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MODELLING MAIZE AND WHEAT CROPS SUPPLY RESPONSE IN SOUTH AFRICA: NEW EMPIRICAL EVIDENCE AND POLICY IMPLICATIONS

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ABSTRACT

Existing empirical evidence on agricultural supply response is very mixed, ambiguous and generally assumed to be inelastic. Using time series data for the period 1970–2019, this study employed vector error correction model to assess the responsiveness of maize and wheat crops farmers to price and non-price factors. This technique provides a more intuitive way of modelling the optimization and rational behavior of farmers.

The results from study indicate that supply response is high and positive given the thousands of hectare's area planted annually. The estimated price elasticities in the short run are maize (0.08), and wheat (0.46), while in the long run, the price elasticity is estimated to be 1.0 for maize. These results confirm the preponderance of econometric evidence from the empirical literature reviewed that supply response is high and elastic in the long run.

The study further identify the most critical factors influencing crops supply response in South Africa, which is producer prices, intermediate input prices, price of substitute/complementary crops and real exchange rate. Besides price, the studies further identify other non-price incentives such as yield factor, average rainfall, climate (drought) and agricultural policy as other important factors. The findings of this study are significant in terms of model specification (the inclusion of real exchange rate as a proxy for trade risk) and policy implications in terms of government intervention and effective policy implementation.

KEYWORDS: Supply Response, Co-integration, Vector Error Correction Model, Agricultural Policy, Macroeconomic variables.

INTRODUCTION

South Africa is middle – income developing country with a highly developed commercial agricultural sector when compared with other countries in Sub-Saharan Africa. The field crop sector has an important role to play in securing food security in South Africa and in contributing to the well-being of the economy. Maize and wheat are the major commercial crops planted both for human and animal consumption. According to SAGIS (2018), South Africa consumes about 10.8 million tonnes of maize and 3.5 million tonnes of wheat per annum. Hence, the production and sustainability of these crops contribute to the livelihoods of millions of people, in terms of staple food and income generation in South Africa.

Previous supply response studies in South Africa indicate low supply response and comparison across several studies is not feasible due to the differences in model specifications and methods used. However, since supply exhibits a pattern of rising responsiveness and elasticity estimates increase with time horizon, there is a need to ascertain the current supply response estimates in order to guide policy makers and agricultural stakeholders; hence for this paper.

Secondly, the effects of exchange rate movements have not been given adequate attention in the previous crop supply response studies in South Africa. Even though, exchange rates affect agricultural crop trade, generally through their effect on price incentives. This paper captures the impact of international macro-economic linkages with the domestic production, pricing and trade of these crops under consideration. No previous study in South Africa has been conducted to test the impact of this hypothesis on supply response.

Furthermore, this paper will enrich our understanding of supply response using co-integration and vector error correction model specification to solve the limitations of time series data in some of the previous studies.

The main objective of this paper is to determine the responsiveness of South African maize and wheat crops farmer’s to changes in market prices and non-price factors. The objective is achieved by specifying and estimating area planted vector error correction supply response models for maize and wheat in South Africa. And secondly, to identify the relative important supply response determinants (prices, cost of production, rainfall, agricultural policy, real exchange rate and yield on agricultural production using co-integration and vector error correction techniques.

Data Description and Sources

Generally, historical time series data for South Africa were used in this study for the period 1970 to 2019, comprising 50 observations. Area planted is calculated in 1000s of hectares and the data series are from DAFF (2021), SAGIS (2021), Grain SA (2021) and FAOSTATS (2021). The average producers’ prices and intermediate input prices are in Rand values, and consist of fertilizer, fuel, farm feed, packing materials, repairs, and maintenance. The data series were constructed by the author from the intermediate input prices from the Abstracts of Agricultural Statistics (DAFF). Labour cost is excluded for lack of readily available historical time series data. All prices data series is deflated by the 2010 consumer price index for grains to capture inflation and uniformity in data.

Data on the exchange rate in Rand values and the consumer price index for food grains were obtained from the statistics and financial economic database of South African Reserve Bank (SARB, 2021) and Statistics South Africa, respectively. Details for the data on the yield values were computed by the author from the annual production data collected from SAGIS, and were supplemented with FAO statistics where there were missing values. In addition, monthly provincial and national rainfall data series from 1960 to 2019 were collected from the South African Weather Bureau Services (2021) and the data were converted to average annual data series.

All the time series data were confirmed to ensure that there would be no major challenge of missing data series (and these are available, on request, from the authors). However, variations in data for the same variables were found among the sources, and so data consistency is a major constraint, in addition to the lack of readily available time series data on actual production costs for each crop such as, labour costs, fertilizer use/cost and expenditures on research and development on field crops.

All data series are transformed to logarithmic forms; therefore, parameter estimates are elasticities and all prices are deflated by the 2010 consumer price index for grain. The implicit assumption is that farmers want to increase the possibility of diversifying their consumption, and are expected to react to changes in relative prices. These changes are usually captured by the crop price, as deflated by the consumer index (Olubode-Awosola, Oyewumi& Jooste 2006, Muchapondwa, 2009).

LITERATURE REVIEW

Several authors in the development literature over the past 50 years (Sadoulet& De Janvry 1995; Binswanger, 1990; Behrman, 1968) have raised the issue of providing the right price incentives to increase agricultural supply. Other studies also have argued that, to increase supply response, a combination of prices, provisions of inputs and public support policy are a prerequisite (Schiff & Montenegro, 1997; Delgado & Mellor, 1984).

The evolution of previous supply response studies in South Africa indicate that farmers respond positively to prices (producer price, prices of inputs, and price of substitute products) and non-price factors such as technology and climate (Nhundu, Gandidzanwa, Chaminuka, Mamabolo, Mahlangu&Makhura, 2022; Shoko, Chaminuka&Belete, 2016; Ogundeji, Oyewumi& Jooste, 2011; Abbott & Ahmed, 1999; Schimmelpfennig, Thirtle& Van Zyl, 1996; Van Zyl, 1991). However, the supply elasticities estimates vary and is generally low, while comparison across the board is not feasible due to the differences in model specifications, different time periods, levels of data aggregation and estimated methods used. Since supply response exhibits a pattern of rising responsiveness and elasticity estimates increase with time horizon, there is a need to ascertain the current supply response estimates given that South Africa agriculture has gone through rapid structural changes starting from the early 1990s.

In addition, empirical evidence from the international arena on supply response studies reveal several constraints in modelling agricultural supply response analysis (Albayrak, 1998; Mamingi, 1996; Askari& Cummings, 1977; Nerlove, 1961; Bachman, 1961).There is a question of price expectation formation in supply response analysis. The specification of supply response is based on variables and structures that are expected to exist in the future, and the predicting of a future supply relationship is based on the observed relation that existed in the past, which may lead to problems in specifying farmers' expectations (Omezzine& Al-Jabri, 1998). Nerlove (1958b)

Therefore in supply response analysis, several proxy variables is normally used to capture prices (in the form of support prices, prices received by farmers, and farm-gate prices) as explanatory variables. Different prices have been used in various studies (Askari& Cummings, 1977). Other studies (Mushtaq& Dawson, 2002; Mshomba, 1989) have included expected yields and production costs, but farmers consider other factors than only expected prices when making decisions on planting strategies to maximize profits. Hence, in modern day farming, it will be more desirable to include explicitly yield and cost variables in model specification, as prices alone do not serve as a proxy for net returns (Tomek& Robinson, 1990).

The disparities in yields, prices and production cost growth, over time, favour expected net returns over expected prices for use as an explanatory variable in an area planted supply response (Albayrak, 1997). However, production costs and yields differ widely between production regions as a result of the spatial nature of agricultural production, and for a particular crop in terms of farm sizes, cost structure and producers' behaviors.

The effects of exchange rate movements have not been given adequate attention in South African agricultural supply response studies (Adeyemi, 2019). Even though, exchange rates affect crop supply responses, generally, through their effect on price incentives. This paper seeks to fill the gap and also to sheds some light on the current dynamics in crop supply response in South Africa.

Furthermore, most of the previous studies of agricultural supply response (ASR) in South Africa suffer from the challenge of omitted or missing variables syndrome due to the complex nature of agricultural production and its dependence on other sectors of the economy, which involves a relatively high number of variables to be included in the supply function. However, data limitations can change the appropriate specification and the interpretation of the results.

Finally, many previous studies have attempted to test for the supply response to risk by including ad hoc empirical measures of risk and have reported some evidence of negative supply response. However, there is no satisfactory approach to this problem and to all the other constraints and issues mentioned earlier. This paper, therefore, addresses all the issues raised in the next sections of this paper.

THEORETICAL SUPPLY RESPONSE FRAMEWORK

The model used in this paper is derived from the seminal work of Nerlove (1956, 1958a, 1958b), Sadoulet and De Janvry (1995) and much of the literature as reviewed by Rao (1989) and the price formation is assumed to be adaptive rational expectation given that South Africa agricultural producers are price takers, as competitive market prices prevail in the domestic market through the SAFEX futures market (NAMC, 2008). The South African agricultural derivative market has developed to such an extent that the cash market price largely relies on the SAFEX price, and this price is considered to be the industry standard and reference price while all farmers are also price takers in the input market.

The motivation of a dynamic supply function is derived on the basis of profit-maximizing behavior The responses of a crop to price and other variables is influenced by several arrays of complex economic and non-economic factors, such as expected prices and physical, psychological, and technological factors. And the theoretical basis of the vector error correction model is to be found in the dynamic optimization behavior of farmers, subject to adjustment cost elements, and this is fundamental to agricultural supply models (Tripathi, 2008).

A profit maximizing farmer desired area planted to a crop in period t is a function of expected prices and exogenous variables (Nosheen&Igbal 2008; Nerlove, 1956, 1958b), as expressed in:

$$A_t^d = \lambda + \beta_1 P_t^e + \beta_2 z_t + \upsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where

$A_t^d \Rightarrow$ 'Desired' area planted in period t;

$P_t^e \Rightarrow$ Expected price in period t;

$Z_t \Rightarrow$ A vector of other variables influencing supply, such as yield, cost of production, rainfall, technology, exchange rate and prices of substitute crops, etc. A random variable with zero mean.

In the full-scale model, P_t^e is a vector of all relevant prices and input costs? 'Desired' area planted is interpreted as the normal yield/output derived from using the specified area of land, and it amounts to what the farmer expects to harvest under normal circumstances.

Equation (1) describes the relationship between desired area(s) planted, expected price, and other factors that influence the farmer. Economic theory postulates that β1 ≥ 0, which is the time lag or adjustment coefficient that this implies, and there are economic reasons to expect λ > 0 as well, due to the nature of the subsistence farming sector, as found in most developing countries.

Since the desired area planted is related to output, the supply adjustment will also be only partial (Albayrak 1997; Mundlak 1985):

$$A_t - A_{t-1} = \lambda(A_t^d - A_{t-1}) + \omega_t \ ,.....0 \le \lambda \le 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where

$A_t =$ Actual area planted at time t;

$\lambda =$ Partial adjustment parameter; and

$\omega_t =$ Random error term.

Equation (2) is the specification of a distributed lag adjustment in actual area planted towards desired area planted, and, is the adjustment coefficient that measures the speed by which the actual area planted adjusts in response to the factors that influence the planned area planted. Hence, provides the link between the short - and long-run elasticities . $\{\tau_{long-run} = \tau_{short-run} / \lambda\}$

The fact that farmers are assumed to respond to expected prices means that an explicit mechanism for expectation formation must be introduced. The simplest version is to assume adaptive expectations on the part of the farmers and to assume that the farmer adjustment to expectations is a fraction of ψ (which represents the previous period error) (Sadoulet& De Janvry, 1995):

$$p_t^e - p_{t-1}^e = \psi(p_{t-1} - p_{t-1}^e) - -or$$
$$p_t^e = \psi\, p_{t-1} + (1-\psi)\, p_{t-1}^e + \varepsilon_t \quad \ldots\ldots \quad (3)$$

Where
$\varepsilon_t =$ Random error term.

Equation (3) implies that the expected price in period t is equal to the expected price in the previous period and the adjustment in the discrepancy in the previous period between the expected and the actual prices. If $\psi = 0$, the adjustment is very low, and if , the adjustment is very quick. The length of the lag or the adjustment is determined by biological factors such as weather conditions.

Another alternative interpretation of Equation (3) is what is called 'the learning process', i.e. that the expected price is a weighted sum of all the past prices with a geometrically declining set of weights where the right-hand side geometric series is the solution to equation (2), which gives the certainty equivalent to p_t^e

Since p_t^e and A_t^d are not observable in reality, we substitute equations (1) and (2) into Equation (3) to derive the following reduced form:

$$A_t = \Pi_1 + \Pi_2\, p_{t-1} + \Pi_3\, q_{t-1} + \Pi_4\, q_{t-2} + \Pi_5\, z_1 + \Pi_6 z_{t-1} + \phi_t \quad \ldots\ldots \quad (4)$$

Where
$\Pi_1 = \lambda\gamma\psi$
$\Pi_2 = \beta_1\gamma\psi$
$\Pi_3 = (1-\gamma) + (1-\psi)$
$\Pi_4 = -(1-\gamma)(1-\psi)$
$\Pi_5 = \beta_2\,\gamma$
$\Pi_6 = -\beta_2\gamma(1-\psi)$

Where
$\Pi_2 \leftarrow and \rightarrow \beta_1 = \Pi_2 / \gamma\psi$ are the short-run and long-run price elasticities of supply.

Equation (4) is the estimable form of the supply response model, as defined by the structural form of Equation (2), according to partial adjustment with adaptive expectation given by Equations (2) and (3), respectively.

The short-run price response is estimated by Π_2 and the long-run prise response is calculated as β_1 where $\beta_1 = {\Pi_2}/{\gamma\psi} \geq \pi_2$ since both $\gamma \; and \psi \leq 1.$ As expected, the long-run supply response exceeds the short-run supply response.

If exogenous shifters (z_{t-1}) are not included in the model, $\beta_3 = 0$ in the structural form and $\Pi_5 = \Pi_6 = 0$ in the reduced form Equation (4).

However, Equation (4) is over-identified with six $\Pi -$ coefficients and five parameters $-\lambda, \beta_1, \beta_2, \gamma, and \psi$. Hence, to derive a distinct solution, a non-linear constraint on the coefficients of the reduced form Equation (4) is proposed (Sadoulet& De Janvry, 1995):

$$\Pi_6^2 - \Pi_4 \; \Pi_6^2 + \Pi_3 \Pi_5 \Pi_6 = 0 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Therefore, the reduced form equation becomes $A_t = \Pi_1 + \Pi_2 \, p_{t-1} + \Pi_3 \, q_{t-1} + \Pi_4 \, q_{t-2} + \phi_t \cdot$

However, rearranging Equation (4) further, the reduced forms now becomes:

$$\phi_t = \omega_t - (1-\psi)\,\omega_{t-1} + \gamma\,\upsilon_{t-1} - \gamma\,(1-\psi)\,\upsilon_{t-1} + \beta_1 \, d\,\varepsilon_t \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

In practice, the reduced form of Equation (4) is usually estimated by using non-linear Maximum Likelihood Estimation (MLE) techniques, and correction needs to be made for serial correlation in the error term. However, the limitations of the assumption that production adjusts to a fixed target supply, which has been criticized by Nerlove (1979) and other researchers in the literature (Abdulai&Reider, 1995; Hallam &Zanoli, 1993; Schimmelpfenniget al., 1996) have necessitated the use of co-integration and vector error correction model representation for this paper.

The co-integration and the vector error correction model (VECM) were estimated using the Johansen (1988) test which estimates Vector Error Correction Models (VECM) of the form:

$$\Delta Y_t = c + \sum_k \alpha_k \, \Delta Y_{t-1} + \lambda\,(Y_{t-1} - \sum_j \beta_j \, X_{jt-n}) + \omega T + \varepsilon_{t-1} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where

Δ is the change operator (i.e. change in current period minus previous period),

ΔYt - ΔYt-1),

$\alpha_j, and \; \beta_j$ are the vectors of short- and long-run supply elasticities with respect to factor j and α_j represents the short-run coefficient, irrespective of its sign but should be individually significant and represent a short-run equilibrium to factor j. It measures the rate at which the previous period of disequilibrium of the system is being corrected. Parameter β_j represents long-run equilibrium to factor j. The sign of β_j should be negative and significant, as well for holding long-run equilibrium.

εt-1 is the disturbance term with zero mean and constant variance.

Y's are the co-integrated time series variables.

While,

$Y_t = \sum \beta_j X_{jt-n} + \varepsilon_t$ ……………………………………………………… (8)

Where

$(Y_{t-1} - \sum \beta_j X_{jt-n})$ = measure 'errors', i.e. (divergences from the long-run equilibrium) and corresponds to the residuals of a lagged version of Equation (8). One period lag error correction term represents the equilibrium position in the short run and in the long run, respectively.

β_j can be estimated from Equation (8), and the value imposed as a restriction on Equation (7). Alternatively, Equation (8) can be estimated in unrestricted form:

$\Delta Y_t = c + \sum \alpha_k \Delta Y_{t-1} + \lambda Y_{t-1} - \lambda \sum \beta_j X_{jt-n} + \omega T + \varepsilon_t$ ……………………………… (9)

Where

$-\lambda \longrightarrow$ measures the level of error correction adjustment in Y, (the negative sign shows the adjustment towards the long-run equilibrium, while in the long-run coefficient, β_j is calculated from $\lambda\beta_j / \lambda$). The vector error correction model is a system of single equations that shows the degree to which the equilibrium behavior drives short-run dynamics, while the equilibrium relationship, in turn, has implications for a short-run behavior, as one or more series move to restore equilibrium.

From our model specification above, we used the Johansen (1991) co-integration technique to represent a vector error correction model of the form:

$\Delta Y_t = \alpha_0 + \Pi Y_{i,t-1} + \sum_{j=1}^{p-1} \Gamma \Delta Y_{t-p} + \varepsilon_t$ ………………………………………….................. (10)

Where

$Y_t \longrightarrow$ is a vector containing the n endogenous variables, such as prices and quantities.

The matrix $\Gamma_j \longrightarrow$ represents the coefficient of the short-run variables.

ε_t is white noise.

The matrix Π contains the information on the eventual co-integration relations among the series in the data

Equation (10) can be reformulated as:

$\Delta Y_t = \alpha_0 - \alpha\beta Y_{i,t-1} + \sum_{j=1}^{p-1} \Gamma \Delta Y_{t-p} + \varepsilon_t$ ……………………………………………… (12)

The reduced rank of the matrix Π captures the stationary variables in the long run. If the matrix Π has a reduced ranked, there is a factorization of $\Pi = \alpha\beta'$

Where

The matrix β contains the r co-integrating vectors, and the matrix α ,contains the adjustment parameters in the error correction model. This implies that if the coefficient matrix of Π has a reduced rank $r < n$ then there exist nxr matrices α and β each with rank r and r is the number of co-integrating relationships. If the variables are co-integrated, then rank (Π) is not equal to zero, but is equal to the number of co-integrating vectors. The number of the co-integrating vectors is less than or equal to the number of variables n and strictly less than n if the variables have unit roots.

However, if the rank of Π is less than then n its determinant is zero, which is useful for solving this problem because the determinant of a square matrix equals the product of the eigenvalues. If the rank of the matrix is less than the number of rows and columns in the matrix, then one or more of the eigenvalues is zero, and the determinant is also zero. Eigenvalues comprise a set of eigenvalues for the nxn matrix A, given the n solutions to the polynomial equation. The Johansen co-integration method was chosen for this study for two important reasons: it resolves a limitation of the ADF unit root statistical test and the simultaneity biases caused by the use of more than one endogenous variable, at the ssame time.

After the confirmation of the stationary properties of the individual data series, co-integration tests are then used to determine the order of integration through the two likelihood ratio tests (namely the Trace and the Maximum Eigen Value statistic tests). Error correction may result from the co-integration test, and this error is corrected by using the residual ε_t to estimate a vector error correction model of the form:

$$\Delta Y_t = c + \sum \alpha_k \Delta X_{t-n} - \lambda \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

The parameters in Equation (12) are α which measures the short-run effect on Y of changes in X and λ measures the extent to which changes in Y can be attributed to the error correct term ε_t . The error correction term λ is the only potential I(1) variable, assuming there are no I(2) variables. The t-statistic of λ will be under the assumption of being closer to the normal distribution, since all the remaining variables are I(0), as their distribution is not affected by ε_t .

In conclusion, our equation (7) becomes an unrestricted regression of the form:

$$\Delta Y_t = c + \sum \alpha_{k-n} \Delta X_{t-n} + \lambda_1 Ln \sum (Y_{t-n} - \beta_j X_{t-n}) + \lambda_{2n} X_{t-n} \ldots\ldots\ldots\ldots \quad (13)$$

Where

$\alpha \longrightarrow$ represents the short-run elasticity.

$\lambda_2 \longrightarrow$ represents the long-run elasticity.

$\lambda_1 \longrightarrow$ represents the error correction term.

Since all the variables used are in logarithm form, the coefficients of $(\alpha; \lambda_1)$ can be interpreted as positive values, when converted back to real numbers. λ_1 is the coefficient of one period lag vector error correction term or residual from the system equations. It guides the variables of the system to restore back to equilibrium or it corrects disequilibrium in the system. For this to happen, the sign of λ_1 should be negative and significant.

The specific empirical VECM model quantified for maize crop with k lag is expressed as follows:

$$D(LAPMAIZE(-1)) = \alpha_0 + \alpha_1 D(LRMPP(-1)) + \alpha_2 D(LRSORP(-1)) + \alpha_3 D(LRSUNP(-1))$$
$$+\alpha_4 D(LRCOP(-1)) + \alpha_5 D(LRER(-1)) + \alpha_6 D(LRF_{-fs}(-1)) + \alpha_7 D(LRYIELD_{-mz}(-1))$$
$$+\alpha_8 D(DT81(-1)) + \alpha_9 D\big(DT98(-1)) + \alpha_{10} D(DT2002(-1)) + \alpha_{11} D(DT2016(-1))\big] - \lambda\,[z_t - b_0$$
$$-b_1 D(LRMPP(-1)) - b_2 D(LRSORP(-1)) - b_3 D(LRSUNP(-1)) - b_4 D(LRCOP(-1)) - b_5 D(LRER(-1))$$
$$-b_6 D(LRF_{\_fs}(-1)) - b_7 D(LRYIELD_{\_mz}(-1)) - b_8 D(DT81(-1)) - b_9 D(DT98(-1)) - b_{10} D(DT2002(-1))$$
$$-b_{11} D(DT2016(-1))\,] + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where

- D represents the first derivative.
- λ represents the level of error correction in maize area planted
- α_i represents the short-run price elasticity.
- b_i represents the long-run supply elasticities.
- $D(LAPMAIZE(-1))$ represents the area planted to maize in the first period. Area planted is measured in hectares and represents crop total area planted for the country.
- $D(LRMPP(-1))$ represents a vector of maize real producer price (Rands) in the first period, and it is deflated by the 2010 consumer price index for grains to capture inflation and uniformity in data.
- $D(LRSORP(-1))$ represents a vector of sorghum real producer price (substitute/complementary crop) in the first period, and it is deflated by the 2010 consumer price index (CPI) for grains. Sorghum, sunflower seed and barley are considered as substitutes/complementary crops for maize and wheat crops models 'respectively. Canola crop (in the case of wheat model) is excluded for lack of historical time series data.
- $D(LRSUNP(-1))$ represents a vector of sunflower seed real producer price (substitute crop) in the first period, and it is deflated by the 2010 consumer price index (CPI) for grains.
- $D(LRCOP(-1))$ measures the price of intermediate inputs (Rands). The effect of input prices should be negative. The intermediate input costs used are fertiliser, fuel, farm feed, packing materials, repairs and maintenance. Labour cost is excluded for lack of readily available time series data.
- $D(LRER(-1))$ represents the real exchange rate measure in the first period and it is deflated by the 2010 consumer price index (CPI) for grains.
- $D(LRF_{\_fs}(-1))$ represents the average annual rainfall (in mm) in the Free State Province while for wheat model the Western Cape provincial annual rainfall is used.
- $D(LRYIELD_{mz}(-1))$ Z_t represents the average yield per tonne for the maize crop. It is computed by dividing production quantities by total area planted to the maize crop.
- $D(DT81(-1))$ and $D(DT2016(-1))$ represents structural break dummies that captures the effects climate (drought) in the first period in the maize model.
- $D(DT98(-1))$ and $D(DT2002(-1))$ represents structural break dummies used to evaluate the effects of the policy regime in the maize model.

- ε_t represents the error term, with zero mean and constant variance from the estimated maize model.

The inclusion of $DT_t \Leftarrow and \Rightarrow DF_t$ (dummy specifications) used in the empirical crop model specified above is to take care of structural transformation in the South African agriculture in the past five decades. In addition, the agricultural policy environment has witnessed several purposeful changes (Liebenberg, 2013; Vink& Van Rooyen, 2009; OECD, 2006) since the liberalisation of agricultural trade and the deregulation of the marketing of agricultural products in 1996. These policy changes make it necessary to test for structural breaks in the time series data for the two crops.

To determine the periods in which structural breaks occur, the series of the residuals from the fitted supply response model were examined by using a recursive least square estimation, and the structural break points, where the absolute values of the residual exceeded two standard deviations, were determined. When the residual exceeds the two-standard error band in a specific year, an intercept and dummy variable are introduced into the supply response equation for that specific year, as specified in Equation (14).

For each break date [BD] identified, 2 dummy variables are fitted, as shown in equation (14):

$$\left.\begin{aligned} &DT_t = 1 \quad \text{i.e.} \quad \text{If } \mathbf{t} = \text{BD, and 0 otherwise} \\ &DF_t = 1 \quad \text{i.e.} \quad \text{If } \mathbf{t} > \text{BD and 0 otherwise} \end{aligned}\right\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14)}$$

In equation (14), the two dummy variables DT and DF represent either periods of drought or policy regime shifts. The dummy variables take a value of 1 for years with structural break dates, such as 1981, 1998, 2002, and 2016, and otherwise 0, as determined from the recursive OLS regression results. Table 1 presents the estimated recursive OLS regression results for the maize model.

Table 1: Structural breaks results from Recursive OLS regression

Model	**Years with outliers**
Maize	1981, 1998, 2002, 2016
Wheat	1981, 1988, 1992, 1998

Source: author's calculation from OLS recursive results.

These dummy variables are therefore incorporated into the two VECM equations, based on the results of OLS recursive analysis that generates the structural break years.

ESTIMATION AND RESULTS

1. Unit root test results

Prior to the estimation of co-integration analysis, it is important to check the stationary of the variables used whether they are I(1) at levels and I(0) at first difference. Tables 2-3 presents the results of the Unit Root Test using Augmented Dickey-Fuller (ADF) and reinforced by Phillips-Perron (P-P) test. The PP test accommodates models fitted with a drift and a time trend, so that they may be used to discriminate between unit root of non-stationary and stationary series about a deterministic trend.

TABLE 2: Table 2: Unit Root Test: ADF test results @levels and first difference

Variable	None	95% critical value	Intercept	95% critical value	Intercept + Trend	95% critical value
LAPMAIZE	*-2.1502**	*-1.9483*	*0.1063*	*-2.9281*	*-5.6675**	*-3.5043*
LRER	*1.1879*	*-1.9478*	*-0.4611*	*-2.9224*	*-2.5919*	*-3.5064*
LRCOP	*0.9455*	*-1.9477*	*-2.6046**	*-2.9224*	*-2.6062*	*-3.5043*
LRMPP	*-0.1750*	*-1.9477*	*-2.6957*	*-2.9224*	*-2.6736**	*-3.5043*
LRSOYP	*-0.0286*	*-1.9481*	*-3.0387**	*-2.9224*	*-2.9859*	*-3.5043*
LRSUNP	*-0.2320*	*-1.9480*	*-2.3345*	*-2.9224*	*-2.2245*	*-3.5043*
LRF_FS	*-0.5317*	*-1.9483*	*-5.7752**	*-2.9224*	*-6.3177**	*-3.5043*
LRYIELD_MZ	*0.6328*	*-1.9480*	*-1.1545*	*-2.9252*	*-4.8928**	*-3.5064*
LAPWHEAT	*-1.2612*	*-1.9477*	*-0.7440*	*-2.9224*	*-3.9470**	*-3.5043*
LRBPP	*0.2359*	*-1.9477*	*-2.3920*	*-2.9224*	*-2.9352*	*-3.5043*
LRF_WC	*-0.1582*	*-1.9478*	*-5.6734**	*-2.9224*	*-5.9150**	*-3.5043*
LRWPP	*-0.2145*	*-1.9477*	*-2.2236*	*-2.9224*	*-2.0918*	*-3.5043*
LRYIELD_WH	*1.8331*	*-1.9483*	*-0.7909*	*-2.9281*	*-5.5431**	*-3.5043*

Variables at first difference

Variable	*None*	*95% critical value*	*Intercep t*	*95% critical value*	*Intercept + Trend*	*95% critical value*
LAPMAIZE	*-6.5258**	*-1.9483*	*-7.1417**	*-2.9281*	*-7.1548**	*-3.5131*

LRER	*-4.4088**	*-1.9478*	*-5.4744**	*-2.9252*	*-5.4126**	*-3.5085*
LRCOP	*-7.5776**	*-1.9478*	*-7.6357**	*-2.9238*	*-7.5705**	*-3.5064*
LRMPP	*-6.9024**	*-1.9480*	*-6.8296**	*-2.9252*	*-6.0905**	*-3.5107*
LRSOYP	*-7.6400**	*-1.9481*	*-7.5503**	*-2.9266*	*-7.7486**	*-3.5107*
LRSUNP	*-7.7081**	*-1.9480*	*-7.6268**	*-2.9252*	*-6.6521**	*-3.5107*
LRF_FS	*-11.1083**	*-1.9478*	*-10.9896**	*-2.9238*	*-10.8822**	*-3.5064*
LRYIELD_MZ	*-9.4950**	*-1.9480*	*-9.6021**	*-2.9252*	*-6.7729**	*-3.5107*
LAPWHEAT	*-8.5858**	*-1.9478*	*-8.8495**	*-2.9238*	*-8.7898**	*-3.5064*
LRBPP	*-9.6568**	*-1.9478*	*-9.5199**	*-2.9238*	*-9.4481**	*-3.5064*
LRF_WC	*-11.4257**	*-1.9478*	*-11.3019**	*-2.9238*	*-11.2322**	*-3.5064*
LRWPP	*-7.2495**	*-1.9478*	*-7.1746**	*-2.9238*	*-6.1267**	*-3.5131*
LRYIELD_WH	*-9.0089**	*-1.9478*	*-7.1406**	*-2.9281*	*-7.0879**	*-3.5131*

* Asterisk indicates statistical significance @ 5%.
ADF: Augmented Dickey Fuller @ Maximum lag length (sic) = 10

Table 3: Unit Root Test: P-P test results @levels and first difference

Variable	*None*	*95% critical value*	*Intercept*	*95% critical value*	*Intercept + Trend*	*95% critical value*
LAPMAIZE	*-1.6884**	*-1.9477*	*-1.7499*	*-2.9224*	*-5.6532**	*-3.5043*
LRER	*1.7240*	*1.9477*	*-0.4911*	*-2.9224*	*-1.9040*	*-3.5043*
LRCOP	*1.0086*	*1.9477*	*-2.6077**	*-2.9224*	*-2.6729*	*-3.5043*
LRMPP	*-0.1859*	*1.9477*	*-2.7128**	*-2.9224*	*-2.7073*	*-3.5043*
LRSOYP	*0.1372*	*1.9477*	*-3.2377**	*-2.9224*	*-3.1853**	*-3.5043*
LRSUNP	*-0.1293*	*1.9477*	*-2.3650*	*-2.9224*	*-2.2442*	*-3.5043*
LRF_FS	*-0.0097*	*1.9477*	*-5.7752**	*-2.9224*	*-6.3030**	*-3.5043*

LRYIELD_MZ	*-0.0575*	*1.9477*	*-2.7233**	*-2.9224*	*-5.6581**	*-3.5043*
LAPWHEAT	*-36465**	*1.9477*	*-0.2054*	*-2.9224*	*-3.7795**	*-3.5043*
LRBPP	*0.2641*	*1.9477*	*-2.5422*	*-2.9224*	*-3.1809*	*-3.5043*
LRF_WC	*-0.2068*	*1.9477*	*-5.6542**	*-2.9224*	*-5.8522**	*-3.5043*
LRWPP	*-0.3375*	*1.9477*	*-2.1428*	*-2.9224*	*-2.0359*	*-3.5043*
LRYIELD_WH	*-0.3667*	*1.9477*	*-1.3120*	*-2.9224*	*-5.3678**	*-3.5043*

Variables at first difference

Variable	*None*	*95% critical value*	*Intercept*	*95% critical value*	*Intercept + Trend*	*95% critical value*
LAPMAIZE	*-12.8564**	*-1.9478*	*-34.5401**	*-2.9238*	*-38.8560**	*-3.5064*
LRER	*-4.4757**	*-1.9478*	*-4.9979**	*-2.9238*	*-4.9273**	*-3.5064*
LRCOP	*-7.5660**	*-1.9478*	*-7.6350**	*-2.9238*	*-7.5693**	*-3.5064*
LRMPP	*-10.8103**	*-1.9478*	*-10.7330**	*-2.9238*	*-12.3718**	*-3.5064*
LRSOYP	*-9.2772**	*-1.9478*	*-9.1123**	*-2.9238*	*-9.4797**	*-3.5064*
LRSUNP	*-8.2675**	*-1.9478*	*-8.1596**	*-2.9238*	*-9.8418**	*-3.5064*
LRF_FS	*-33.9872**	*-1.9478*	*-34.8046**	*-2.9238*	*-39.1918**	*-3.5064*
LRYIELD_MZ	*-14.2016**	*-1.9478*	*-26.1030**	*-2.9238*	*-33.2802**	*-3.5064*
LAPWHEAT	*-8.7718**	*-1.9478*	*-17.2721**	*-2.9238*	*-22.6805**	*-3.5064*
LRBPP	*-9.9189**	*-1.9478*	*-9.9097**	*-2.9238*	*-10.4740**	*-3.5064*
LRF_WC	*-26.8597**	*-1.9478*	*-26.7601**	*-2.9238*	*-38.8108**	*-3.5064*
LRWPP	*-9.2313**	*-1.9478*	*-9.3780**	*-2.9238*	*-14.3704**	*-3.5064*
LRYIELD_WH	*-8.7511**	*-1.9478*	*-18.2484**	*-2.9238*	*-18.1628**	*-3.5064*

* Asterisk indicates statistical significance @ 5%

The tests were applied to each variable over the period of 1970 -2019 with none, constant, and constant and trend at the variables level as well as their first difference. The test results are compared against the Mackinnon (1991, 1996) critical values for the rejection of the null hypothesis of no unit root. For a series to be stationary, the autocorrelation function should converge quickly to zero. Hence, the autocorrelation function and the visual inspection of the graphical representation of each series support the conclusion reached by using the ADF and PP unit root statistical tests, that there is a no unit root in the data series after first difference.

Tables 2-3 shows that all variables are integrated of order one I(1) in levels and of order I(0) in first differences. This implies that all the variables are I(1). These results give empirical evidence of the presence of unit root in South African time series data and that the use of first difference series eliminates the unit root (Brooks, 2008). Furthermore, Table 4 shows the optimal lag selection results based on Schwartz information Criterion (SIC). This is needed to ensure that the error terms are white noise in the ADF and P-P tests. In this paper, we used Schwartz Information Criterion (SIC) and Likelihood Ratio (LR) test, which suggested that the optimal lag selection is one in both the maize and wheat model respectively. This is very appropriate specification for the order of vector autoregressive (VAR) model.

Table 4: Optimal lag selection
MAIZE MODEL

Lag	LogL	LR	FPE	AIC	SC	HQ
0	21.38323	NA	7.72e-11	-0.581880	-0.263855	-0.462746
1	217.9697	316.2477*	2.52e-13	-6.346507	-3.484286*	-5.274302
2	276.1585	73.36848	4.18e-13	-6.093846	-0.687428	-4.068570
3	351.3666	68.66826	5.47e-13	-6.581155	1.369460	-3.602807
4	485.4167	75.76749	1.75e-13*	-9.626814*	0.867997	-5.695395*

WHEAT MODEL

Lag	LogL	LR	FPE	AIC	SC	HQ
0	58.37675	NA	1.55e-11	-2.190294	-1.872269	-2.071160
1	245.2000	300.5417*	7.72e-14*	-7.530434	-4.668213*	-6.458229*
2	291.1129	57.89017	2.18e-13	-6.744038	-1.337620	-4.718762
3	374.7392	76.35448	1.98e-13	-7.597357	0.353258	-4.619009
4	495.4974	68.25465	1.13e-13	-10.06511*	0.429705	-6.133687

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

2. Co integration test results

The results of the Johansen co-integration (Trace and Maximum-Eigen value) tests presented in Table5which indicate at least two co-integration relationships among the variables used in the VECM models, at 5% significant level, and the lag length for the Johansen specification is based on the justification of the economy cycle, starting from five-year lag lengths, and observing the result as the lag length is reduced to 2 years without appreciably altering the results.

Table 5: Summary of Johansen co-integration test results.

Hp: rank = P (No deterministic trend in the data)

Hr: rank r<P (Co-integration relations)

Relationships	**Co-integration test**	**Test statistic**	**95% critical values**	**Prob.**	**Decision**
Maize model Lapmaize, Lrmpp, Lrsoyp, Lrsunp, Lrcop,Lrer, Lrf_fs, Lryield_mz, Dt(81), Dt(98), Dt(2002), Dt(2016)	Max Eigen value test r=0*	148.2560	76.57845	0.0000	At least 2 co-integrating relationships
	Trace r = 0*	505.9370	334.9837	0.0000	
	Max Eigen value test r = 1*	101.2741	70.5351	0.0000	
	Trace r = 1*	357.6810	285.1425	0.0000	
	Max. Eigen value test r = 2*	66.3828	64.5047	0.0327	
	Trace r = 2*	256.4068	239.2354	0.0066	
Wheat model Lapwheat, Lrwpp, Lrmpp, Lrbpp, Lrcop, Lrer, Lrf_wc, Lryield_wh, Dt (81), Dt (88), Dt(92), Dt (98)	Max Eigen value test r=0*	131.6343	76.5784	0.0000	At least 4 co-integrating relationships
	Trace r = 0*	533.1038	334.9837	0.0000	
	Max Eigen value test r = 1*	111.1963	70.5351	0.0000	
	Trace r = 1*	401.4694	285.1425	0.0000	
	Max. Eigen value test r = 2*	82.1108	64.5047	0.0005	
	Trace r = 2*	290.2732	239.2354	0.0000	

Notes: * Rejection of hypothesis no co-integration at 0.05 levels. ** Probability values: Mackinnon, Haug&Michelis (1999).

3. Vector error correction results

The results and analyses of the estimated supply response models for areas planted to maize and wheat is presented and discussed below. And prior to the estimation of the two vector error correction models (VECM), and all the data series were tested for unit root and co-integration. The results confirm that the data series are stationary and ergodic in first difference (as discussed above). In addition, the results of the residual diagnostics test shows no evidence of serial correlation and the models are dynamic stable based on the Chow test.

3.1 Empirical results of the maize model

The estimation of the maize VECM, with two co-integrating equations, is presented in Table 6 below, where the log of maize area planted, producer prices of maize, price of substitute crops (sunflower seed, sorghum), real exchange rate, intermediate input price, average rainfall and yield factor corresponding to D(LAPMAIZE(-1)), D(LRMPP(-1)), D(LRSORP(-1)), D(LRSUNP(-1)), D(LRER(-1)), D(LRCOP(-1)), D(LRF_fs(-1)) and D(LRYIELD_mz(-1)), respectively. The structural break variable, D (DT81(-1)) and D(DT2002(-1)), captures periods of drought, while D(DT98(-1)) and D(DT2016(-1)) capture periods of agricultural policy regime.

Most of the estimated coefficients have the expected signs and suggest reasonable supply response to producer price, intermediate input prices (a proxy representing cost of productions), yield, real exchange rate, average rainfall and structural break dummy variables (DT781, DT98, DT2002 and DT2016, respectively).

The price of substitute crops sunflower seed (0.02) and sorghum (0.17), and yield factor (0.16) are statistically significant at the 5% level. The significance of these coefficients indicates that past information (lagged variables of sunflower seed price D (LRSUNP(-1)), sorghum price D(LRSORP(-1)) and yield factor D(LRYIELD_mz(-1)), can explain the present supply response. This means that these are the most sensitive factors to be considered in making a decision by maize farmers.

In addition, the price of the substitute crop (sorghum) and yield factor have a positive (0.40 and 0.32) relationship with area planted in the short run, the coefficient of real exchange rate(0.02) have a positive relationship to area planted while intermediate input prices (-0.24) have an inverse relationship to maize area planted. This implies that, as the area planted to maize increases, the cost of inputs used decreases, while real exchange rate has a positive impact on maize production and trade.

The estimated price elasticities of maize D (LRMPP(-1)) is 0.08 and 1.00 in the short and long runs, respectively. The high price elasticity values show a significantly maize supply response to producer price signals and market forces of demand and supply, in the long run. In the short run, the supply response is low, since the area planted cannot be altered. However, in the long run, as all factors of production are variable, this will shift the supply curve to the right as maize prices move towards import parity price. The results of maize vector error correction model are presented in table 6 below:

Table 6: Results of maize vector error correction model

Variable	Coefficient	Standard errors	t-values	P-values
Short run effects				
C	-0.0134	0.0200	-0.6713	0.5024

Variable	Coefficient	Standard errors	t-values	P-values
E_{ct-1}	-0.9816	0.3821	-2.5688*	0.0106
D(LAPMAIZE(-1))	0.1699	0.1965	0.8649	0.3876
D(LRMPP(-1))	0.0800	0.1128	-0.7096	0.4784
D(LRSORP(-1))	0.1672	0.0933	1.7918**	0.0739
D(LRSUNP(-1))	0.0217	0.1299	0.1667**	0.0868
D(LRCOP(-1))	-0.2377	0.1904	-1.2486	0.7213
D(LRER(-1))	0.0235	0.1436	0.1638	0.8700
D(LRF_$_{fs}$(-1))	0.0352	0.0702	0.5010	0.6167
D(LRYIELD_$_{mz}$(-1))	0.1551	0.0654	2.3721*	0.0182
D(DT81(-1))	0.0709	0.1351	0.5245	0.6002
D(DT98(-1))	-0.0126	0.1272	-0.0989	0.9213
D(DT2002(-1))	0.0064	0.1550	0.0410	0.9673
D(DT2016(-1))	-0.0386	0.1577	-0.2448	0.8067
Long run effects				
C	-7.3103	-	-	-
LRMPP(-1)	1.00	-	-	-
LRSORP(-1)	0.3194	0.0386	8.2754	-
LRSUNP(-1)	-0.5342	0.0498	-10.7282	-
LRCOP(-1)	0.0619	0.0348	1.7800	-
LRER(-1)	0.1554	0.0225	6.9073	-
LRF_fs(-1))	0.0741	0.0349	2.1378	-
LRYIELD_mz(-1)	-0.0417	0.0373	-1.1179	-
DT81(-1)	-0.1894	0.0386	-4.9102	
DT98(-1)	-0.1341	0.0267	-5.0316	-
DT2002(-1)	0.3661	0.0277	13.2300	-

Variable	Coefficient	Standard errors	t-values	P-values
DT2016(-1)	0.0070	0.0296	0.2385	-

VECM R^2: 0.6089 Mean dependent: -0.0135

VECM Adjusted- R^2: 0.4430 S.D dependent: 0.1507

F - statistic: 3.6703 Log likelihood: 45.7815

*significance @1% level

**significance @5% level

The error correction term has a negative value (-0.98) and is statistically significant at the 1% level. This means that the adjustment speed to the long-run equilibrium is very high, about 98%. It indicates that farmers do indeed make immediate production decisions, as they consider several factors, such as weather, import-parity price, and demand and supply relations, as well as the fluctuations in exchange rates.

3.2 Empirical results of the wheat model

The estimation of the wheat VECM, with four co-integrating equations and the one perfect equation that fitted the data series is shown in Table 7 below. The log of wheat area planted is a function of wheat producer price, producer price of substitute crops (maize and barley), the intermediate input prices, real exchange rate, average rainfall, yield factor and structural break variables corresponding to D(LAPWHEAT(-1)), D(LRWPP(-1)), D(LRMPP(-)), D(LRBPP(-1)), D(LRCOP(-1)), D(LNRER(-1)), D(LRF_wc(-1)), D(LRYIELD_wh(-1)), D(DT81(-1)), D(DT88(-1)) D(DT92(-1)) and D(DT98(-1)) respectively.

Wheat producer priced D(LRWPP(-1)), maize producer price D(LRMPP(-1)), real exchange rate D(LNRER(-1)) intermediate input prices D(LRCOP(-1)), yield factor D(LRYIELD_wh(-1)), and the structural break variables D(DT92(-1)) and D(DT98(-1)) that captures agricultural policy regime have a positive effect, jointly on wheat area planted, while barley producer prices D(LRBPP(-1)), average rainfall for Western Cape D(LRF_wc(-1)), structural break variables (drought) D(DT81(-1)) and D(DT88(-1)) have a negative effect in the short run, but not statistical significant with the exception of D(DT88) which is statistically significant, at 5%. This implies that wheat and barley compete for land and that the negative relationship between wheat and barley suggests decision interdependence by farmers, as wheat is a competitive crop with barley and the cross-elasticity effect (-0.11), provides evidence of the change in wheat area planted in response to a given change in expected price of barley.

On the other hand, wheat producer D (LRWPP(-1)) and maize producer price D(LRMPP(-1)) have a positive relationship with wheat area planted, and are statistically significant at the 5% and 1%

level respectively. This indicates that the wheat producer price tracks the maize producer price as the dominant crop in South Africa.

The price elasticity of wheat (LRWPP-1)) is 0.46 in the short run, and is significant at the 5% level. This means that supply response is elastic and positive. Farmers are responsive to the producer price variable in the short run through intensive cultivation. In addition, maize price (LRMPP(-1)), barley producer price D(LRBPP(-1)), intermediate input prices D(LRCOP(-1)), real exchange rate D(LRER(-1)), average rainfall D(LRF_wc(-1)), yield factor D(LRYIELD_wh(-1)), climatic factors (drought) as represented by D(DT81(-1)), D(DT88(-1)), and agricultural policy regime as represented by dummy variable D(DT92(-1)) and D(DT98(-1)) are the dominant factors that influence the current wheat supply response in South Africa. This result suggests that farmers are rational and forward looking in response to changes in expected prices due to price sustainability, over time.

The constant term has negative co-efficient (-0.06 and -14.22) in the short run and in the long run respectively, which implies that even if wheat is not planted, a certain amount will be imported to satisfy domestic demand. Hence, the including of the exchange rate is very important to assess import cost of this demand. The coefficient of the error correction term, which measures the speed of adjustment towards the long-run equilibrium, is negative (-0.49) and statistically significant at 5% level and is less than one. This means that the adjustment speed to the long-run equilibrium is 49%. This shows that farmers adjust from the deviation in the long-run equilibrium level in the current period is corrected by 51% in the next production season. Furthermore, all the explanatory variables jointly explained 52% of the variations in the wheat supply response model, while the remaining 48% can be attributed to the influence of other omitted variables, such as soil management practice and technology. The results of wheat vector error correction model are presented in table 7 below:

Table 7: Results of wheat vector error correction model

Variable	Coefficient	Standard errors	t-values	P-values
Short run effects				
C	-0.0630	0.0275	-2.2934*	0.0224
E_{ct-1}	-0.4947	0.1861	-2.6575*	0.0082
D(LAPWHEAT(-1))	-0.5786	0.2491	-2.3232*	0.0207
D(LRWPP(-1))	0.4644	0.2200	-2.1111*	0.0354
D(LRMPP(-1))	0.4802	0.1830	2.6243*	0.0090
D(LRBPP(-1))	-0.1127	0.1525	-0.7391	0.4603
D(LRCOP(-1))	0.2988	0.2570	1.1626	0.2457

Variable	Coefficient	Standard errors	t-values	P-values
D(LRER(-1))	0.0816	0.2375	0.3438	0.7312
D(LRF_wc(-1))	-0.0758	0.1290	-0.5873	0.5574
D(LRYIELD_wh(-1))	0.1957	0.1930	1.0140	0.3112
D(DT81(-1))	0.1191	0.1866	0.6384	0.5236
D(DT88(-1))	0.3758	0.1949	1.9282*	0.0546
D(DT92(-1))	0.0174	0.2436	0.0715	0.9430
D(DT98(-1))	-0.3669	0.2434	-1.5072	0.1326
Long run effects				
C	-14.2182	-	-	-
LRCOP(-1)	0.3425	0.1346	2.5445	
LRER(-1)	-0.3634	0.0951	-3.8229	-
LRF_wc(-1))	0.7542	0.1531	4.9257	-
LRYIELD_wh(-1)	-0.7876	0.1675	-4.7030	-
DT81(-1)	0.9333	0.0872	10.7018	
DT88(-1)	0.8087	0.1019	7.9347	-
DT92(-1)	-0.3336	0.1150	-2.9015	-
DT98(-1)	1.0317	0.0983	10.4956	-

VECM R^2: 0.5225 Mean dependent: -0.0312

VECM Adjusted- R^2: 0.2760 S.D dependent: 0.1738

F - statistic: 2.1198 Log likelihood: 34.1355

*significance @1% level

**significance @5% level

CONCLUSION

This study finds that supply response is high, positive and elastic to price signals and non-price factors in the production of maize and wheat crops in South Africa considering the thousands of hectare's planted yearly, and that the historical time series data of theses crops exhibit different patterns, which implies non-stationary as it has a unit root. The results of the co-integration tests further reinforce the equilibrium relationship between area planted and its determinants, which are producer's prices, price of substitute/complementary crops, intermediate input prices, average rainfall, yield factor, real exchange rate, climatic conditions (drought), and policy regime.

The supply response varies from a modest 0.08 for maize and 0.46 for wheat in the short run to 1.00 in the long run for maize, while the short run fluctuations in supply response is due to both price push and demand pull effects. In addition, the error correction term in the models display an appropriate (negative) sign and is statistically significant at the 5% level, and the rate of adjustment to the long-run equilibrium is different, but occurs within an acceptable level for each of the models. This finding is consistent with the validity of an equilibrium relationship among the variables, as supported by the co-integration test.

The findings of this study are significant in terms of model specification and policy response implications for stimulating the production of agricultural crops and an efficient value chain system in South Africa. The inclusion of real exchange rate, intermediate input prices, and structural break dummies to capture the effect of policy regime and weather (drought) into our VECM approach improved the model specification and logical analysis. Some of the previous studies in South Africa have ignored these variables, leading to miss-specification and methodological errors.

POLICY IMPLICATIONS

Policy-makers in partnership with major role players in the grain value chain, need to redesign an effective and purposeful implementations of agricultural policy choices, with the aim of increasing the productivity, investment, profitability, and competitiveness of the sector. The impact of changes in the relative prices of different crops on the allocation of area planted among crops could help to determine an integrated structure for agricultural price incentives that is necessary to achieve an optimal crop mix.

Policy reform should target how to boost supply response, efficient management of exchange rate and to reduce intermediate input prices through setting up a new fertilizer manufacturing complex and subsidizing costs of key inputs, like fertilizer, fuel, farming equipment and machines, and how to boost non-price factors, such as the rehabilitation of old irrigation facilities and adequate mitigating strategies to combat climate change. This gives empirical support for continue government interventions and support in agriculture, and a larger role for government in this regard is supported by empirical findings in the literature reviewed (Schiff 1987).

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