that more than one cointegrating vector actually exists.

The Johansen estimation procedure deals with this problem but like the Engle-Granger procedure, it presupposes that the order of integration of the all variables is the same and known with certainty. However, the power of unit root test is low hence it can never be known with certainty whether the postulated order of integration is correct.

The relatively recent autoregressive distributed lag (ARDL) approach to cointegration proposed by Pesaran *et al.* (2001) overcomes some of these problems. Firstly, this approach captures both short-run and long-run dynamics when testing for the existence of cointegration. Secondly, it permits the estimation of cointegration relationships when variables are I(0), I(1) or a mixture of the two hence one does not have to pre-test for the order of integration of the variables in the model. Thirdly, it offers explicit tests for the existence of a unique cointegration vector rather than assuming one. Finally, it takes into account the possibility of reverse causality (i.e. the absence of weak exogeneity of the regressors) thereby ensuring that the parameter estimates are efficient and consequently valid. A summary of the ARDL approach is given below.

Consider $\{\mathbf{z}_t\}_{t=1}^{\infty}$, a $(k+1)$-vector random process whose data generating process is the VAR model of order p presented in equation (7)

$$\mathbf{\Phi}(L)(\mathbf{z}_t - \boldsymbol{\mu}\boldsymbol{\gamma}t) = \boldsymbol{\varepsilon}_t \quad ; \quad t = 1, 2, ... \tag{7}$$

where L is the lag operator, μ and γ are unknown $(k+1)$ vectors of intercept and trend coefficients and $\mathbf{\Phi}(L) = \mathbf{I}_{k+1} - \sum_{i=1}^{p} \mathbf{\Phi}_i L^i$ is the $(k+1, k+1)$ matrix lag polynomial. Ruling out explosive roots for the elements of $\mathbf{z}_t$ and assuming a Gaussian vector error process, equation (7) may be rewritten in vector ECM as

$$\Delta\mathbf{z}_t = \mathbf{a}_0 + \mathbf{a}_1 t + \mathbf{\Pi}\mathbf{z}_{t-1} + \sum_{i=1}^{p-1} \mathbf{\Gamma}_i \Delta\mathbf{z}_{t-i} + \varepsilon_t; t = 1, 2, \ldots \tag{8}$$

The ARDL is a single equation framework therefore $\mathbf{z}_t$ is partitioned to $\mathbf{z}_t = (y_t, \mathbf{x'}_t)'$ where y_t is the variable to be modelled given the k-vector $\mathbf{x}_t$, past values $\{\mathbf{z}_{t-i}\}_{i=1}^{t-1}$ and the initial observations $\mathbf{Z}_0$. The error term is also partitioned into $\boldsymbol{\varepsilon}_t = (\varepsilon_{yt}, \boldsymbol{\varepsilon'}_{xt})'$ and its variance as

$$\boldsymbol{\Omega} = \begin{pmatrix} \omega_{yy} & \boldsymbol{\omega}_{yx} \\ \omega_{xy} & \Omega_{xx} \end{pmatrix}$$

and then expressing ε_{yt} conditionally in terms of $\boldsymbol{\varepsilon}_{xt}$ as $\varepsilon_{yt} = \omega_{yx}\Omega^{-1}\boldsymbol{\varepsilon}_{xt} + u_t$ where $u_t \sim IN(0, \omega_{uu}), \omega_{uu} = \omega_{yy} - \omega_{yx}\omega$ and $\omega = \Omega_{xx}^{-1}\omega_{xy}$. Also partitioning $a_0 = (a_{y0}, a'_{x0})'$and $a_1 = (a_{y1}, a'_{x1})'$ and similarly partitioning the other parameter vectors to conform with $\mathbf{z}_t = (y_t, \mathbf{x'}_t)'$ we get that the conditional ECM has the form in equation (9) after some manipulations.

$$\Delta y_t = c_0 + c_1 t + \pi_{y.x} z_{t-1} + \sum_{i=1}^{p-1} \psi'_i \Delta z_{t-i} + \omega' \Delta x_t + u_t; t = 1, 2, \ldots \tag{9}$$

Also partitioning the long run multipliers conformably with $\mathbf{z}_t = (y_t, \mathbf{x'}_t)'$ as

$$\boldsymbol{\Pi} = \begin{pmatrix} \pi_{yy} & \boldsymbol{\pi}_y \\ \pi_{xy} & \Pi_{xx} \end{pmatrix}$$

then assuming that $\boldsymbol{\pi}_{xy} = 0$ we have

$$\Delta x_t = a_{x0} + a_{x1} t + \Pi_{xx} x_{t-1} + \sum_{i=1}^{p-1} \Gamma_{xi} \Delta z_{t-i} + \varepsilon_{xt}; t = 1, 2, \ldots \tag{10}$$

After substituting for equation (10) in equation (9), the conditional ECM now takes the form

$$\Delta y_t = \alpha_0 + \alpha_1 t + \pi_{yy} y_{t-1} + \pi_{yx.x} x_{t-1} + \sum_{i=1}^{p-1} \psi'_i \Delta z_{t-i} + \omega' \Delta x_t + u_t \;; t \; = 1, 2 \ldots \tag{11}$$

The bounds testing for cointegration tests for the absence of any level relationship between $y_t$and $\mathbf{x}_t$ by testing for the exclusion of the lagged variables y_{t-1} and $\mathbf{x}_{t-1}$. This implies testing for the joint significance of π_{yy} and $\boldsymbol{\pi}_{yx.x}$ in equation (11) hence we test $H_0 : \pi_{yy} = 0; \boldsymbol{\pi}_{yx.x} = 0$ against the alternative $H_1 : \pi_{yy} \neq 0; \boldsymbol{\pi}_{yx.x} \neq 0$. There are three cases that may arise: (i) $\pi_{yy} \neq 0$ and $\boldsymbol{\pi}_{yx.x} = 0$ i.e. $y_t = I(0)$ and Δy_t depends only on its own lagged level y_{t-1} (ii) $\pi_{yy} = 0$ and $\boldsymbol{\pi}_{yx.x} \neq 0$ i.e. Δy_t depends only on $\mathbf{x}_{t-1}$ through the linear combination of mutually cointegrating relations for the process $\{\mathbf{x}\ _t\}_{t=1}^{\infty}$ and (iii) $\pi_{yy} = 0$ and $\boldsymbol{\pi}_{yx.x} = 0$, there is no possibility of any cointegration between $y_t$and $\mathbf{x}_t$. The first two cases are degenerate. However, the alternative $H_1 : \pi_{yy} \neq 0; \boldsymbol{\pi}_{yx.x} \neq 0$ accommodates for both the case of interest (i.e. case (iii)) and the degenerate cases (i.e. cases (i) and (ii)). Thus, the ARDL approach does not require pre-testing for the order of integration of the variables in the model.

The test statistic for the null hypothesis is the Wald statistic or the F-statistic. However, their asymptotic distribution which depends on the dimension and cointegration rank of the forcing variables $\{\mathbf{x}_t\}$ is non-standard. Pesaran *et al.* (2001) consider two polar cases where, (i) the process for $\{\mathbf{x}_t\}$ is purely integrated of order zero and (ii) the process for $\{\mathbf{x}_t\}$ is purely integrated of order one. They generate two sets of critical values for the F-statistic, i.e. the lower bound corresponding to the case where all variables are $I(0)$ and the upper bound corresponding to the case where all variables are $I(1)$. These provide critical value bounds for all possible classifications of $\{\mathbf{x}_t\}$ into $I(0), I(1)$ and mutually cointegrated processes. If the F-statistic if below the lower bound one concludes that there is no cointegration and if the F-statistic is above the upper bound, one concludes that there is cointegration. However, inference would be inconclusive when the F-statistic falls within these bounds. Thus, knowledge of the cointegration rank of the forcing variables $\{\mathbf{x}_t\}$ would be required to proceed further.

Narayan (2005), however, argues that critical values generated by Pesaran *et al.* (2001) cannot be used in small samples since they are based on large samples – they are generated for sample sizes

500 and 1000 with 20000 and 40000 replications respectively. Narayan (2005) compares the critical values generated from smaller samples of 30-80 observations, using the same Gauss code as Pesaran *et al.* (2001) and finds that the critical values generated by Pesaran *et al.* (2001) are smaller than those generated from a small sample. Hence Narayan (2005) argues against the use of the Pesaran *et al.* (2001) critical values in small samples and provides critical values for 30 to 80 observations for use in small samples. Akmal (2007) uses the Nayaran (2005) critical values in an empirical test for cointegration.

The assumption that $\boldsymbol{\pi}_{xy} = 0$ restricts consideration to cases where there exists at most one cointegration *equation* between y_t and $\mathbf{x}_t$. This is the major disadvantage of the ARDL approach to cointegration since ARDL estimation is valid only in the case of a single cointegrating relation in which case equation (11) is estimated. In the event of more than one cointegration relation, ARDL estimation will not be valid. However, rather than assuming uniqueness, it offers explicit tests for the existence of a unique cointegrating vector. To determine the number of cointegration relations, the exclusion restrictions in H_0 are tested k+1 times, one at a time, with the first difference for each element of $\{\mathbf{z}_t\}$ as the dependent variable. When there is a unique cointegrating vector, estimation is done based on equation (11) or its variation when a trend is not included.

5 Data

The data used to estimate the aggregate agricultural supply response is obtained from Zimbabwe's Central Statistical Office's publication, the Compendium of Statistics 2000, and Government of Zimbabwe's publication, the Agricultural Sector of Zimbabwe Statistical Bulletin 2001. Data on the agricultural sector in Zimbabwe has not been regularly released since the beginning of the so called "fast-track" land reform programme in 2000. Consistent yearly data on agricultural production and prices is available from 1970 to 1999 after which it becomes erratic. Thus, we use time series with 30 observations. During this period, the agricultural pricing policy changed several times. Therefore, the estimates are suitable for inferring the long-run relationship between aggregate agricultural supply and prices. The key variables of interest are aggregate agricultural production, which we use as a proxy for supply, and prices in Zimbabwe. These variables are computed from data for the major crops namely maize, cotton, tobacco, wheat, coffee, groundnuts and sorghum.

Since agricultural production volumes and prices are available only for individual crops, issues of aggregation arise. The aggregation method adopted is based on equal weights to each crop since the units of measurement for each of the crops are the same i.e. production output in tons and prices in ZWD million/ton. Moreover such an aggregation method is appropriate when farmers substitute among crops from one year to another. If fixed weights are used, a substitution from a crop with a higher weight to crops with lower weights is reflected as a decline in output when actually production might have gone up. Thus fixed weights induce substitution bias (Triplett 1992). Consistent with output aggregation, the aggregate agricultural producer price is similarly based on a simple average of the yearly average of individual crop prices. This is deflated by the GDP deflator to obtain real producer prices for agriculture. Other variables used in the estimation are area under cultivation which is also aggregated using equal weights, mean annual rainfall and annual fertilizer consumption. All the variables are converted to their natural logarithms.

6 Results

We estimate the supply response using the ARDL approach. Although this approach does not require the pre-testing for unit roots, we follow the general times series procedure and test the variables for unit roots using the ADF test with the optimal lag length chosen on the basis of the Schwarz Bayesian Criterion. The unit root test show that supply, rainfall and price are stationary but price has a deterministic trend. Area under cultivation and fertilizer consumption are integrated of order 1. Thus the variables are a mixture of I(0) and I(1) variables. The unit root test results are presented in the table below.

The reduced form equation derived from the Nerlove model implies that agricultural supply is a function of its own lagged value and prices. We first estimate this relationship but in a cointegration framework. We estimate equation (12) below where ECT is the error correction term similar to the Nerlove model but captures both short-run and long-run dynamics as well as incorporating the forward looking behaviour.

$$\Delta X_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p} \beta_{1i} \Delta P_{t-i} + \sum_{i=1}^{q} \beta_{2i} \Delta X_{t-i} + \lambda ECT_{t-1} + \varepsilon_t \qquad (12)$$

Firstly cointegration tests using the bounds test outlined above is carried out to establish the existence of a unique cointegrating vector. The conclusions are based on the critical values provided by Narayan (2005) for sample size 30 for the case of unrestricted intercept and restricted trend with two variables (i.e. k=2). When supply is the dependent variable, the F-statistic is 4.9872, which is above the upper bound of 4.535 at the 10% level of significance. However, when price is the dependent variable, the F-statistic is 2.1215, which is below the lower bound of 3.770 at the 10% level of significance Therefore, at the 10% level of significance we conclude that there is a unique cointegrating vector and estimate equation (12).

The results from the estimated ARDL(1,1) model show insignificant long run supply response to price changes. The short-run elasticities for current price (-1.19) and lagged price (1.21) are both elastic and significant, however the elasticity for the current price is negative, a result similar to that of McKay *et al.* (1999) in the Tanzanian study. The explanation for this result is that price is endogenous i.e. price is determined after supply has been observed resulting in low prices during bumper harvests and high prices when supply is low hence the negative elasticity. This result is consistent with post-planting price announcements, which Zimbabwe tends to use. This result also implies that single equation estimations that fail to take this endogeneity into account provide inconsistent estimates. As mentioned earlier, the ARDL estimates are valid even if regressors are endogenous. Thus in our case, we have taken into account the fact that price is endogenous. The significance of the lagged price elasticity reinforces the belief that agricultural producers have adaptive price expectations thus lending support to the Nerlove price expectations model. It should be noted that the table of results for the ARDL(1,1) model has not been presented in the text as we will soon be motivating that this model suffers from specification error.

The above Nerlove model can be criticized on the basis of misspecification since it omits other important determinants of output such as rainfall, fertilizer consumption and area under cultivation. Indeed the test for the exclusion of these variables yields a significant F-statistic of 13.25 hence the above Nerlove model is misspecified. Therefore, we now estimate an extension of the Nerlove model, where rainfall, fertilizer consumption and area under cultivation are incorporated. We start off by verifying the existence of a unique cointegrating vector again in table 2 after which we estimate an ARDL for the extended Nerlove model in table 3.

Note that the bounds test was not done for the rainfall equation since it is assumed to be weakly exogenous. At 5% level of significance we conclude that there is a unique cointegrating vector.

The results of the estimated ARDL(1,1,0,0,0) i.e. the extended Nerlove model are presented in table 3 below.

The above results show that aggregate agricultural supply does not respond well to price incentives because the numerical estimates of supply response parameters are very small. The short-run elasticity with respect to the lagged price variable is inelastic and significant and its magnitude falls in the range of elasticities found elsewhere. Both the short-run and the long-run elasticities with respect to the current prices are inelastic but the long-run elasticity is only significant at 10% and is smaller in magnitude than the short-run elasticity. However, both elasticities are negative reinforcing the endogeneity argument made earlier.

Although the magnitude of its elasticity is small, it seems that rainfall is a key determinant of agricultural supply in the long-run. Thus, in this respect, the authorities could embark on an intensified widespread construction of dams to provide water for supplementary irrigation. The error correction term of -0.82187 indicates a high speed of adjustment towards the long run equilibrium.

In view of the low responsiveness of aggregate agricultural supply to price and rainfall one needs to note that agriculture also uses land which is fixed in the short term. One may thus argue that low aggregate supply response is attributable to lack of technical progress and the slow rate of agriculture mechanization by small scale farmers. For aggregate agricultural supply to be responsive to price the excess capacity in agricultural land utilization should be eliminated. In addition, mechanization of agriculture should take place. This does not, however, mean that positive agricultural prices can be neglected for aggregate output growth - undoubtedly they are essential - rather that not too much can be expected from changing the general agricultural price level alone. Price reform measures before some of the necessary non-price supply side reforms have been initiated may be ineffective. A package of changes may bring out better response from farmers than a price change alone.

7 Conclusion

The study estimated the aggregate agricultural supply response taking into account theoretical and methodological issues raised in earlier literature. The ARDL approach to cointegration was used to estimate the short-run and long-run relationship between aggregate agricultural supply and price. The aggregate agricultural supply does not respond well to price incentives because the numerical estimates of supply response parameters are small. The estimated short-run and long-run elasticities indicate that aggregate agricultural supply response to price is inelastic confirming similar findings in literature. This result means that the agricultural price policy is rather a blunt instrument for effecting growth in aggregate agricultural supply in Zimbabwe. The provision of non-price incentives must play a key role in reviving the agricultural sector. The low price elasticity could also be attributable to the presence of hysteresis in the agricultural sector in which case the aggregate agricultural supply response can only be stimulated through technical progress and mechanization of agriculture rather than by just pricing reforms. Given the significance of the rainfall variable, other policies such as irrigation investment are also likely to have a direct effect on aggregate agricultural supply. In fact, a package of changes may bring out better response from farmers than a price change alone.

Acknowledgements
Excellent research assistance from Obert Pimhidzai is gratefully acknowledged.

References

[1] Akmal S. M, 2007. Stock returns and inflation: An ARDL econometric investigation utilizing Pakistani data. *Pakistan Economic and Social Review* 45(1) 89-105

[2] Banerjee A, Dolado J. J, and Mestre R, 1998. Error correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis* 19(3): 267-83

[3] Bond M. E, 1983. Agricultural response to price in sub-Saharan African countries. *IMF Staff Papers* 30(4) : 512-520.

[4] Central Statistical Office, 2001. *Compendium of Statistics-2000.* Harare. CSO

[5] Chibber A, 1989. The aggregate supply response: A survey. In Simon Commander (ed.), *Structural Adjustment and Agriculture: Theory and Practice in Africa and Latin America*. London. ODI

[6] Food and Agriculture Organization of the United Nations (FAO), 2006. FAOSTAT Online Statistical Service. Rome: FAO. Available online at: http://faostat.fao.org.

[7] Government of Zimbabwe 2001. *The Agriculture Sector of Zimbabwe Statistical Bulletin 2001.* Harare. Government Printers

[8] Lim, D. 1975. *Supply Responses of Primary Producers*. Penerbit Universiti Malaya, Kuala Lumpur.

[9] McKay A, Morrisey O, and Vaillant C, 1999. Aggregate supply response in Tanzanian agriculture. *The Journal of International Trade and Economic Development* 8(1): 107-23

[10] Muir-Leresche K, and Muchopa C, 2006. Agriculture Marketing. In Rukuni M, Tawonezvi P, Eicher C, Munyuki-Hungwe M, and Matondi P (ed.), *Zimbabwe's Agriculture Revolution Revisited*. Harare. University of Zimbabwe Publications

[11] Mumbengegwi, C. 1990, An econometric analysis of the maize sector in Zimbabwe. *Unpublished DPhil Thesis*, Department of Agricultural Economics, Washington State University. U.S.A.

[12] Narayan K. P, 2005. The saving and investment nexus for China: Evidence from cointegration tests. *Applied Economics* 37 1979-90

[13] Nerlove, M. 1958, *The Dynamics of Supply: Estimation of Farmers' Response to Price.* Baltimore, Johns Hopkins Press.

[14] Nickell S, 1985. Error correction, partial adjustment, and all that: an expository note. *Oxford Bulletin of Economics and Statistics* 47(2): 119-29

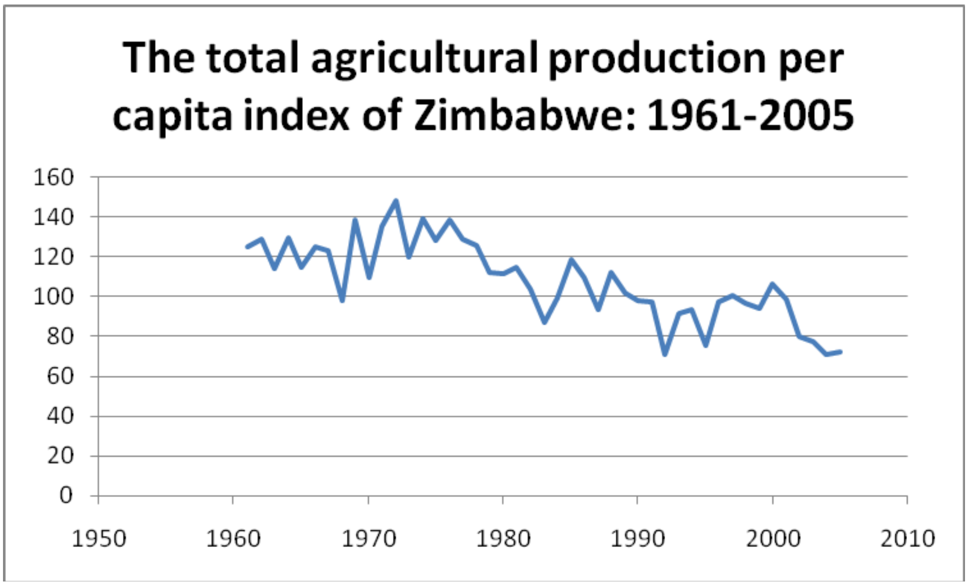
[15] Pesaran M. H, Shin Y, and Smith J. R, 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* 16(3) 289-326

[16] Schiff M, and Montenegro E. C, 1997. Aggregate agriculture supply response in developing countries: A survey of selected issues. *Economic Development and Cultural Change* 45(2)

[17] Thiele R, 2000. Estimating aggregate agriculture supply response: A survey of techniques and results for developing countries. *Keil Working Paper* No. 1016, Keil Institute of World Economics, Germany

[18] Triplett E. J, 1992. Economic theory and BEA's alternative quantity and price indexes. *Survey of Current Business* 72 (April).

Figure 1: Total agricultural production per capita index of Zimbabwe: 1961-2005



Source: Food and Agriculture Organization of the United Nations (FAO). 2006. FAOSTAT Online Statistical Service. Rome: FAO. Available online at: http://faostat.fao.org. 1999-2001=100

Table 1: ADF Unit Root Tests

Variable	Levels		First Difference	
	Test-Statistic	95% Critical Value	Test-Statistic	95% Critical Value
Supply	-5.5072	-2.9850		
Price	-4.3874	-3.6027		
Fertilizer	-2.7660	-2.9850	-6.0099	-2.9907
Area under Cultivation	-2.4280	-2.9850	-5.3301	-2.9907
Rainfall	-4.2817	-2.9850		

Table 2: Bounds Test for Cointegration

Dependant Variable	Output	Price	Fertilizer Consumption	Area under Cultivation
F-Statistic[a]	5.1423**	3.2419	2.4824	4.4942
**Significant at 5% level of significance a-The critical values for case of unrestricted intercept and restricted trend for k=5, are Lower Bound I(0)– 3.504; Upper Bound I(1)– 4.743 using Narayan (2005) critical values				

Table 3: Short-run and Long-run elasticities of aggregate agricultural supply

	Short-run elasticities		**Long-run elasticities**	
Variable	**Coefficient**	**Std Error**	**Coefficient**	**Std Error**
Output(-1)	0.17813	0.14155		
Price	-0.52634***	0.15678	-0.18125*	0.088860
Price (-1)	0.37738**	0.16240		
Fertiliser	0.39257	0.16240	0.47766	0.36748
Rainfall	0.43567**	0.16554	0.53010**	0.21296
Area	0.38804	0.28701	0.47215	0.32054
ECM	-0.82187***	0.14155		
Adjusted R^2		0.72478		
Serial Correlation LM Test		0.092238[p-value 0.761]		
F (5, 22)		15.2205[p-value 0.000]		
***Significant at 1% level of significance (L.O.S); **Significant at 5% LOS; *Significant at 10% L.O.S				