

# AGRICULTURAL SUPPLY RESPONSE AND PRICE RISK OF MAIZE AND SORGHUM IN SOUTH AFRICA

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**Abstract.** The study used the Autoregressive Distributed Lag-Error Correction Model (ARDL-ECM) approach to estimate the responsiveness of South African maize and sorghum producers to price risk, price incentives and non-price incentives. The price risk variable was incorporated in the supply response models to examine its impact on maize and sorghum production decisions. The study used annual historical time series data of 49 observations for the 1970-2018 period, which was used in the analysis. The empirical results reveal that maize and sorghum producers' response to own prices is reasonably low. The study further shows that both maize and sorghum crops demonstrate a high speed of adjustment to the long-run equilibrium, which means that in the event of a shock to the system, grain output will quickly re-establish itself at a faster rate. The findings underscore the relevance of price risk in determining production output in South Africa.

**Keywords:** ARDL-ECM, supply response, price risk, sorghum, maize

## INTRODUCTION

Agriculture contributes substantially to food supply and employment in South Africa, and its significant linkages with other sectors of the economy are essential to reducing poverty, fostering development, and stimulating economic growth. Although its share of the total gross domestic product (GDP) is relatively small (about 3%), agriculture remains important to the South African economy. During the past two decades, the government

has attempted to boost the agricultural sector by introducing comprehensive measures to address past injustices, including land redistribution and agrarian support programmes to disadvantaged farming communities (OECD, 2016). Other policy reforms such as the Marketing of Agricultural Products Act (No 47 of 1996) constituted major policy instruments to stimulate agriculture production in South Africa.

Maize and sorghum are the most important summer grains in the South African grain industry, contributing significantly to the gross value of agricultural production (DAFF, 2016). Maize (*Zea Mays*) is a staple food, source of livestock feed, an export crop, and it is produced in most parts of South Africa (DAFF, 2017b). On average, between 2.5 and 2.75 million hectares of commercial maize are planted in the country each year, accounting for nearly two-thirds of the commercial area in field crops (DAFF, 2017b). Sorghum (*Sorghum bicolor*) on the other hand is a crop indigenous to South Africa and a basic staple food for many rural communities where it provides household food security. Sorghum is the most important grain crop produced in South Africa after maize and wheat and is largely grown in drier areas, particularly on shallow and heavy clay soils (DAFF, 2017a). The annual production of sorghum in South Africa varies from 100,000 tonnes to 180,000 tonnes and the total area planted ranges from 130,000 to 150,000 ha, respectively (DAFF, 2017a).

Given the importance of the grain industry to economic growth and food security, the South African

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government needs to determine what policies are best suited to stimulate grain production. The role of providing the right incentives to increase supply (e.g. production) has been repeatedly emphasised in the development literature (Behrman, 1968; Krishna, 1982; Rao; 2004). Therefore, the focus of this study is the incentive context of prices in their effect on the choice of production alternatives based on the available resources. Previous studies have also emphasised the role of price risk on farmers' production decisions (Astover and Motte, 2003; Ayinde et al., 2017). Therefore, if a risk has an essential influence on farmers' production decisions, the incorporation of risk variables in this study should improve the estimated supply response elasticities. This study aims to estimate the supply response of maize and sorghum to past prices, price risk and non-price factors.

## LITERATURE REVIEW

Price and non-price incentives influence farmers' production decisions and determine how farmers allocate farm resources. Some studies on agricultural supply response, such as Nerlove (1958) and Mythili (2006), have given more attention to price incentives; however, other studies have found that non-price variables have a greater effect than price incentives on the farmers' decisions (Mamingi, 1996; Leaver, 2004; Rao, 2004 and Shoko, 2016). Non-price variables such as technology, natural conditions, social factors, and institutional factors influence agricultural production decisions. Hence, their inclusion in agricultural supply response analysis is critical as their omission generally brings about omitted variable bias (Mamingi, 1996).

In South Africa, few studies have focused on the econometric approach to price risk and its impacts on agricultural supply. Schimmelpfennig et al. (1996) applied cointegration techniques to investigate the supply response for maize and sorghum in South Africa. The results of the study showed that rainfall, farmer education, research and development and the cooperative extension changed the grain crop supply environment. The study also illustrated the dominance of maize and maize policies in production decisions in the summer-rainfall areas of South Africa. Nhundu et al. (2018) studied the supply response for sunflower in South Africa using panel data for the 1947–2016 period. The study revealed that sunflower farmers were not responsive to price changes, with short-run and long-run price elasticities

of 0.2387 and 0.3135, respectively. However, none of the studies discussed incorporated the variables of risk in the analysis of supply response.

## MATERIALS AND METHODS

The study used annual historical time series data of 49 observations for the 1970-2018 period, which were obtained from secondary sources. State-level data pertaining to the production volumes (measured in tonnes) and area planted (measured in hectares) for each grain crop were obtained from the South African grain information services (SAGIS). Also, data on average monthly rainfall (measured in mm) were obtained from the South African weather services. Domestic producer prices of the grain crops (measured in ZAR/Rands) were collected from DAFF and the South African grain information services (SAGIS). Time series data on the producer price index were obtained from the Abstract of Agricultural Statistics (DAFF, 2019). Fertiliser consumption data were obtained from the Fertiliser Association of Southern Africa (FERTASA). Data on the index of intermediate costs of fuel in agriculture were obtained from the Abstract of Agricultural Statistics (DAFF, 2019).

### Specification of Model and Variables

Two supply models were estimated, each representing maize and sorghum. The general relationship between the dependent variable for maize and sorghum and its associated explanatory variables can be presented in the form of a simple supply function, which is specified as follows:

$$PD_t = f(P_t, PS_t, PR_t, PC_t, FC_t, RF_t, Dm_t) \quad (1)$$

where:

- $PD_t$  – supply variable measured by production volumes in tonnes,
- $P_t$  – own price of grain measured in Rands,
- $PR_t$  – price risk variable measured by the standard deviation of log returns,
- $PC_t$  – production costs measured by the value of intermediate costs of fuel,
- $FC_t$  – fertiliser consumption,
- $RF_t$  – weather variable measured by average rainfall,
- $PS_t$  – price of a competing crop which measures the cross-price effect,
- $Dm_t$  – dummy variable for years before and after the liberalisation of the grain industry (period 1:

1970–1997; period 2: 1998–2018). The first and second periods take the value of 0 and 1, respectively. The variable is included in the analysis to measure the impact of the Agricultural marketing policy (Act No 47 of 1996) that was introduced in 1997.

Most economic time series data such as prices are subjected to inflation, and as such, the Producer Price Index (PPI) for summer crops was used to adjust maize and sorghum prices. The average rainfall received in the production months for each grain crop was used in the production response function as a proxy for the weather factor. Production costs influence farmers’ production decisions. Thus, the value of the intermediate costs of fuel was used to measure the technical change in the analysis. The fuel costs represent a large share of the production costs in grain farming, and hence its inclusion as a proxy for production costs is justified.

In this study, production volume was used as a proxy for output and introduced as a dependent variable in supply response functions for maize and sorghum. The use of production volume as a proxy for the output was justified by the fact that farmers may respond to changes in price by changing production practices and adopting farming methods without necessarily changing the area planted. Similarly, Leaver (2004) argued that farmers might respond to price incentives by using either more intensive or more extensive farming. Several other supply response studies have used production volume (measured in tonnes) as a proxy for output (Leaver, 2004; Muchapondwa, 2009; Haile et al., 2015; Shahzad et al., 2018).

### Autoregressive Distributed Lag (ARDL) Model

The ARDL model provides a significant opportunity to test and estimate long-run relationships from actual time series data (Hassler and Wolters, 2006). The model is also ideal for short time series (Duasa, 2007). Pesaran et al. (2001) suggested that the key advantage of the ARDL model is its flexibility to analyse variables of different orders of integration. The Johansen cointegration test approach necessitates that all the variables be integrated of the same order, i.e. I(1) (Johansen, 1991). Hence, this method is not appropriate for this study and cannot be applied. The simple function of a simple ARDL (1,1) model is specified as follows:

$$A_t = m + \phi_1 A_{t-1} + \Phi_0 x_t + \Phi_1 x_{t-1} + u_t \quad (2)$$

$$t = 1, 2, \dots, T$$

$$u_t \sim \text{i.i.d} \{0, \sigma^2\}$$

$A_t$  and  $x_t$  – are stationary variables and  $u_t$  – is white noise.

The model is autoregressive because of the lagged values of the dependent variable  $A_t$  partially explains itself. The distributed lag component of the function is present in the form of successive lags of the explanatory variable  $X_t$ .

The study used E-views 10 econometric software to carry out the analysis. Optimum lag lengths were chosen based on Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). All the variables except the policy dummy variable were expressed in natural logarithms. The two supply models for the grain crops under study are specified below.

### Maize supply response function

The maize supply model that was used to measure the long-run relationship among the variables is specified as follows:

$$\begin{aligned} \text{LnMPD}_t = & \alpha_0 + \sum_{i=1}^q \alpha_{1i} \text{LnMPD}_{t-i} + \sum_{i=1}^{P_1} \alpha_{2i} \text{LnMP}_{t-i} \\ & + \sum_{i=1}^{P_2} \alpha_{3i} \text{LnMPR}_{t-i} + \sum_{i=1}^{P_3} \alpha_{4i} \text{LnFC}_{t-i} + \sum_{i=1}^{P_4} \alpha_{5i} \text{LnWP}_{t-i} \quad (3) \\ & + \sum_{i=1}^{P_5} \alpha_{6i} \text{LnPC}_{t-i} + \sum_{i=1}^{P_6} \alpha_{7i} \text{LnRF}_{t-i} + \sum_{i=1}^{P_7} \alpha_{8i} Dm + u_t \end{aligned}$$

$$\forall i = 1, 2, \dots, k$$

where:

$\text{LnMPD}_t$  – is the natural logarithm of maize production,

$\text{LnMPD}_{t-1}$  – represents the natural logarithm of maize production in the previous period,  
 $\text{LnMP}_{t-1}$  – is the natural logarithm of maize real price,

$\text{LnMPR}_{t-1}$  – represents the natural logarithm of the price risk variable for maize,

$\text{LnFC}_{t-1}$  – represents the natural logarithm of the fertiliser consumption variable,

$\text{LnPC}$  – represents the natural logarithm of production costs and

$Dm$  – represents the policy variable.

$LnRF_{t-1}$  – is the natural logarithm of average annual rainfall and  $LnWP_{t-1}$  represents the natural logarithm of the wheat price, with wheat being a close competitor of maize in terms of the area planted. The short-run coefficients were estimated by the error correction term (ECT) in the following error correction model:

$$\begin{aligned} \Delta LnMPD_t = & \alpha_0 + \sum_{i=1}^q \alpha_{1i} \Delta LnMPD_{t-i} \\ & + \sum_{i=1}^{P_1} \alpha_{2i} \Delta LnMP_{t-i} + \sum_{i=1}^{P_2} \alpha_{3i} \Delta LnMPR_{t-i} \\ & + \sum_{i=1}^{P_3} \alpha_{4i} \Delta LnFC_{t-i} + \sum_{i=1}^q \alpha_{5i} \Delta LnWP_{t-i} \quad (4) \\ & + \sum_{i=1}^q \alpha_{6i} \Delta LnPC_{t-i} + \sum_{i=1}^q \alpha_{7i} \Delta LnRF_{t-i} \\ & + \sum_{i=1}^q \alpha_{8i} Dm + \alpha_{9i} ECT + u_t \end{aligned}$$

where:  $\Delta$  is the difference operator and  $\alpha_{9i}$  represents the coefficient of the ECT, which measures the deviation of  $MPD_t$  from the long-run equilibrium level.

### Sorghum supply response function

The sorghum supply model that was used to measure the long-run relationship among the variables is specified as follows:

$$\begin{aligned} LnSPD_t = & \alpha_0 + \sum_{i=1}^q \alpha_{1i} LnSPD_{t-i} + \sum_{i=1}^{P_1} \alpha_{2i} LnSP_{t-i} \\ & + \sum_{i=1}^{P_2} \alpha_{3i} LnSPR_{t-i} + \sum_{i=1}^{P_3} \alpha_{4i} LnSA_{t-i} + \sum_{i=1}^{P_4} \alpha_{5i} LnWP_{t-i} \quad (5) \\ & + \sum_{i=1}^{P_5} \alpha_{6i} LnPC_{t-i} + \sum_{i=1}^{P_6} \alpha_{7i} LnRF_{t-i} + \sum_{i=1}^{P_7} \alpha_{8i} Dm + u_t \\ & \forall i = 1, 2, \dots, k \end{aligned}$$

where:

$LnSPD_t$  – is the natural logarithm of sorghum production,  
 $LnSPD_{t-1}$  – represents the natural logarithm of sorghum acreage in the previous period,

$LnSP_{t-1}$  – is the natural logarithm of real sorghum price,  
 $LnSPR_{t-1}$  – is the natural logarithm of the price risk variable for sorghum,  
 $LnSA_{t-1}$  – is the natural logarithm of sorghum acreage,  
 $LnPC$  – represents the natural logarithm of the production cost variable,  
 $Dm$  – represents the policy variable,  
 $LnRF_{t-1}$  – is the natural logarithm of average annual rainfall and  
 $LnWP_{t-1}$  – represents the natural logarithm of the real wheat price, since wheat is a close competitor of sorghum in terms of the area planted.

The short-run coefficients were estimated using the following error correction model:

$$\begin{aligned} \Delta LnSPD_t = & \alpha_0 + \sum_{i=1}^q \alpha_{1i} \Delta LnSPD_{t-i} \\ & + \sum_{i=1}^{P_1} \alpha_{2i} \Delta LnSP_{t-i} + \sum_{i=1}^{P_2} \alpha_{3i} \Delta LnSPR_{t-i} \\ & + \sum_{i=1}^{P_3} \alpha_{4i} \Delta LnSA_{t-i} + \sum_{i=1}^q \alpha_{5i} \Delta LnWP_{t-i} \quad (6) \\ & + \sum_{i=1}^q \alpha_{6i} \Delta LnPC_{t-i} + \sum_{i=1}^q \alpha_{7i} \Delta LnRF_{t-i} \\ & + \sum_{i=1}^q \alpha_{8i} Dm + \alpha_{9i} ECT + u_t \end{aligned}$$

where:  $\Delta$  is the difference operator and  $\alpha_{9i}$  represents the coefficient of the ECT, which measures the deviation of the  $SPD_t$  from the long-run equilibrium level.

### Unit root test

This study used the Augmented Dickey-Fuller (ADF) test and the Dickey-Fuller generalised least square (DF-GLS) de-trending test proposed by Elliot et al. (1996) to test the variables for stationarity. The use of the DF-GLS test is justified because it performs well in terms of small sample size and power, conclusively dominating the ordinary Dickey-Fuller test. The ARDL method is based on the assumption that the variables are integrated of order 0 or 1 (I(0) or I(1)). The objective is to ensure that none of the variables is I(2) to avoid spurious results or a crash of the ARDL model.

### Diagnostic tests

Relevant diagnostic tests such as the Jarque Bera test for normality, Breusch-Godfrey LM test for serial correlation were applied to confirm the quality of the estimated ARDL models. The White test was used to test for heteroscedasticity within the model.

### Stability tests

The Cumulative Sum (CUSUM) and CUSUM Squared tests were used to test for model stability. These tests have been utilised by several authors such as Janjuaa et al. (2014) to assess if a model is stable across various subsamples of the data.

### Measuring price risk

Several realised volatility measures are documented in supply response literature. However, Díaz-Bonilla (2016) argued that choosing the most appropriate volatility measure depends on the context, data availability and research objectives. Thus, to achieve the objective of the study, volatility in the prices of maize and sorghum were measured by the standard deviation (SD) of annual logarithmic returns, as adopted from Haile et al. (2015). This method was selected because it is relevant in an analysis conducted over a long period of price changes. Thus, the standard deviation was calculated from the historical prices of the grain commodities under study. First, the log-returns were computed as follows:

$$\log - \text{returns} = u_i = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where  $P_t$  and  $P_{t-1}$  represent prices in the current and previous period, respectively.

∴

$$\text{Volatility} = \sigma_n = \sqrt{\frac{1}{m} \sum_{i=1}^m (u_i - \bar{u})^2}$$

where  $\bar{u}_i$  = drift = Average ( $u_i$ )

The study used a 5-year moving average to conduct the statistical analysis proposed by Huchet-Bourdon (2011). The volatility values generated using this method were then included in the maize and sorghum supply response functions to estimate the effect of price risk on grain production.

## RESULTS AND DISCUSSION

The results of the ADF and DF-GLS unit root tests are presented in Table 1. All variables involved in the maize and sorghum supply equations were tested for their levels and first differences to determine the degree of integration. The test results show that the fertiliser consumption variable is non-stationary at level. As expected, the variable became stationary after the first differences. All other variables used in the supply models of

**Table 1.** Unit root test results

Variables	ADF Test				DF-GLS Test			
	Level		First Difference		Level		First Difference	
	t-stat	Critical value at 5%	t-stat	Critical value at 5%	t-stat	Critical value at 5%	t-stat	Critical value at 5%
1	2	3	4	5	6	7	8	9
LNMPD	-5.6070	-3.5064	-9.8200	-3.5155	-4.806	-3.1900	-7.9230	-3.1900
LNSPD	-6.0366	-3.5064	-8.2037	-3.5107	-5.650	-3.1900	-7.0969	-3.1900
LNSA	-3.7153	-3.5063	-8.2251	-3.5085	-3.7896	-3.1900	-7.6396	-3.1900
LNWA	-3.6577	-3.5063	-8.4115	-3.5085	-3.2314	-3.1900	-8.4577	-3.1900
LNFC	-3.3750	-3.5063	-4.9588	-3.5130	-2.5902	-3.1900	-8.7293	-3.1900
LNSYP	-4.1194	-2.9237	-6.9141	-2.9297	-3.056	-3.1900	-6.2954	-3.1900

**Table 1 – cont.**

1	2	3	4	5	6	7	8	9
LNSP	-3.9452	-3.5085	-5.1305	-3.5266	-3.126	-3.1900	-5.6241	-3.1900
LNMP	-5.3008	-3.5064	-7.0234	-3.5107	-4.8980	-3.1900	-6.8173	-3.1900
LNWP	-4.1903	-3.5064	-6.4625	-3.5107	-2.7744	-3.1900	-6.5483	-3.1900
LNMPR	-3.3457	-2.9238	-7.3212	-2.9252	-2.8533	-1.9478	-7.2802	-1.9480
LNSPR	-6.3188	-2.9237	-7.7837	-2.9281	-6.2680	-1.9478	-10.135	-1.9479
LNWPR	-0.6869	-2.9237	-5.8664	-2.9251	-0.451	-1.9478	-5.8961	-1.9479
LNRF	-7.4036	-2.9238	-5.6525	-3.5131	-1.6095	-3.1900	-5.6525	-3.1900
LNPC	-0.4249	-3.5064	-5.9957	-3.5131	-0.2845	0.7773	-7.9636	-3.1900

Note: Analysis includes trend and intercept

The model includes constant and trend and all variables are in natural logarithmic form.

LNMPD, LNSA, LNSPD, LNWA, LNMA represents the natural logarithm of maize price, maize production, sorghum acreage, sorghum production, wheat acreage, maize acreage, respectively.

LNMP, LNSP, LNWP represents the natural logarithm of maize price, wheat price, barley price, respectively.

LNSPR, LNMPR represents natural logarithm sorghum price risk and maize price risk, respectively.

LNPC, LNFC, LNRF represents the natural logarithm of production cost, fertiliser consumption, weather variable, respectively.

Source: own elaboration.

the grain crops under study are stationary at level. These results also demonstrate that the variables are integrated of order one I(1) and order zero I(0). Thus, since there is no I(2) variable, the ARDL model is estimated and a valid bounds test is applied.

### Diagnostic test results of maize and sorghum

The diagnostic test results are shown in Table 2. Both the sorghum and the maize models passed all diagnostic tests. The F-statistics values and their associated p-values for the completed tests demonstrate that both models are homoscedastic, normally distributed and have no problems of serial correlation. By rejecting the null

hypothesis for each test conducted, we conclude that the estimated supply models are adequate in terms of their specifications.

### Stability test results of maize and sorghum

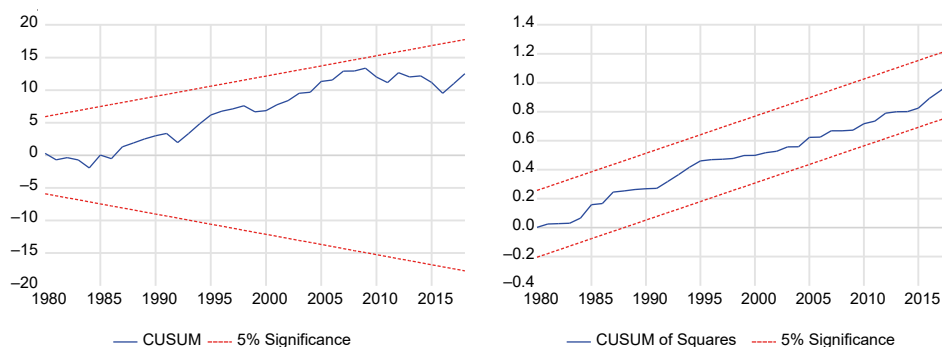
The results of the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUM) are applied. Tests results are presented in graphical form (see Fig. 1 for the maize model results and 2 for the sorghum model results).

The output shows that the CUSUM lines in all figures are positioned between the critical bound of a 5% significance level over time, indicating that both models are mostly stable throughout the entire period of study.

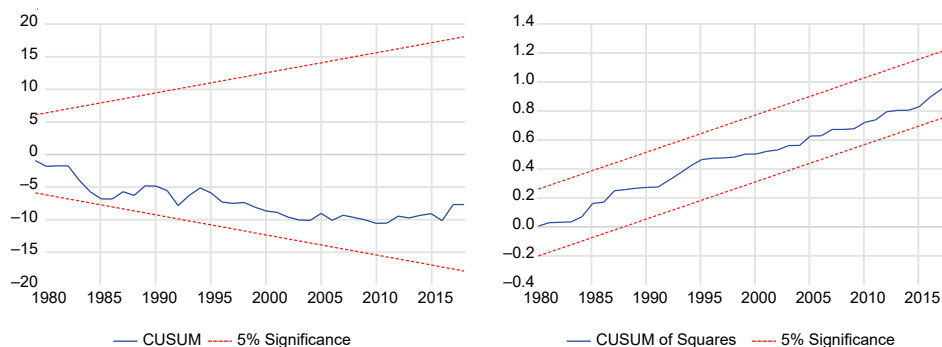
**Table 2.** Diagnostic test results

Diagnostic Method	Serial Correlation Test		Heteroskedasticity Test		Normality Test	
	Breusch-Godfrey H <sub>0</sub> : Serial correlation		Breusch-Pagan-Godfrey H <sub>0</sub> : Homoscedastic		Jarque-Bera H <sub>0</sub> : Not normally distributed	
	F-statistic	P-value	F-statistic	P-value	F-stat	P-value
Maize	1.123141	0.3358	1.398437	0.2329	0.2376	0.8879
Sorghum	0.275538	0.7607	0.743706	0.6529	2.2884	0.3134

Source: own elaboration.



**Fig. 1.** CUSUM and CUSUM of Squares test results for maize model  
Source: own elaboration.



**Fig. 2.** CUSUM and CUSUM of Squares test for sorghum model  
Source: own elaboration.

### Cointegration test results

The results of the bounds test for maize and sorghum models are presented in Table 3. The F-statistic values of 19.45 for maize and 27.14 for sorghum are greater than the upper bound critical value at a 5% level. Likewise, the F-statistic values for wheat (8.23) and barley (6.1) are greater than the upper bound critical value at 5%. Accordingly, the study rejects the null hypothesis

of no long-run relationship and concludes that there is a long-run relationship among the estimated variables for maize, sorghum, wheat and barley supply models.

The existence of a long-run relationship among the variables validates the estimation of ARDL long-run models to obtain the long-run parameters for the respective grain crops.

**Table 3.** F-Bounds test for cointegration results

Variables	F-Statistic value	Lower bound value I(0) at 5%	Upper bound value I(1) at 5%	Conclusion
Maize	19.45	3.79	4.25	Cointegration
Sorghum	27.14	2.69	3.83	Cointegration

Source: own elaboration.

### Long-run elasticities of maize and sorghum

The results of long-run elasticities for maize and sorghum analysis are presented in Tables 4 and 5. The dependent variables are maize production (MPD) and sorghum production (SPD) volumes measured in tonnes. The results show that price-related production responses for both maize and sorghum are positive and significant

**Table 4.** Long-run parameters for maize supply response model

Maize long-run parameters				
Variable	Coefficient	Standard error	T-statistic	P-value
LN(MP)	0.7542	0.1442	5.2313	0.000*
LN(MPR)	-0.3928	0.0695	-5.6536	0.000*
LN(WP)	-0.2571	0.0925	-2.7791	0.008*
LN(RF)	0.9137	0.2683	3.4057	0.002*
LN(PC)	0.8871	0.3040	2.9183	0.006*
R-Squared	0.5620	Durbin-Watson Statistic		2.0175

\*, \*\*, \*\*\* represents the 1%, 5% and 10% level of significance, respectively.  
All variables are in logarithmic form.  
Source: own elaboration.

**Table 5.** Long-run parameters for sorghum supply response model

Sorghum long-run parameters				
Variable	Coefficient	Standard error	T-statistic	P-value
LN(SP)	0.5116	0.2088	2.4497	0.0189**
LN(SPR)	0.1880	0.0862	2.1793	0.0354**
LN(RF)	0.7534	0.2637	2.8570	0.0068*
LN(PC)	-0.0667	0.0957	-0.6967	0.4901
LN(SA)	0.8082	0.1353	5.9712	0.0000*
LN(FC)	0.8340	0.2841	2.9359	0.0056*
LN(WP)	-0.5773	0.3247	-1.7777	0.0833***
R-Squared	0.8640	Durbin-Watson Statistic		1.9426

\*, \*\*, \*\*\* represents the 1%, 5% and 10% level of significance, respectively.  
All variables are in logarithmic form.  
Source: own elaboration.

at a 5% level. The results are also consistent with economic theory. The size of the adjusted R-squared is 0.56 for the maize model and 0.86 for the sorghum model. The F-statistic values are 7.35 and 25.33 and significant at a 5% level for maize and sorghum, respectively. This is acceptable to show the overall fitness of the model.

The results indicate that maize has greater production responses to its own price as compared to sorghum. The coefficient of the own price variable for maize is positive and significant at a 1 per cent level, suggesting that a 10 per cent increase in maize price will be followed by an increase in maize production of about 7.5 per cent in the long run. Likewise, sorghum's own-price elasticity is also positive and significant at a 5 per cent level, suggesting that a 10 per cent increase in sorghum prices will induce an increase in sorghum production by 5.1 per cent in the long run.

The price risk variable for maize measured by the standard deviation of log returns is significant at a 1 per cent level, with a long-run parameter of -0.39. As expected, the sign of the coefficient is negative, and this effect of price risk corresponds to the findings of Just (1974), Seale and Shonkwiler (1987) and Holt and Aradhyula (1990). The results suggest that a greater expected price risk leads to decreased maize production volumes. Specifically, the estimated results indicate that an increase in price volatility causes producers to allocate less land to maize and reduce production-improving investments, resulting in a decline in maize production. Interestingly, the long-run parameter of expected sorghum price risk (SPR) has a positive sign and is significant at a 5 per cent level. Although price risk is anticipated to lead to a reduction in output (Just, 1974; Seal and Shonkwiler, 1987; Holt and Aradhyula, 1990), this result suggests that sorghum producers in South Africa are risk-tolerant and may be willing and able to absorb price risks in the long run. Thus, the high price risk appetite displayed by sorghum farmers may be explained by the nature of the sorghum market, and the variability of sorghum prices in comparison with other grain products produced by farmers.

The empirical results also reveal that the prices of competitive crops play an important role in determining the supply of maize. As expected, the coefficient of wheat prices is negative and significant in both maize and sorghum models. The cross-price elasticity for maize is 0.25, indicating that a 5 per cent increase in wheat price leads to a 2.5 per cent decrease in maize



production. The cross-price elasticity for sorghum is 0.57 and is higher than that for maize. The finding suggests that a 10 per cent increase in wheat price decreases sorghum production by 5.7 per cent. Implications of these results are that there is a tendency for farmers to substitute maize and sorghum with wheat, whenever its price is more favourable than that of competitive crops. This effect of cross-price elasticities on maize and sorghum is smaller than that found by Shahzad et al. (2018) who obtained a long-run cross-price elasticity of -0.79 for tobacco.

With respect to the rainfall variable, the estimated long-run elasticity of supply for maize is close to unitary with a value of 0.91. The results suggest that a 10 per cent increase in rainfall increases maize production by 9.1 per cent in the long run. Moreover, the implied long-run elasticity for sorghum in the case of rainfall is 0.75, suggesting that a 10% increase in rainfall will boost sorghum production by 7.5 per cent. The results suggest a strong effect of rainfall on maize and sorghum production in the long run. In South Africa, grain production is still mostly rain-fed, and hence rainfall still plays a major role in determining maize and sorghum production. The estimated long-run supply elasticities for maize and sorghum with respect to rainfall are within the range of acceptable estimates (e.g. Leaver, 2004; Muchapondwa, 2009).

Concerning the sorghum model, the long-run elasticity for fertiliser consumption variable given by the estimated coefficient FC is 0.83. The long-run parameter is significant and higher than the estimates obtained by Muchapondwa (2009) who recorded long-run estimates of 0.36 for fertiliser consumption. The positive coefficient suggests that an increase in fertiliser use by 10% will be followed by an increase in sorghum production by 8.3 per cent in the long run. The coefficient of sorghum area is positive and significant at a 1 per cent level. This finding is to be expected and indicates that sorghum production could rise by 7.4 per cent every time the area planted is increased by 10 per cent in the long run. These results confirm the importance of dedicating more land to sorghum production in South Africa. Although land for production expansion is limited, land can be made available by shifting resources from other crops (such as maize and wheat) to sorghum in the long run.

The long-run coefficient of production costs for maize, measured by the fuel cost index, is positive and

significant at a 1 per cent level, indicating that a 10 per cent increase in production costs increases maize production by 8.8 per cent. The implication is that high production/fuel costs signify technical change which in turn stimulates maize production. Interestingly, the long-run coefficient of production costs for sorghum is insignificant at all levels of significance. This finding could imply that other variables, such as rainfall and fertiliser consumption, explain sorghum production better than production costs. The Dummy variable (Dm) was not included in either the sorghum or maize supply model as it was not significant. Removing the variable improved the supply estimates in both models.

### Short-run equilibrium elasticities of maize and sorghum

The results of the ECMs for sorghum and maize are reported in Table 6. The ECT of -0.90 for the maize model and -0.97 for the sorghum model indicates a high speed of adjustment towards the long-run equilibrium. The ECT suggests how quickly variables converge to equilibrium and it should have a statistically significant coefficient with a negative sign. The estimated results of the maize and sorghum models show that the ECT in both models is negative and highly significant. Banerjee et al. (1993) argued that a highly significant ECM further confirms the existence of a stable long-run relationship.

**Table 6.** Short-run equilibrium elasticities

Maize-short-run parameters				
Variable	Coefficient	Std. Error	t-Statistic	Prob-Value
Constant	8.5958	0.7516	11.4361	0.0000*
Trend	-0.0728	0.0068	-10.7298	0.0000*
ECT(-1)*	-0.9098	0.0794	-11.4595	0.0000*
R-squared	0.7447	Durbin-Watson Statistic		2.1075
Sorghum short-run parameters				
Variable	Coefficient	Std. Error	t-Statistic	Prob-Value
Constant	-9.9772	0.6335	-15.7504	0.0000*
ECT(-1)*	-0.9759	0.0620	-15.7312	0.0000*
R-squared	0.8432	Durbin-Watson Statistic		1.9426

All variables are significant at 1% level.  
The maize model includes trend and intercept.  
Source: own elaboration.

With regard to the maize model, the ECT demonstrates that after a 10 per cent shock to the system, the long-run equilibrium relationship of maize production is quickly re-established at the rate of about 90 per cent per annum. Similarly, the ECT for the sorghum model implies that the change in sorghum production between the short-run and the long-run is corrected by about 97 per cent per year. Thus, disequilibrium caused by a shock will take slightly more than a year to correct.

## CONCLUSION AND POLICY RECOMMENDATIONS

Maize and sorghum play a key role in the South Africa food chain, and their production is of paramount importance to food security and economic growth. Considering the importance of grain crops, this study attempted to examine the influence of past prices, non-price factors and price risk on the farms' production decisions. The results of the study showed that price incentives are not sufficient to stimulate maize and sorghum production in South Africa. Non-price factors such as rainfall, fertiliser use, technological changes and area expansion are more relevant explanatory variables. In light of the above, it is recommended that policies aimed at stimulating maize and sorghum production should be directed towards investment in irrigation and drought-resistant varieties. The study has also shown that incorporating price risk variables in supply response models improves the supply estimates. The results underscore the relevance of price risk in determining grain production output and showed that greater price risk leads to reduced production levels, particularly for maize. Given the results, the study recommends that any policy initiatives aimed at stabilising the grain industry should consider proposing packages (e.g. forward contracts, futures contracts, contract farming) that reduce the adverse effects of the price risk. The findings revealed that grain crops – maize and sorghum – demonstrate a high speed of adjustment to the long-run equilibrium, which means that in the event of a shock to the system, grain output will quickly re-establish itself at a faster rate.

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