ANALYSING THE SUPPLY RESPONSE AND PRICE RISK OF MAJOR GRAIN CROPS IN SOUTH AFRICA

BY

RANGARIRAI ROY SHOKO

A RESEARCH THESIS SUBMITTED FOR THE FULFILLMENT OF THE DEGREE DOCTOR OF PHILOSOPHY (AGRICULTURAL ECONOMICS), DEPARTMENT OF AGRICULTURAL ECONOMICS AND ANIMAL PRODUCTION, SCHOOL OF AGRICULTURAL AND ENVIRONMENTAL SCIENCES, FACULTY OF SCIENCE AND AGRICULTURE, UNIVERSITY OF LIMPOPO, SOUTH AFRICA

SUPERVISOR: PROF A BELETE

CO-SUPERVISOR: PROF I P MONGALE

APRIL 2021

ABSTRACT

The issues regarding the determinants of agricultural production and food supply are currently of great interest in developing countries. This, in turn, has led to the undertaking of this study focusing on the effectiveness of incentives that can be offered within the agricultural sector to boost production. The study aims to model the supply response of key agricultural commodities to price incentives, price risk and non-price incentives. Special focus is given to four major grain crops, namely; maize, wheat, sorghum and barley, which are of strategic interest to South Africa. The emphasis of the study is on two significant aspects of agricultural supply response: First, an attempt is made to determine the level of price risk among the selected grain crops using two distinct price risk measures. Second, the Autoregressive Distributed Lag-Error Correction Model (ARDL-ECM) approach to cointegration is used to estimate the responsiveness of grain producers to price risk, price incentives and non-price incentives. Annual historical time series data of 49 observations for the period 1970 to 2018 is used in the analysis. Data is tested for stationarity using the Augmented Dickey-Fuller test and the Dickey-Fuller Generalised Least Square (DF-GLS) de-trending test. The empirical results reveal that grain supply in South Africa is reasonably responsive to price incentives. However, the degree of responsiveness is low and varies among different crops. Depending on the crop, the results show that own price supply elasticities range from about 0.24 to 0.75. Supply elasticities for non-price factors are much higher, indicating that non-price incentives (i.e. rainfall, fertiliser, technology) are better production drivers than price incentives in South Africa. Thus, instead of regarding price mechanisms as being the only tools to promote agricultural production, it is concluded that further expansion of irrigation facilities and encouraging the adoption of drought-resistant varieties will stimulate grain production. The results underscore the relevance of price risk in determining production output and show that greater price risk leads to reduced production levels, particularly for maize and barley. In light of such evidence, any policy initiatives undertaken to stabilise the grain industry should look into proposing packages (i.e., forward contracts, futures contracts, contract farming) that reduce the negative impacts of price volatility in grain commodity markets.

Key words: supply response, ARDL-ECM, Price factors, non-price factors, price risk

ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my supervisor Professor. A. Belete for the continuous support of my PhD study and related research, for his patience, motivation, and immense knowledge. His guidance really assisted me throughout the time of writing of this thesis. I could not have imagined having a better supervisor and mentor for my PhD study.

Besides my supervisor, I would like to thank my second supervisor Professor. I.P. Mongale for his insightful comments and encouragement, and also for the questions which incited me to view my research from various perspectives.

I'm indebted to Entsika bursary programme for taking care of all my financial needs.

I'm thankful to my family: my mother and my siblings for motivating and supporting me in every way and for all of the sacrifices that you've made on my behalf. Your prayer for me was what sustained me thus far.

Lastly, my deepest gratitude goes to all the individuals, who may have contributed to this work either directly or indirectly.

DECLARATION

I declare that the dissertation hereby submitted by me to the University of Limpopo for the degree of Doctor of Philosophy (Agricultural Economics) is my own independent work and has not previously been submitted by me to any other university. It is my own work in design and execution, and that all material contained herein has been duly acknowledged.

Signature:………………………..   Date : ……………………….. ……

Shoko Rangarirai Roy [redacted]

TABLE OF CONTENTS

APPENDIX

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
CUSUM	Cumulative Sum
DAFF	Department of Agriculture Forestry and Fisheries
ECM	Error Correction Method
GARCH	General Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GRAINSA	Grain South Africa
JSE	Johannesburg Stock Exchange
MA	Moving Average
NAGARCH	Nonlinear Asymmetric General Autoregressive Conditional Heteroskedasticity
OECD	The Organisation for Economic Co-operation and Development
R&D	Research and Development
SAB	South African Breweries
SADC	Southern African Development Community
SAFEX	South African Futures Exchange
SAGIS	South African Grain Information Services
SSA	Sub Saharan African
Stats SA	Statistics South Africa
UECM	Unrestricted Error Correction Model

CHAPTER 1: INTRODUCTION

1.1. Background

Since the democratic dispensation in 1994, the South African economy has undergone a drastic transformation characterised by rapid urbanisation and increased incomes. The extensive changes in economic and social structure require fast growth in the food supply. Agriculture contributes substantially to food supply and employment in South Africa, and its significant supply and demand linkages with the rest 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 (about 3%) relatively small, agriculture remains vitally important to the South African economy. About 70% of agricultural output is used as intermediate products in the manufacturing sector (DAFF, 2017d). Hence, the stability and future growth of the sector is essential to provide food security to the South African population. In the past 2 decades, the government has made attempts to boost the agricultural sector by introducing comprehensive measures to address past injustices including land redistribution and agricultural support programmes to disadvantaged farming communities (OECD, 2016). Other policy reforms such as the marketing of agricultural products act (No. 47 of 1996) have been significant policy instruments to stimulate agriculture production in South Africa.

Despite the reforms, the agricultural sector is currently facing challenges driven mainly by climate change, highly volatile domestic prices, rising input costs and heavy reliance on highly volatile international markets. The output from the agriculture sector declined by 13,2% in the first quarter of 2019, thus contributing to the overall negative economic growth of 3,2% for South Africa over that period (Stats SA, 2019). Agriculture was also the worst-performing sector in the second quarter of 2019, registering another decline in output of (4.2%). According to Stats SA (2019), the agriculture sector’s poor performance was a result of a slowdown in the production of field crops, including wheat, sunflower seed and tobacco, and horticultural products. This is due to the fact that field crops account for 30% of total agriculture value and hence, a slump in the production of field crops could result in a decline of the overall agricultural sector. Consequently, South Africa has witnessed a distinct downward trend in the area planted with wheat over the past few years. During the 2018/19 season South Africa recorded the lowest area planted with wheat in 50 years, a situation that further pushed production levels down. At this rate, it is estimated that wheat production volumes and area will further plummet in subsequent years. The situation is the same for sorghum. Maize production has also been unstable in recent years, largely due to poor climatic conditions.

According to Gouws (2018), reduction of wheat and sorghum production has been increasing as a result of farmers switching land to other more profitable crops. For example, farmers have transferred grain cropland to sunflower and oil seeds. In this context, 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 incentive context of prices and their effect on the choice of production alternatives with available resources is the focus of this study. Many researchers have attempted to estimate the responsiveness of supply to price incentives (Askari and Cummings, 1977; Rao, 1989; Schiff and Montenegro, 1997; Ogazi, 2009; Shoko *et al,* 2016; Nhundu et al., 2018).

Despite the range of methods that have been employed and the variety in the findings, it can be said that supply does respond to price changes. However, some economists have recorded poor supply response to price changes, particularly in developing countries (Bhagat, 1989; Ogazi, 2009; Liu *et al,* 2010; Khan *et al,* 2019). Thus, there has been controversy as to whether agricultural supply really is not responsive to price incentives. Bhagat (1989) argued that if farmers did not respond much to changes in incentives, it was not so much due to their inability to adapt to changing circumstances but rather to the constraints they were facing. Agreeably, Schiff and Montenegro (1997), maintained that 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. Hence, besides prices, the importance of non-price factors (such as technology, weather, institutional and social factors) has drawn adequate attention in the literature. Thus, the extent to which farm decisions, respond to economic and non-economic incentives should be of central concern to policy-makers and is the focus of this thesis.

1.2. Problem statement

South Africa's population is growing rapidly, with estimates indicating that the population grew from 38.6 million in 1994 to 56.5 million in 2017 (Stats SA, 2017). The continued increase in population and the global increase in the demand for livestock and livestock products (Steinfeld *et al,* 2006) will likely cause a rise in the demand for grain products. Sustainable growth and development in the agricultural sector are required to meet the country's growing demand and trade. To accomplish this, the efficient utilisation of resources in the agricultural sector is necessary. Although the government has made remarkable efforts to liberalise the agricultural sector and make technology, and inputs accessible and improve market access, it remains unclear to what extent farmers respond to these incentives. Rao (2004) argued that the impact of price policies on agriculture's growth crucially depends on how the farmers respond to various price incentives. Hence, the extent to which farm decisions react to economic and non-economic incentives is highly critical to policymakers, which is the focus of this study.

Furthermore, price fluctuations have been linked to significant price risk, especially in agricultural products (Rezitis and Stavropoulos, 2009). Thus, an increase in price volatility implies higher uncertainty about future prices, which can affect producers' welfare, especially in the absence of a hedging mechanism. Therefore, this study also focuses on the role of price risk on farmers' production decisions.

1.3. Rational

The grain industry (maize, wheat, sorghum, oats, barley) is one of the largest agricultural industries in South Africa, contributing more than 30% to the total gross value of agricultural production (Department of Agriculture Forestry and Fisheries, DAFF, 2016). Given the importance of the agriculture industry to economic growth and food security, the South African government needs to determine what policies are best suited to stimulate grain production. Reliable supply elasticities are essential for efficient planning of crop production and can possibly assist in making informed policy decisions (Muchapondwa, 2009). The basic parameters needed to evaluate the impact of price and non-price interventions are the elasticities of supply. These parameters quantify farmers' responsiveness to price and non-price changes and provide the basis for predicting production changes induced by the market intervention.

Previous studies have emphasised the role of price risk on farmers' production decisions (Astover and Motte, 2003; Ayinde *et al,* 2017). Agricultural prices tend to be more volatile due to seasonality, inelastic demand, and production uncertainty (Holt and Moschini, 1992). In general, increasing price volatility translates into greater price risk exposure for farmers. In this context, suitable risk measurements become very important for policymakers interested in mitigating the negative impacts of price changes. Therefore, if risk has an essential influence on farmers' production decisions, incorporating risk variables in this study should improve estimated supply response elasticities. Reasons for conducting this study focusing on agricultural supply response are two-fold. Firstly, literature review has revealed that very few researchers have focused on the econometric approach to supply response behaviour of major grain crops in South Africa. Hence, this study intends to bridge that gap. Secondly, few studies have focused on the econometric approach to price risk and its impacts on agricultural supply. Previous works in South Africa have not comprehensively considered the implications of price risk on grain farmers production decisions. Hence, the purpose of this study is to contribute towards a better understanding of the grain industry and determine the impact of past prices, price risks and other supply shifters on grain production in South Africa.

1.4. Aim of the study

This study aims to model the supply response of the South African grain industry to past prices, price risk, and non-price factors. The research focuses on four major grain crops: maize, wheat, sorghum, and barley, which are of strategic interest to South Africa in several ways, most important of which are food security and agricultural trade balance. The crops also contribute more than 30% of agricultural production's total gross value (DAFF, 2016).

1.5. Objectives of the study

The objectives of the study are to:

i. Estimate the supply response of the selected grain crops to changes in the price and non-price factors.
ii. Determine the short and long-run price elasticities for the selected grain crops in South Africa.
iii. Determine the level of price risk among the selected grain crops in South Africa.

iv. Estimate the effect of price risk on the output for the selected grain crops in South Africa.

1.6. Hypotheses

The hypothesis of this study is as follows:

i. Past prices, price risk and non-price factors do not affect grain supply in South Africa.

1.7. The structure of the study

This thesis is organised into eight chapters, including this chapter: A brief background and the research objectives are presented in Chapter 1. Chapter 2 provides the literature review on the current research subject. The first part of the literature review contains the overview of agricultural supply response while the second part is extended with some crucial methods/techniques that have been utilised in the past to model agricultural supply response. Chapter 3 is designed to provide the basic principles of supply response. Chapter 4 presents a profile of the South African grain industry. The chapter gives an overview of the South African agricultural sector, with a focus on the grain industry, particularly the four major grain crops (maize, wheat, barley, sorghum) selected for this study. Chapter 5 deals with the methodology that has been employed for estimating the (price) elasticity of supply response. Chapter 6 provides the results, as well as a quantitative analysis of price risk for major grain crops. Chapter 7 provides the results and quantitative analysis of production response to price risk, price and non-price factors. Finally, in Chapter 8, a summary of the entire study's main findings, some policy recommendations and proposals for future research are given. Symbols of variables used in the supply functions are given in Appendices at the end of the thesis.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

This chapter's focus is to review the literature on agricultural supply response to have a better understanding of the related literature, methodological details, and to identify the gaps in previous studies. In that respect, this chapter adds to the existing knowledge on the subject and sheds light on essential concepts about supply response. The studies in the area of supply response have come out with different views about the nature of supply response in agriculture. Many have used different modelling techniques and have come out with different results, and showed the differences in the price responsiveness between countries, between crops and between the study period.

Generally, the body of literature on supply response can be classified on the basis of different attributes. Based on the methodology used, the studies can be divided into two general categories, namely, studies using indirect structural form approach and those who followed the statistical analysis of time series data. Based on countries of origin, the studies can be grouped into two categories: studies done in developed countries, and studies done in developing countries. On consideration of chronological order, the empirical studies can also be divided into studies done before the 1990s, and studies done after the 1990s. This chapter is structured as follows; the first part of the chapter gives an overview of supply response literature. The second part deals with methods that have been used in literature to model agricultural supply response. The third part is concerned with the review of studies that were conducted in South Africa and other developing countries on the subject of agricultural supply response.

2.2. Overview of agricultural supply response

Various crop level studies available for developing countries have argued that supply response is less elastic than in developed countries (Bhagat, 1989; Liu *et al,* 2010). The reasons these studies cite for the low response range from limitations on irrigation and infrastructure to the lack of complementary agricultural policies and subsidies. Gulati and Kelly (1999) provided two sets of explanations for the varying results on the degree of response. The first set of reasons focused on conceptual problems in identifying correct prices and exogenous variables. The second set of reasons pointed to the formulation of empirical models; for instance, the specification of supply function, use of distributed lag, failure to recognise model identification problems and wrong choice of non-economic factors.

Previous studies have argued that agriculture faces unfavourable prices in most developing countries (Haile, 2016; Jongeneel and Gonzalez-Martinez, 2020). In the belief that both private and public resources allocated to agriculture are highly responsive to prices, they claim that adverse terms of trade are largely to blame for slow agricultural growth and the consequent problems of poverty, balance of payments disequilibrium and slow overall growth.

While acknowledging the importance of price policies, Krishna (1982) have maintained that agricultural transformation is brought about through a complex combination of price incentives and public investments in irrigation, research, technology diffusion and reforms in the social and institutional structure. Bhagat (1989) also shared the same view and concluded that if farmers did not respond much to changes in incentives, it was not so much due to their inability to adapt to changing circumstances but rather to the constraints they were facing and that the potential for a significant supply response did exist if the constraints were relaxed.

Rao (1989) surveyed the literature on agricultural supply response to prices in developing countries. The results showed that empirical estimates of elasticities depend on the methodology adopted and country-specific factors relating to technology, economic structure, and macro constraints. Specifically, Rao argued that the reason why elasticities differ among crops and among countries is attributed to technological factors such as crop-specific yield risks, the feasibility of multiple-cropping and the availability of arable land. Rao also cited economic factors such as crop-specific price risks, the relative importance of the crop, farm incomes and farm size, and the incidence of tenancy; and sociological dimensions such as the level of farmer literacy.

From the above discussion, one can assume that farmers in developing countries do respond to incentives, but the response might be restricted and subject to various constraints. Table 2.1 below shows observations reported in different studies for developing countries.

Table 2.1:Observations reported in developing countries

Commodity	Country/region	Author	Estimated model	Own price elasticities	
				Short-run	Long run
Maize	Kenya	Mose *et al,* 2007	Cointegration/Error correction	0.53	0.76
Wheat	Zambia	Foster and Mwaunauno (1995)	Dynamic distributed lag model	0.54	1.57
Maize	Nigeria	Ogazi (2009)	Autoregressive Distributed Lag model (ARDL)	0.04	0.27
Maize	Ethiopia	Alemu *et al,* (2003)	Vector error correction Model	0.38	0.51
Potato	Bangladesh	Anwarul and Fatimah (2010)	Vector error correction model	0.45	0.62
Wheat	Ethiopia	Alemu *et al,* (2003)	Error correction Model	0.15	0.28
Maize	Zimbabwe	Townsend *et al,* (1997)	Cointegration/Error correction	1.44	1.76
Rice	Sierra Leone	Conteh *et al, (*2014)	Nerlovian Model	0.18	0.36
Maize	South Africa	Shoko *et al,* (2016)	Nerlovian Model	0.24	0.36
Tobacco	Pakistan	Shahzad *et al,* (2018)	Autoregressive Distributed Lag model	0.55	1.14
Sunflower	South Africa	Nhundu *et al,* (2018)	Nerlovian Model	0.23	0.31
Rice	Pakistan	Khan *et al,* 2019	Vector auto regression model	0.59	1.48
Barley	Ethiopia	Tenaye (2020)	Nerlovian Model	1.52	1.10
Wheat	Barley			0.04	0.08

2.3. Modelling of supply response

Modelling supply response to prices has a long history in agricultural economics and has gone through several significant empirical and theoretical modifications, out of which major frameworks have been developed. Kohli (1996) ascribed the evolution of different modelling frameworks to advancements in computational facilities and econometric techniques. This section reviews the most popular methods in supply response literature namely the Nerlovian model, the Cointegration methods (Johansen test and autoregressive distributed lag (ARDL) bounds test), Error correction method, and the profit function framework. Studies which have used other econometric methods are also discussed in brief later in this section.

2.3.1. The Nerlovian Model

Majority of empirical research on supply response is based on direct application, modification or extension of the pioneering work of Nerlove (1958). The Nerlove supply response model paved the way for developing agricultural supply response analysis and has received a lot of praise for its significant contribution to production economics. Braulke (1982) considers the model to be one of the most influential and successful supply models, judged by many studies that utilised this approach. The model is a dynamic partial adjustment model based on the adaptive expectation's hypothesis. It states that output (quantity or area) is a function of expected price, output (area) adjustment and some exogenous variables (Maming, 1996).

The basic form of the Nerlove model is based on three equations;

$$A_t^* = \alpha_0 + \alpha_1 P_t^* + u_t \quad (1)$$

$$P_t^* = P_t^* + \beta(P_{t-1} - P_{t-1}^*) \quad (2)$$

$$A_t = A_{t-1} + \gamma(A_t^* - A_{t-1}) \quad (3)$$

Where A_t and A_t^* are actual and desired area under cultivation at time t. P_t and P_t^* are actual and expected price at time t, and β and γ are expectation and adjustment coefficients, respectively. Substitution of unobserved variables, P^* and A^* into equation 3 leads to the reduced form

$$A_t = b_0 + b_1 P_{t-1} + b_2 A_{t-1} + b_3 A_{t-2} + v_t \quad (4)$$

This model assumes that farmers continuously adjust their crop area (production output) overtime and base their land allocation decisions on their expectations of the crop's future price (Braulke, 1982). The model also assumes that price expectations are based on last period’s price.

Many researchers, over other approaches favour the Nerlove model because it involves fewer computational steps to generate supply response coefficients, and it minimises the specification errors that accumulate over successive stages (Kohli, 1996). The approach is also simple in terms of data requirements and estimation of supply parameters.

However, the model has been criticised for its lack of adequate theoretical basis and statistical problems which arise when the ordinary least square (OLS) method of estimations is used to obtain the supply parameters (Hallam and Zanoli, 1993). Askari and Cummings (1977) found evidence of a serious collinearity problem that appears to be built within the Nerlove model. The model also does not incorporate farmer’s reaction to risk and does not capture the effect of technological change (Baltas, 1986).

The Nerlovian model has been used in different ways in many empirical studies such as Askari and Cummings (1977) and Rao (2004) whose subsequent modifications and revisions have been made to the basic model to suit the crop under investigation. In their extensive survey of studies that had successfully used the Nerlove model to measure agricultural supply, the authors identified the reasons for the different estimated supply response across crops and countries. They documented this variability and attributed it to differences in the quality of estimates, due to differences in definitions of price and output measures, as well as data measurement errors.

Interestingly, the result of Askari and Cumming’s study conforms with the findings of Brauke (1982). The author conducted a review on the Nerlovian model focusing on estimation errors and the possibility of a collinearity problem within the model. The study concluded that the variability in supply response estimates could be ascribed to multicollinearity. The author advised users of the Nerlove model to run diagnostic checks for the alleged collinearity problem. In another review of the model, Kohli (1996) indicated that caution must be exercised when using the model in studies attempting to make projections of crop pattern changes because the model can yield erroneous results.

Another benchmark study in agricultural supply response was undertaken by Baltas (1986). A modified Nerlovian model to a rational expectations model was developed and employed to investigate Greek cereals' supply response between 1961-1982. Attention was given to the impact of weather conditions and technical progress by including appropriate variables related to the alternative concepts of technical progress in the model. The estimated price elasticities suggested that Greek farmers were reasonably responsive to price changes, though the degree of responsiveness varied considerably from product to product.

Using a model similar to Baltas, Singh (1998) used farm harvest price to study oilseeds' supply response in Uttar Pradesh for the years 1966-67 to 1989-90. The result of the study showed that the price variable had a negative impact on area allocation for groundnut, linseed and rapeseed-mustard, but it was statistically significant only in the case of groundnut. The study also concluded that price variables positively affected sesame acreage.

Begum *et al,* (2002) studied the supply response of wheat in Bangladesh by using partial adjustment model. They estimated the wheat response to the selected factor and the short run and long run supply elasticities from 1972-73 to 1998-99 in Bangladesh. They found the significant price responses of wheat supply in the short run and long run and the response of supply to the factor lagged irrigation was relatively high. The price response of wheat supplies in the short run and long run were 0.67 and 1.06, respectively. They suggested that the government's farm price support and price stabilization policy could increase the wheat supply in Bangladesh.

Rao (2004) examined agricultural supply response at aggregate level for Andhra Pradesh using Nerlove Partial Adjustment Model. The study estimated the supply elasticities with respect to terms of trade for aggregate agricultural output, crop output, food grain crop and non-food grain crop. The study concluded that non-price factors are more important determinants in aggregate agricultural supply than price-related factors in the state of Andhra Pradesh.

Leaver (2004) used Nerlovian adjustment model to estimate the supply response of Tobacco between 1938 and 2000. The results revealed a short-run elasticity of 0.34 and a long-run elasticity of 0.81, suggesting that tobacco farmers are highly unresponsive to price changes (Leaver, 2004).

Mythili (2006) also used the Nerlove model to examine the supply response for major crops during pre-and post-reform periods in India. The study found no significant difference in supply elasticities between pre-and post-reform periods for the majority of the crops. This study also showed that farmers increasingly respond better to non-price incentives such as better technology, use of better quality of inputs and intensive cultivation.

Conteh *et al,* (2014) attempted to estimate the acreage response of rice crops to changes in their respective prices as well as other related factors in Sierra Leone. The study utilised rice crop data from 1980-2011. The coefficients of the acreage response models for the rice crop varieties were estimated using the OLS technique. The study revealed low short run and long-run price elasticises for ROK and NERICA rice varieties in Sierra Leone. Open farm gate prices, and reduced government involvement when acquiring agricultural inputs are some of the policy transformations that were recommended by the study.

From the review of above studies, it is observed that the modifications to the model have focused on the following;

- Inclusion of additional variables associated with the crop under study.
- Change in the concepts of variables used by Nerlove.
- Representing quantitative scenarios not considered by Nerlove such as perennial crops and short duration vegetable crops.

However, the underlying dynamic form of the approach remained unchanged.

More recently, Teyane (2020) used the Nerlovian expectation and adjustment model in combination with the generalised method of moments to investigate the dynamic supply responses of wheat, barley and teff to price and non-price factors in Ethiopia. Household panel data spanning from 1994 to 2009 was used. The study revealed that wheat, barley and teff are influenced positively by their own prices and negatively by the prices of substitute crops in Ethopia. The study also underscored the importance of non-price factors in influencing production decisions.

2.3.2. Cointegration

The cointegration analytical approach is considered an improvement over the Nerlove methodology to overcome spurious regression (Triphati, 2008), and downward biases in the estimates of supply response (Granger and Newbold, 1974).

The approach analyses non-stationary time series processes that have variances and means that vary over time. In other words, the method allows one to estimate the long-run parameters or equilibrium in systems with unit root variables (Rao, 2007). This approach does not impose any restrictions on the short-run behaviour of prices and quantities. It only requires a co-movement of the two variables in the long run. This implies that there is a linear combination of Q_t and P_t which is stationary even though both Q_t and P_t may not be stationary. The basic long-run equilibrium relationship can be written as;

$$Q_t = \alpha_0 + \beta P_t + \mu_t \tag{5}$$

Where the coefficient β measures the long-run supply parameter, and where μ_t is the residual which is only stationary if Q_t and P_t are co-integrated. The cointegration tests identify the presence of a stable, long-run relationship between sets of variables. However, Rao (2007) noted that if the test fails to find such a relationship, it only suggests that one does not exist.

2.3.3. Error correction model

Suppose the presence of the long-run relationships between sets of variables is established (which is an indication of cointegration). In that case, there exists an error-correction representation which incorporates both short- and long-run behaviours (Engle and Granger, 1987). The error correction model (ECM) is given by;

$$\Delta Q_t = \sum_{i=0}^{p} \alpha_i \Delta Q_{t-p} + \sum_{j=0}^{q} \gamma_j \Delta P_{t-q} - \mu \varepsilon_{t-1} + V_t \tag{6}$$

with $\varepsilon_{t-1} = Q_{t-1} - \beta P_{t-1}$

Where α_i and γ_j capture the short-run dynamic adjustment of quantities and prices, whereas ε_{t-1}represents the error correction mechanism which measures the speed at which the system gets closer to the long-run equilibrium relationship, with the residual

of the cointegrating regression representing the divergence from equilibrium (Thiele, 2000).
The most popular tests for cointegration which apply the error correction term of the error correction model (ECM for the short run analysis in supply response literature are the Johansen cointegration test and the ARDL bounds test.

2.3.3.1. Johansen test

The Johansen (1991) test is a multi-equation approach which approaches the testing for cointegration by examining the number of independent linear combinations *k* for an *m* time series variable set that yields a stationary process.

The Johansen method provides two likelihood ratio tests, namely the Trace and the Maximum Eigen value statistic tests, which are used to determine the number of cointegration equations given by the cointegration rank r. A cointegration equation is the long run equation of co-integrated series. The Trace statistic test tests the null hypothesis of r co-integrating relations against the alternative of *k* co-integrating relations, where *k* is the number of endogenous variables for r=0, 1, k−1. The Maximum Eigen Value statistic test tests the null hypothesis of r co-integrating vectors against the alternative of r+1 co-integrating vectors (Tripathi, 2008). The test's weakness is that it relies on asymptotic properties and is therefore sensitive to specification errors in the limited samples. Cointegration analysis requires that the variables under consideration be integrated of the same order (Charemza and Deadman, 1992).

In general, criticism of the Johansen cointegration method has been related to their demand for accurate time-series data sets which are often a problem to obtain in large quantities, especially in developing countries. Hall *et al,* (2002) argued that the different identification methods proposed in the literature are almost impossible to implement in practice due to the limited sample size available for most empirical research. Pesaran and Shin (2001) criticised this approach as a pure mathematical convenience and instead have advocated a theory-based approach.

Boansi (2014) used a Johansen’s Full Information Maximum Likelihood test to estimate Nigeria's yield response model using national-level data for the period 1966-2008. The results showed that the interplay of biophysical, socio-economic and structural forces are needed to boost paddy rice growth in the country. The study also found that rice farmers in the country respond more to maize price changes than their own rice price. The author attributed this finding to the differences in the supply chain's efficiency for rice and maize, with the transmission of price increment presumed to be higher in the maize market than in the local rice market.

Thiele (2002) employed the Johansen’s multivariate cointegration approach to investigate the long-run effect of pricing policies, macroeconomic distortions, and certain non-price factors on agricultural production in ten selected Sub Saharan Africa (SSA) countries. The study's findings revealed that in those cases where cointegration relationships are found, estimated supply elasticities tend to lie between 0.20 and 0.50. Among the non-price factors, the study concluded that drought occurrences significantly reduced agricultural growth in six out of ten sample countries.

To avoid spurious regressions, Townsend *et al,* (1997) used the ECM which employs the concept of cointegration to investigate the supply of maize and tobacco for commercial agriculture in Zimbabwe. The factors affecting percentage area planted to maize were, expected real maize price, real price of tobacco, real price of fertilizer and government intervention. The study showed that factors affecting the percentage area planted to tobacco were the real price of tobacco, the expected real price of maize and the institutional factors. The price elasticity of maize was 1.44 and 1.76 in the short and long run respectively. For tobacco, these were 0.28 and 1.36 in the short and long run, respectively.

By adopting the cointegration and error correction method, Ghatak *et al*., (1999) attempted to estimate the supply response of wheat production in Greece by using the time series data from 1960 to 1995. The empirical results revealed that wheat production was dominated by real gross returns rather than wheat prices. This finding suggests that Greek wheat farmers trade-off increases of agricultural production with the possible reduction of real wheat prices. The study recorded revenue elasticity of wheat of 0.41 in the long run, while the short run is 0.5115.

Using the Johansen approach to cointegration analysis, Mushtaq and Dawson (2002) examined the yield response of wheat and cotton in Pakistan. The aim of using this procedure was to overcome the problem of spurious regression. The results revealed that wheat supply was significantly influenced by the prices of wheat, cotton and fertilizer, the percentage area under high yielding wheat varieties, and water availability. The study included non-price factors such as irrigated area and rainfall.

Mohammad *et al,* (2007) improved the rainfall variable by taking a more appropriate rainfall measure for sowing seasons of crops when rain could affect sowing. The study used the Johansen cointegration approach to estimate the supply response of wheat in all the agro-ecological zones in Punjab, India. The study concluded that wheat acreage is significantly influenced by the price of wheat, and other competing crops such as cotton and sugarcane. The study also found that non-price factors such as irrigation and rainfall have a positive effect on wheat acreage in the short run.

A relatively comprehensive study for teff, wheat, maize and sorghum was undertaken by Alemu *et al,* (2003) in Ethiopia. Using the cointegration and error correction methods to quantify the responsiveness of producers to price incentives, they suggested that planned supply of these crops is positively affected by own price, negatively by prices of substitute crops and variously by structural breaks related to policy changes and the occurrence of natural mishaps. The study found a significant long-run price elasticity for all crop types and insignificant short-run price elasticities for all crops but maize. The study concluded that higher and significant long-run price elasticities as compared to lower and insignificant short-run price elasticities are attributable to various factors, namely structural constraints, the theory of supply and the conviction that farmers respond when they are certain that price changes are permanent.

Using time-series data for 23 years from 1982 to 2005, Anwarul and Fatimah (2010) applied the vector autoregression (VAR) approach to examine the supply response of potato in Bangladesh. Based on the short-run price elasticity of 0.45 and the long run elasticity of 0.62, the study concluded that price policies are useful in obtaining the desired level of output for potato. If intervention in the market is necessary, it must be implemented during the harvest season to alter price expectations. The author also emphasised the need to increase potato export and establish export-oriented potato processing industries.

Similarly, Khan *et al,* (2019) also used the VAR model to investigate the supply response of rice in Khyber Pakhtunkhwa by analysing the time series data from 1976 to 2010. The augmented Dickey-Fuller test was used to determine the order of integration of the variables and stationarity was obtained at first difference. The logarithm (log) of production was used as the dependent variable and lag-log production, lag-log rice price and lag-log competitive crop price as independent variables. The results of the study indicated that rice farmers in Khyber Pakhtunkhwa respond to price changes with short and long run elasticities of 0.597 and 1.481 respectively. The study recommended the stabilisation of prices by the government so that farmers can easily take their decision regarding allocation of land to a specific crop. Loans should also be made available at reasonable interest rates for farmers in order for them to adopt new farm technology.

2.3.3.2. ARDL Bounds test

ARDL bounds testing approach is a cointegration method developed by Pesaran *et al,* (2001) to test the long-run relationship between the variables. This procedure has many advantages over the Johansen approach (Iqbal and Uddin, 2013). Firstly, the approach is used irrespective of whether the series are I(0) or I(1). Secondly, the unrestricted vector error correction model (VECM) can be derived from the ARDL bounds testing through a simple linear transformation. This model has both short and long-run dynamics. Thirdly, the empirical results show that the approach is superior and provides consistent results for a small sample.
The model has been successfully used in various supply response studies such as Muchapondwa, (2009); Ogazi, (2009); Tanko and Alidu, (2016) and many more. The general function of a simple ARDL (1,1) model is specified as;

$$Y_t = \delta + \theta Y_{t-1} + \emptyset_0 X_t + \emptyset_1 X_{t-1} + \varepsilon_t \tag{7}$$

The model is autoregressive because the lagged values of the dependent variable Y_t partially explains itself. A distributed lag component is presented in the form of successive lags of the explanatory variable $\mathrm{X_t}$.

Muchapondwa (2009) used 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. He applied the ARDL approach to cointegration and produced consistent estimates of supply response in the presence of regressor endogeneity. The study also permitted the estimation of distinct estimates of both long-run and short-run elasticities when variables are not integrated of the same order. The results confirmed that agricultural prices in Zimbabwe are endogenous, and the variables were not integrated of the same order; hence the usage of ARDL was appropriate. The study concluded that agricultural price policy is rather a blunt instrument for effecting growth in aggregate agricultural supply.

Another study which applied the ARDL approach to cointegration was undertaken by Kavhinya (2014). The study attempted to estimate the hectarage response of smallholder maize farmers to price and non-price incentives in Lilongwe District, Central Malawi. Time series data for a period of 20 years spanning from 1989 to 2009 was used for the analysis. The study's findings showed that the lagged hectarage allocated to maize, labour availability, and inorganic fertilizer are essential factors affecting maize output for smallholder farmers in Malawi. The study concluded that price incentives on their own are inadequate to influence smallholder farmers' decisions to allocate land to maize since the farmers are constrained by non-price factors such as land and cash resources, inorganic fertilizer and so forth.

The Error Correction version of the ARDL approach to cointegration was employed to estimate rice output supply responsiveness to real prices in Nigeria. Time series data from 1974 to 2006 was used in the analysis, and the study reported inelastic domestic rice supply response to price. However, the author acknowledged the role that is played by non-price factors in stimulating rice output such as agricultural and trade policies, as well as weather (Ogazi, 2009).

Tanko and Alidu (2016), examined the relationship between domestic rice response and associated price risk in northern Ghana from 1970-2015 applying the ARDL, error correction models and double logarithmic model of the Cobb-Douglas linear model employing documentary analyses survey. Their results revealed that rice producers showed a significant relationship to price, exchange rate, and associated price risk. As a result, their recommendations encouraged the reduction of price risks to stimulate rice output.

2.3.4. The Profit function approach

Based on the evidence from the literature reviewed on conventional methods of the Nerlove model and cointegration/error correction models discussed earlier in the chapter, the supply response has been mainly studied using time series data. The quantity supplied was regressed on price, allowing for various lags and shifters in these models. However, these models only focused on the output supply side and how demand factors such as price changes affect output. That being said, the concern is that the estimation of output supply alone may give inefficient estimates of the underlying supply relationship. Therefore, it is desirable to estimate the interlinked output supply and factor demand equations simultaneously.

In Suriagandhi (2011) the profit function approach derives output supply and factor demand equations simultaneously. This method requires detailed input prices and simultaneous estimation of input demand and output supply equations (Ball, 1988). However, in many countries, data on input market prices, land and labour markets are either missing or imperfect. Therefore, most researchers use production models which are less demanding in terms of data requirements. Kohli (1996) defined the profit function and the derived output supply and demand functions as functions of exogenous variables. The author finds the approach useful when testing the hypothesis about farmer behaviour; when examining the effect of a price change on output and evaluating the impact of technological changes or policy amendments.

Suriagandhi (2011) suggested that the profit function method can be used to explain the production behaviour of farmers better, as it incorporates prices as explanatory variables and allows for imperfect profit maximisation by farmers at the micro-level. The profit function method expresses the maximised profits of a farmer as a function of the prices of output and variable inputs and the quantities of fixed factors of production (Kohli, 1996). Since profits are defined as revenue less variable costs, a typical profit function is expressed as;

$$\Pi(P,w) = \left[max_{yx}\, P'y - w'x : (x,y)\varepsilon\, \tau\right] \tag{8}$$

Where *P* is a vector of output prices, *w* is a vector of prices, *y* is a vector of output quantities, *x* is a vector of input quantities, and τ is closed, bounded, smooth, and strictly convex production possibility. The major advantage of using the profit function approach is that it allows testing for differences in technical, price, and economic efficiencies (Kohli, 1996). The approach also enables the analysis of multiple output supply response (Suriagandhi, 2011). The profit function approach is based on the following assumptions;

a) Farmers always seek to maximise profits given the resources and technology with which they operate.
b) Farmers are price takers with respect to prices received for output and prices paid for inputs and,
c) The production function of farmers which underlies the profit function exhibits decreasing returns to scale in variable inputs.

The model's major limitations are that it ignores technical efficiency (Kohli, 1996), and it is assuming the existence of competitive markets that are doubtful in developing economies. The model is also presented under certain conditions that are highly unlikely in agriculture where input and output prices are uncertain. Sadoulet and de Janvry (1995) argued that the elasticities derived from the profit function approach results in overestimating the short-run elasticity of supply, since partial adjustment or adaptive expectations are not considered.

Notably, pioneering studies to use the profit function approach are that of Kalirajan and Flinn (1981) and Flinn *et al,* (1982). Kalirajan and Flinn (1981) adopted a restricted profit function approach to examine farmers' supply response producing a modern variety of rice in Coimbatore district, India. The study showed positive evidence on famers' degree of responsiveness to price changes for paddy production. The findings of the study also showed the difference in the price responsiveness between farmers producing exotic modern variety and locally bred varieties.

Bapna *et al,* (1984) derived a system of output supply and factor demand equations from the profit function for semiarid tropical India. The study began with monotonically increasing profit function and derived output supply and factor demand curves. Two systems are derived from the maximisation of the profit function, namely, generalised Leontief and normalised quadratic systems. The authors pooled the time series and cross section data by following an error component model. The authors confirm that a maximum likelihood estimation procedure would be better than the three-stage least-squares procedure. The results were obtained for 96 districts spread over semi-arid tropical regions of India. The authors indicated that 25 out of the 32 own elasticities had the anticipated sign and demonstrated the remarkable extent of the semi-arid tropical farmers' price responsiveness. A high supply elasticity was noted for sorghum despite the small proportion of its marketed surplus.

In their pioneering study about estimating multi-output functions, Chambers and Just (1989) used dual methods to solve fixed but allocatable input allocations. The authors developed a flexible profit function approach for estimating input non-joint technologies with allocatable fixed factors. The study then derived a correct test for input non-jointness that discriminates between true and apparent jointness in a framework that permits fully linear estimation of a second-order flexible technology.

Anarde and Kelchi (2007) extended the Chambers and Just (C&J) two-step profit function to estimate area elasticities and supply response of agricultural producers in Iowa. Annual time series data for a period of 39 years was used dating back from 1960 to 1999. A profit function which includes land allocations as quasi-fixed factors, was used to derive shadow price equations for each crop area allocation. The Shadow price equations were jointly estimated with output supply and input demand equations. The individual crop area response and output response to a change in prices were derived from these estimated equations. The study concluded that the response of any crop or input can be higher when allocations are held fixed than when allocations are allowed to vary. The reason for this response is attributed to the C&J uncompensated supply response formula.

Using a restricted profit function, Junaid (2014) estimated rice farmers' supply response analysis in Gujranwala district, Pakistan. Data were collected from 100 respondents using a proportional allocation sampling technique. The results show that farmers are price-responsive with a rice own price elasticity of 1.873. The output supply elasticity of rice with respect to education, land, fertilizer price and irrigation cost were 0.169, 1.274, -0.873 and -0.953 respectively. The study recommended that the government provide reliable electricity with stable rates in order to improve irrigation through electric tube wells. It also encouraged the stabilisation of fertilizer prices by the government to promote its use.

Olwande *et al,* (2009) employed the normalised restricted translog profit function to estimate the maize supply and variable input demand elasticities in Kenya. The study assessed how responsive maize output is to price and non-price factors and how sensitive fertilizer and labour demand are to prices and non-price factors using cross-sectional farm-level data for 334 maize producing households in the High Potential Maize Zone of Kenya. The findings of the study showed that maize price support is an inadequate policy for expanding maize supply in Kenya. The study also found fertiliser to be necessary for the decisions on resource allocation in maize production. Therefore, the authors have suggested that making fertilizer prices affordable to smallholder farmers would encourage maize supply. Intensive use of other productivity-enhancing inputs in addition to fertilizer was also recommended in the study.

2.3.5. Other econometric approaches

Other than the econometric methods discussed above, several other approaches have been used in applied work to model agricultural supply response. Some of these models are; frontier production function, Multinomial logit model, Cobb-Douglas production function and recursive programming models. Even though these models are not going to be discussed in detail, the empirical studies which have applied them are reviewed below.

Narayana and Parikh (1981) used the Autoregressive Integrated Moving Average (ARIMA) technique combined with Box-Jenkins approach to estimate supply response for Indian agriculture. The study formulated an expectation function for each crop by isolating stationary and random components in past prices and attaching suitable weights for both predictions. The model used in the study deviates from the traditional Nerlovian model by estimating acreage response for different crops by using expected revenue instead of expected prices as a proxy for expected profits.

Rezits and Stavropoulos (2009) used a General Autoregressive Conditional Heteroskedasticity (GARCH) process to model pork supply response and price volatility in Greece. The study jointly estimated the price and supply equations and expected prices and price volatility. Different symmetric, asymmetric, and non-linear GARCH models were also estimated. The results indicated that the quadratic Nonlinear Asymmetric General Autoregressive Conditional Heteroskedasticity (NAGARCH) model seemed to better describe producers' price volatility, which was found to be an important risk factor of the supply response function of the Greek pork market. Empirical findings have also shown that uncertainty restricts the expansion of the Greek pork sector.

Ferjani and Zimmermann *et al,* (2013) used a dynamic and recursive sector agricultural approach for estimating supply response for 22 crops in Switzerland. The results indicated significant economic interrelationships in the Swiss agricultural sector. The partial and total effects of price changes on production were examined and the results showed that the quantity supplied of each of the commodities examined was positively related to its own price.

On the other hand, Filipe (2008) used a mathematical programming analysis to examine bean farmers' supply response in Mozambique. The study's production data were obtained from bean growers in all major bean producing areas in Mozambique. The findings suggested that bean producers respond to price increases with a 1% increase in price leading to about 0.38% increase in output. The study identified labour and capital as major constrains to bean supply. The lack of technology was also identified as another hindrance to production output. The authors recommend government programmes that support technology development, especially the technologies aiming at improving labor productivity, such as animal traction or yield increasing technologies, such as improved varieties.

2.4. Price risk in Supply response

The role of risk and uncertainty in producer decision making has been recognized as a potentially important determinant of agricultural production (Seale and Shonkwiller, 1987). Agricultural prices are highly volatile due to seasonality, inelastic demand, and production uncertainty (Rezitis and Stavropoulos, 2009). Thus, price volatility represents a key aspect of price risk for all market participants (Figiel and Hamulezuk, 2012). In other words, volatility increases the risk of receiving lower or paying higher prices for a specific commodity.

Läänemets *et al,* (2011) defined risk as a situation characterised by a range of possible outcomes, and where each outcome has some chance of occurring. Hence, risk and uncertainty stem from the perception of reality and knowledge about the probabilities of events. Risk in agriculture can be classified into two namely, production and market risk. Production risk stems typically from the unpredictable nature of the weather and risks in crop yields and livestock performance. The market risk stems mainly from fluctuations in price and currency exchange rates and market demand. However, this study focuses on commodity price risk since it is one of the very clearly perceived risks by producers, processors and traders in agriculture.

Batra and Ullah (1974) have shown that an increase in price risk leads to a decline in the firm's output in the case of decreasing absolute risk aversion. If producers are assumed rational and risk averse, they should consider expected output prices when allocating resources and expected variability in output prices (Seale and Shonkwiller, 1987). Hence, the extent to which price risk affect producer decisions is an empirical question that most researchers seek to answer. Given the rapid growth of literature concerned with risk in agricultural markets, most empirical supply response studies do not incorporate risk variables into supply equations (Nerlove, 1958; Leaver, 2004; Rao; 2004; Mythili, 2006). However, several researchers have included price risk into supply response models (Berman, 1968; Just, 1974; Traili, 1978; Chavas and Holt, 1990; Lin and Dismukes, 2005), but they have done so in an ad-hoc manner. Most of these studies measured risk in terms of variance, standard or absolute deviation of commodity prices or net returns. Berman (1968) was the first to incorporate risk variables into econometric supply response models. In Berman's model, price risk was defined as a moving standard deviation on the past three periods for observed prices and producers formed their price expectations adaptively. However, Nowshirvani (1971) criticised Berman's analysis for being an empirical exercise without an explicit theoretical model. Nowshirvani developed a theoretical model for farmers' land allocation decisions that accounts for uncertainties in prices and yields.

Just (1974) developed an adaptive expectation geometric lag model for analysing farmers' acreage decisions and measured risk in terms of subjective variances of gross returns. The author found risk to be important in farmers' acreage decisions. Another popular measure of price risk is when risk is measured in terms of the variance and covariance of commodity prices, where the variance is a weighted sum of the squared deviations of past prices from their expected values, with declining weights. Majority of these risk measures represent a direct relationship between price expectations and price risk. However, these earlier models' major weakness is that they generally used arbitrary, extrapolative measures of expected price risk determined by past values of the variable being forecasted. To deal with the weakness, Goodwin and Sheffrin (1982) proposed the Rational expectations approach which allows producers to form expectations for a subsequent period based on current information contained in all exogenous variables.

There has been considerable progress in the past two decades in developing methods for measuring farmers' risk behaviour. The empirical evidence is mixed as to whether increasing price risk leads to decreases in quantity. Many studies found evidence to support this hypothesis (Behrman, 1968; Just, 1974; Seal and Shonkwiler, 1987; Holt and Aradhyula, 1990). Others recorded inconclusive results (Trail, 1978; Bailey and Womack, 1985; Lin and Dismukes, 2005).

2.5. The South African perspective

This section provides a review of previous literature on supply response from South African agriculture. However, according to theses, it should be noted that in the context of the South African agriculture, very few studies are available on supply response, which are reported in this section. At the time of writing this thesis, there were only four studies that had been identified focusing on agricultural supply response in South Africa. Two of them focused on grain crops (maize and sorghum), and the other two focused on beef and sunflower supply response, respectively.

Of the four supply response studies from the South African agriculture, the earliest study was conducted by Schimmelpfennig *et al,* (1996). The study applied time series techniques to investigate the supply for maize and sorghum in South Africa. After establishing the variables' time series properties, cointegration was determined and used as the theoretical foundation for an error correction model (ECM) to establish the short run dynamics. The maize area planted in the short run or the long run (or both), was found to depend on two sets of variables. One group changed the quantity or supply (area) of maize directly, like own price, the prices of substitutes like sorghum and sunflowers, and complementary intermediate input prices. The other variables changed the supply environment such as rainfall, farmer education, research and development and cooperative extension. Sorghum was found to be a secondary crop dominated by expected changes in the maize variables, and the area planted depends simply on intermediate input prices and rainfall over both the short and long run. These results further illustrate the dominance of maize and maize policies in production decisions in the summer rainfall areas of South Africa.

Ogundeji *et al,* (2011) attempted to estimate beef supply in South Africa using the ECM. The explanatory variables adopted in the study were rainfall, real producers' price of beef, lamb, pork, chicken, yellow maize, imports and cattle population to represent climatic, economic, trade and demographic factors. The findings of the study confirmed that beef producers respond to the economic, climatic, trade and demographic factors in the long run. In the short run, however, the article showed that cattle marketed for slaughtering are responsive to climatic factors (i.e. rainfall) and imports of beef. Animal demographics, producer price of yellow maize and the producer price of beef were found not to have a short run effect on cattle marketed for slaughtering.

Shoko *et al,* (2016) estimated the supply response of maize farmers to price and non-price incentives in South Africa. A Nerlovian partial adjustment model was applied to historical time series data of area under maize cultivation during a period from 1980-2012. Their results indicated a short-run price elasticity of 0.24 and a long-run price elasticity of 0.36, signifying that maize farmers are less sensitive to price changes than non-price incentives. The results also confirmed that non-price incentives such as rainfall and technology seem to affect maize supply more than price incentives in South Africa. Given the findings, the study recommended policies and programs that focus more on non-price incentives, such as technology and infrastructure development, investment in irrigation and research services, as the means of stabilising maize production in South Africa.

Recently, Nhundu *et al,* (2018) have studied the supply response for sunflower in South Africa using panel data from 1947 to 2016. By adopting the Nerlovian partial adjustment model, the data was first tested for stationarity. The study showed that sunflower farmers were not responsive to price changes with short run and long run price elasticities of 0.2387 and 0.3135, respectively. The study also recorded a low adjustment coefficient of 0,2718 suggesting that farmers make slow adjustments to reach the desired production levels by 27% within a year. The authors suggested that policy instruments to enhance sunflower growth could be aided by empirical knowledge of structural parameters of supply responsiveness to facilitate producers' decision-making behaviour to spearhead external and internal adjustment processes. This will reduce the country’s dependency on imports and be able to sustain the sunflower industry.

2.6. Concluding remarks

This chapter aims to review previous literature on agricultural supply response to gain insight into the subject, methodological details, and identify the gaps in previous studies. The review was only limited to the research related to this study since the volume of literature on supply response has grown significantly in recent years. Based on the findings of the review the following inferences are drawn;

- Most studies on supply response have used the same methodology by Nerlove in the original form or with some modifications.
- Most of the supply response studies differ according to modifications and revisions made to econometric models, explanatory variables used and the crop under study.
- There are very few studies on supply response from South African Agriculture.
- Most supply response studies in developing countries reported low supply estimates both in the short and long run.
- Very few studies on agricultural supply response have included the variables of risk in the analysis.

CHAPTER 3: THE BASIC PRINCIPLES OF AGRICULTURAL SUPPLY RESPONSE

3.1. Introduction

Production systems in agriculture involve multiple inputs and outputs, and hence, to model such systems, it is useful to take account of the theoretical issues provided by production theory. This chapter aims to review that part of the production theory that is relevant to the estimation of supply response elasticities. The chapter provides the foundation for the rest of the research, and it is intended to introduce the theory of supply and highlight some of the key determinants of agricultural supply. The Chapter is divided into 2 sections. The first section provides some clarity regarding the basic theory of production and a brief synopsis of the production theory focusing on the derivation of the supply curve from the production functions. Section 2 is concerned with the determinants of agricultural supply, price expectations, and concludes by discussing the concept of short and long run supply response.

3.2. The basic theory of production

Production theory is documented in several texts. It provides an important conceptual framework for analysing agricultural production. It is concerned with producers' behaviour in acquiring and combining productive resources into supply goods at suitable prices. Generally, a competitive producer takes the given input and output prices and chooses a production plan (a set of technologically viable inputs and outputs) to maximize profits. The production function describes that relationship between the use of inputs and level of output. Penson *et al,* (2015) described a production function as a rule associating an output to given levels of inputs function used. Wall and Fisher (1987) also characterised the production function as a fundamental approach used in studying production decisions. The production function in its general form is;

$$Y = (\mathrm{X}_1, \mathrm{X}_2, \mathrm{X}_3, \mathrm{X}_4, \mathrm{X}_\mathrm{n}) \tag{3.1}$$

Where Y is output and X_n represents exogenous variables such as land, fertilizer, labour and so forth. In other words, the production function describes the rate at which these exogenous inputs are transformed into final produce (single output, Y). Wall and Fisher (1987) also described a production function as a production technology consisting of the alternative methods of transforming factors of production (inputs) into goods and services (outputs). The relationship between output and a single input (holding other inputs constant) can be plotted on a simple total physical product curve presented in the upper part of Figure 3.1. Output Y measured in physical terms, is increasing but at a diminishing rate, as increasing amounts of input X are combined with a fixed area of land. This can be viewed as the short run situation, whereby the size of the farm cannot be increased, and remains fixed. Hence, there will always be diminishing returns to the variable input if the other input is fixed. The curve O, C, D which is also referred to as the production function represents the total physical product (TPP) curve of a single variable input X.

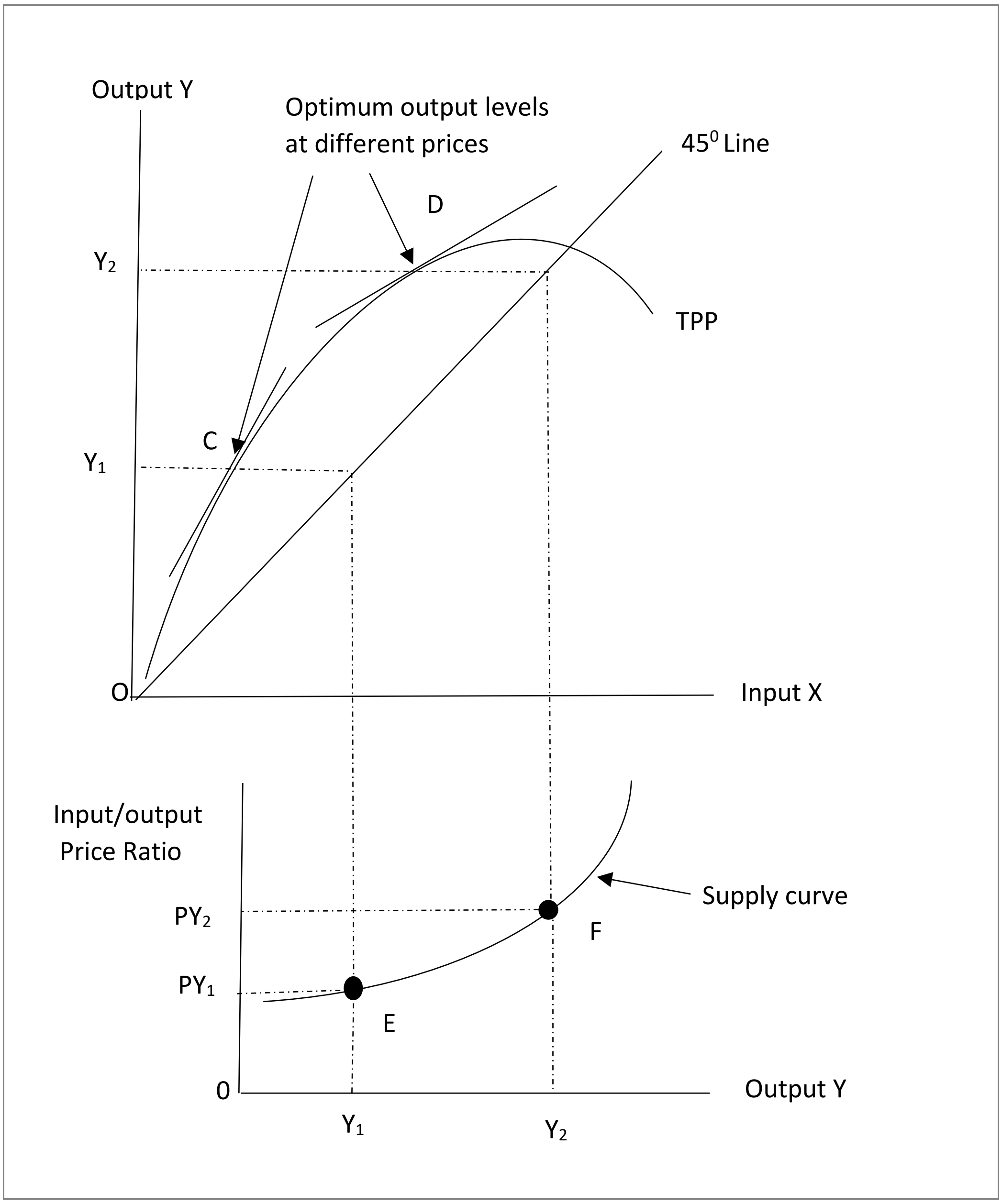

Figure 3.1: The production function and derivation of supply curve

The supply curve in the bottom half of the diagram is derived by plotting the original price of the output, PY_1 and the higher price PY_2, on the vertical axis and using the 45^0 line in the upper half of the graph to transfer the output levels, Y_1 and Y_2 onto the horizontal axis. This ultimately gives the relationship between the level of output and output price, which represents the supply curve. In the short run, the supply curve will be upward sloping since land is fixed and diminishing returns to the variable factor exist. The steepness of the supply curve will depend on the elasticity of supply. If we assume that the farmer maximises profit, that happens at points C and D which represent the optimum levels of output corresponding to different (input/output) price ratios, plotted via the 45^0 line to the supply curve in the bottom half of the diagram. Thus, the optimum level of output is also obtained by equating marginal cost (supply curve) to marginal revenue (output price).

3.3. The law of supply as the basis of agricultural supply response

The law of supply states that the supply of a good will increase when its price rises. Conversely, the supply of a good will decrease when its price decreases. In a perfectly competitive market, producers' primary goal is to maximise profits. However, profits are never constant across time or across different goods. Therefore, producers shift resources towards those goods that are more profitable and away from goods that are less profitable. This causes an increase in the supply of highly valued goods and a decrease in supply for less-valued goods. As illustrated graphically in Figure 3.1, the supply curve at the market level will have the upward sloping due to the fact that if the market price increases, suppliers are motivated to produce more, and other suppliers are motivated to enter the market, also increasing quantity supplied. Therefore, it is theoretically correct to say that output prices are key drivers of production (output supply). However, it is not only output prices that are important, input prices are equally vital as well. According to usual economic reasoning, low input prices reduce production costs which encourage producers to increase quantity supplied. Agreeably, Maming (1996) observed that high input prices increases input costs and decreases the incentive to produce, and hence reducing the quantity supplied. Thus, the market supply of an agricultural product will depend on a vector of relative prices including the price of the crop itself, the input prices, and the prices of other competing crops. The relationship can be expressed in the form of a simple supply function:

$$Q_y = f(P_y, P_f, P_s, P_c, \dots P_n) \quad (3.1)$$

Where Q_y represents the market supply of a product, P_y is the price of the product being supplied. The competing products let's say product F and production S are given as P_F and P_S, and P_C….P_n represents price of various inputs.

3.4. Elasticity of Supply

A suitable measure of how much producers respond to price changes is called the own price elasticity of supply. More specifically, the elasticity of supply measures how much producers of a product change the quantities they are willing to sell in response to a change in price. If the change in quantity supplied is larger compared to a unit change in price, supply is said to be elastic (see graphical illustration in Figure 3.2). On the other hand, if the change in the quantity supplied is small relative to a unit change in price, supply is said to be relatively inelastic. The sign on the price elasticity coefficient is usually positive since a higher price can be expected to encourage supply and a smaller price will usually result in less quantity supplied according to economic theory. Figure 3.2 below represents an elastic supply curve, whereby an increase in price results in a significant change in quantity supplied. As illustrated in the diagram, let's assume that the price of crop A goes up from P_1 to P_2. Economic reasoning suggests that farmers will respond positively to the price change by increasing supply of crop A from Y_1 to Y_2. Hence, the concept of supply elasticity can also be referred to as supply response. Generally, normal supply response occurs when η > 0. Where η represents elasticity of supply.

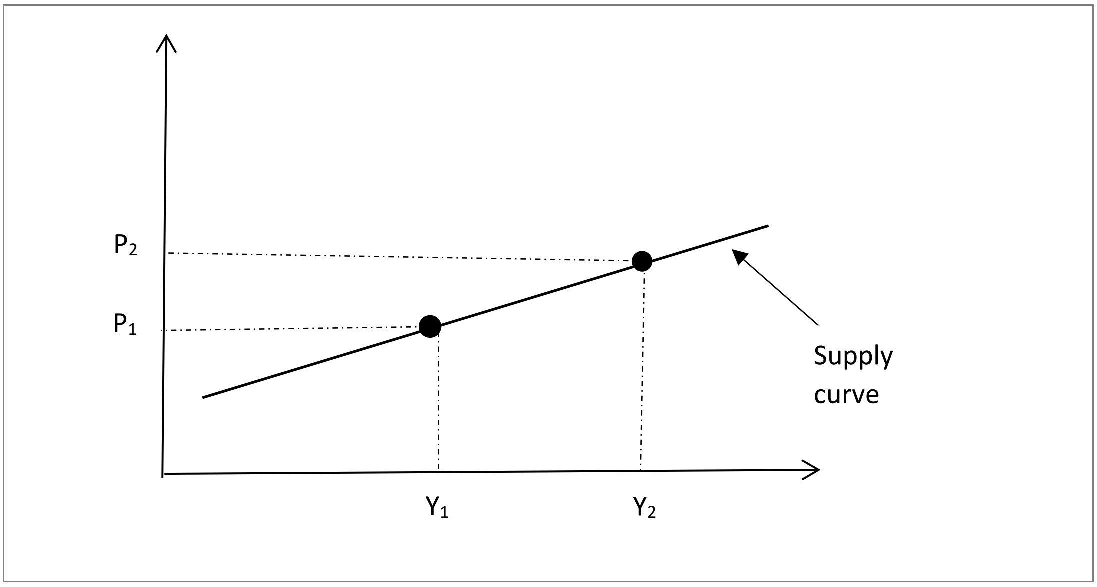

Figure 3.2: Elasticity of Supply

3.5. Supply Shifters

It is important to recognize the difference between changes in quantity supplied and shifts in supply. Based on economic theory, changes in quantity supplied happen only due to a change in the price of a product and are represented as a change in position along a product's supply curve with all other factors remaining constant. Shifts in supply occur because of a change in one or more of the supply influences (such as technological advances, weather, institutional factors and so forth). Therefore, in addition to the prices of agricultural inputs and outputs, quantity supply is also influenced by numerous factors such as the cost and accessibility of consumer goods, farm subsidies and taxes, research, extension, road infrastructure, and services such as marketing or credit. The response of individual crops to some of these supply shifters-research and extension, for example, has been widely studied (Rao, 1989; Binswanger, 1987; Maming, 1996). Some of them will also be discussed in detail later in the chapter. Figure 3.3 shows a graphical illustration of an outward shift in Supply which occurs when producers are willing to produce more of a product at all price levels. This usually occurs, for example, when there are advances in production technology or improvements in institutional settings. Technological advances are an important factor in agriculture supply and have made substantial contribution to farmers' ability to produce more.

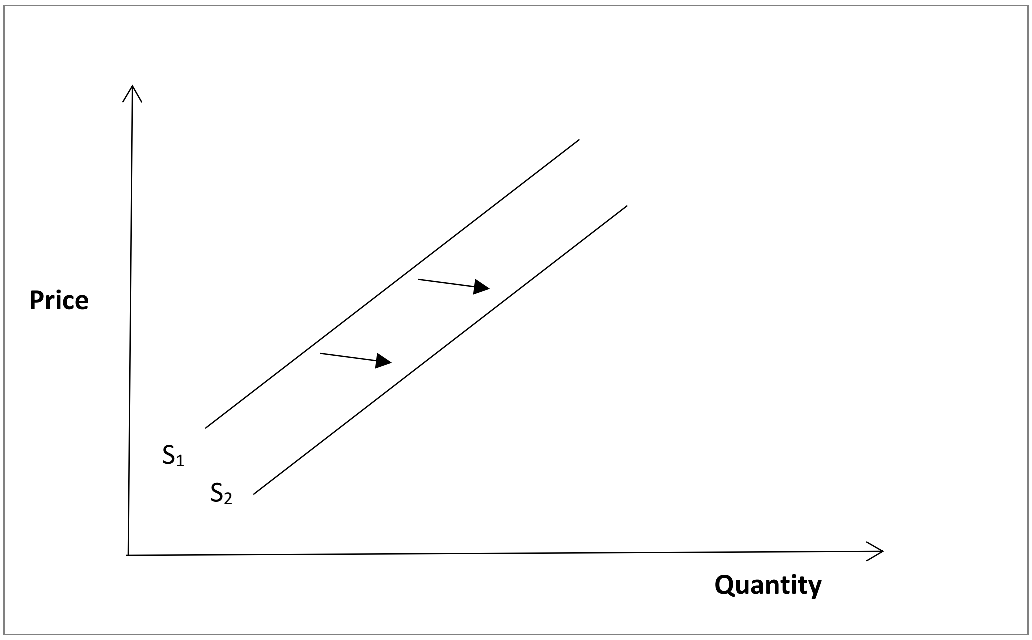

Figure 3.3: Shift of agricultural Supply

It should however be noted that the supply function specified in equation (3.2) is inadequate as it does not make any clear reference to supply shifters such as technological change. As maintained by (Nerlove, 1979; Rao, 1989; Maming, 1996) major shifts in agricultural supply curve over time have been attributed to factors such as improvement in technology, institutional factors and weather conditions. Hence, omission of these variables is serious as it could lead to estimation bias. By adding these factors to equation 3.2, we can develop a supply function which clearly describes production in agricultural markets;

$$Q_y = f(P_y, P_f, P_s, P_c, \ldots P_n, \mathrm{T}, \mathrm{W}, \mathrm{Z}) \tag{3.3}$$

Where Q_y represents the quantity of agricultural product supplied, P_y is the price of the product being supplied. The competing products let's say product F and production S are given as P_f and P_S, and P_C….P_n represents price of various inputs, T represents the production technology, W represents weather conditions, and Z represents institutional factors, e.g. government policies. Therefore, in order to obtain accurate supply estimates, the supply model should clearly specify these factors above.

However, equation 3.3 above is still inadequate. This is because it is static, which implies that a change in an explanatory variable will lead to an instantaneous response in supply. Meaning, there are no delays in adjustment. However, economic theory suggests that production in agriculture is not instantaneous due to the time lag between the decision to produce and the time when the actual production is realised. In truth, there are numerous reasons for delayed adjustment in agricultural markets and hence it is important to differentiate between short run response and long run response. Therefore, equation 3.3 should be presented in dynamic form, which recognises the time lags in agricultural supply response. Empirical details of this concept will be discussed in Chapter 5.

3.6. The Role of price factors in agricultural supply response

Output prices are an important determinant of farm incomes, which in turn, affect the farmer's ability to adjust the quantity and improve the quality of resources available to him (Rao, 1989). Maming (1996) also reported that agricultural prices determine agricultural output or supply of a product. Meaning, farms prices provide the primary incentive to produce. Based on a study conducted by Rao (1989) the incentive content of agricultural prices rests on: (a) their effect on the choice of production alternatives with available resources, and (b) their impact on resource accumulation. However, the question is, how do we measure real output prices?

As reported by Maming (1996), it is necessary to represent the price in different ways to capture the various incentives that farmers faced. Generally, four price measures are used in the regressions to understand clearly what triggered producers to shift their production:

a) the actual price of each crop,
b) the ratio of the price of the crop received by farmers to some consumer price index;
c) the ratio of the price of the crop received by farmers to some consumer price index of the farmers' inputs,
d) the ratio of the price of the crop received by farmers to some index of the price of competitive crops

In the original work of Nerlove (1958), actual prices were phrased in terms of those currently obtainable in the market, whilst expected prices were described in terms of past market prices. Generally, the majority of researchers use domestic output prices to estimate crop supply response. However, contrary to the commonly understood agricultural supply response, which estimates how output supply responds to domestic prices, Haile (2016) estimated the supply response of output supply to changes in international prices. Haile justified the use of international prices by assuming a complete transmission of international prices to domestic producer prices. Thus, one of the challenges confronting researchers who study agricultural supply response in developing countries is the unavailability of accurate domestic price data. Hence, the choice of a price variable will also depend on the availability of accurate price data.

3.7. The role of non-price variables in agricultural supply response

Many studies (Nerlove, 1958; Mythili, 2006) give more attention to price incentives; however, recent studies have found non-price variables to have more effect over price incentives in farmers' decision problem (Maming, 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 (Maming, 1996). It could be said that the price variables at best, explains only a part of the variation in the response variable. Schiff and Montenegro (1997) reported that both price and non-price variables mutually reinforce each other. Krishna (1982) maintained that agricultural transformation is brought about through a complex combination of price incentives and public investments in irrigation, research, technology diffusion and reforms in the social and institutional structure. Thus, both price and non-price incentives are equally important in supporting production decisions.

3.7.1. Institutional and social factors

As discussed in Chapter 2, majority of supply response studies conducted in developing countries have recorded inelastic agricultural supply elasticities (Askari and Cummings, 1977; Rao, 1989; Schiff and Montenegro, 1997; Rao, 2004). Thus, should we conclude that famers in developing countries do not respond to incentives? Rao (1989) observed that farmers in developing countries do respond to price incentives, but the response might be restricted and subject to various constraints. Thus, structural and institutional impediments may prevent producers from increasing output in response to rising prices in developing countries (Maming, 1996). Platteau (1996) observed that non-price variables, such as unreliable rural infrastructure and limited access to credit, are the main bottlenecks for agricultural development. However, Schiff and Montenegro, (1997) argued that a potential for a significant supply response would exist if these constraints were relaxed. Hence, the impact of public goods, for instance, access to credit, investment in irrigation, research, adult literacy, life expectancy, and extension, are often considered essential for agricultural growth (Binswanger, 1987).

Previous literature suggests that investment in rural extension and Irrigation services has a positive impact on agricultural output through its effect on productivity. The development of new road networks in rural areas is linked to improved agricultural production. Adult literacy, by capacitating individuals to adopt technology faster, is positively associated with agricultural output. Population density has an impact on agricultural production and is expected to be positively linked to agricultural output through land-use intensification or increase in cropping frequency (Krautkraemer, 1994).

In developing countries, poor people reside in deep rural areas with little access to transport services, communication, roads, agriculture services, marketing facilities, and so forth. Hence, if farmers cannot get the supplies and services they need, infrastructure investments may be required to give these farmers the capacity to increase production output (Demery and Addison, 1987).

3.7.2. Technology

In Sub-Saharan Africa, technology or spending on research is a major source of agricultural growth (Maming, 1996). Nerlove (1979) maintained that technical change through improvements in varieties of plants and animals and other inputs has had a major impact on agricultural supply. Thus, an increase in research in the sense of technology advance can help reach the goal of agricultural output growth. Several studies have incorporated the technology variable in agricultural supply response models (Berman, 1968; Thiele, 2002; Leaver 2004; Shoko *et al,* 2016). These studies vary depending on the method they use to measure technical change. The state of technology is unobservable; therefore, researchers generally use various proxies to measure the effects of technological changes. Some of the commonly used proxies for technical change are simple time trend and public expenditures on research and development (R&D).

Generally, researchers use the level of R&D expenditures since it is presumed to be the source of technical change. The relationship between R&D expenditures and technology-based productivity growth in agriculture has attracted many researchers' attention (Nerlove,1979). While acknowledging the importance of using public expenditures on agricultural research as a proxy for technology advances, Thiele (2002) used a simple time trend as a proxy for technical progress in the empirical analysis.

The time variable is mainly used as a proxy to detect time-related effects on overall output, such as advances in agricultural technology. The decision to use trend variables rather than a more direct measure is their perceived ability to capture the effects of omitted or unmeasurable variables, which are thought to have an effect over time. The omitted variable is frequently assumed to be technology. Justification for using the simple trend is also based on difficulties in obtaining reliable time series data for the variable in question. The time trend variable has been frequently used in various empirical studies to measure technical change (Ghatak *et al*, 1999; Thiele, 2002; Leaver, 2004; Shoko *et al,* 2016). However, the use of a simple time trend to measure technical change has been criticised in the past for its lack of validity since it implies that technology increases at a constant rate every year. Also, time as an independent variable is also likely to capture the effect of some explanatory variables since there is a tendency among economic variables to move together over time.

Previous studies have also used unique measures of technical change such as fertilizer data, level of irrigation, improvements in input varieties, etc. However, Kohli (1996) cautioned against the simultaneous inclusion of price variables and proxies for technology as this may introduce multicollinearity. In their study, Li and Ouyang (2020) used patent statistics to measure technical change. Thus, the choice to use a proxy variable is often limited by the unavailability of reliable data.

3.7.3. Weather

A measure of weather variation is very common in many supply response studies, with a wide variety of methods used to capture this concept; indices of rainfall, temperature; humidity and frost and so forth. The weather factor assumes greater importance in a country like South Africa, where the extent of irrigation facility available is small. Heavy dependence on rainfall results in uncertainty regarding production. Favourable weather conditions have a positive impact on agricultural supply. Thus, weather is an important risk factor that farmers must take into account when making production decisions. Meaning, in certain situations, a farmer will choose the crop with the most drought-resistant properties rather than the crop with the highest return (Bond, 1983). The role of irrigation is also substantial since it can alter the negative effect of poor rainfall.

Since weather conditions have an important influence on agricultural production, the use of appropriate weather variables in models of supply response should improve estimation results. While there are many climatic parameters, in general rainfall is the only climatic factor that has been applied in many empirical studies. Solomou, (1999) argued that selecting only one element of weather will be an oversimplification of the empirical analysis. However, including several weather indicators is often not possible because of the limited degrees of freedom implied by the data set. Omitting possible relevant factors could lead to statistical bias, but including suitable available information provides a better alternative than completely ignoring weather influences in the analysis.

3.7.4. Other supply Shifters

The prices of inputs are also an important aspect of economic incentives to agricultural production. Generally, input price policies seek to change output and to guide farmers to expand production in the face of market imperfections. Hence, the commonly used input price incentives in agricultural supply response studies are fertilizer prices, seed prices, interest rates, and wage rates. However, some studies have recommended the use of the ratio of output prices to fertilizer prices. This basically implies that raising output prices or equivalently, reducing input prices will bring about rapid agricultural growth (Rao, 1989). The inclusion of alternative crop prices in supply response models improves the supply estimates and is common in many studies (Leaver, 2004; Shahzad *et al,* 2018). Behrman (1968) extended the original supply response model by explicitly including the prices of other crops.

Natural conditions, such as low soil fertility and extreme heat, are also considered key constraints for agricultural development. In their study, Bloom and Sachs (1998) recorded low-price elasticities of supply for Sub-Saharan Africa. The results showed that soil quality and rainfall are likely to be the most decisive factors for agricultural supply response. Thus, supply response studies vary in this regard based on the availability of data and the authors' judgments on the relevance of non-price variables. To sum up, many factors determine agricultural supply, and the non-inclusion of important determining factors leads to estimate biases. Some important determining factors are measurable to most researches and thus are directly included in the statistical analysis model. However, others are difficult to quantify and represented by proxy variables. Thus, caution should be exercised when selecting relevant variables since the inclusion of correlated variables could lead to multicollinearity problems.

3.8. Response variables (Measurement of supply)

Models of agricultural supply response can be expressed in the form of area planted (acreage), yield, or production response of individual crops. However, most supply response studies have often preferred to use acreage as a proxy for the desired output supply. Acreage is seen as a better measure for output because acreage is thought to be more subject to the farmer's control than output. Also, acreage unlike yield and production, is not influenced by external shocks that occur after planting (Haile *et al,* 2013). However, acreage elasticities may only serve as a lower bound for the total supply elasticity (Rao, 1989) because area planted depends also on how yield responds to output prices. It is generally agreed that yield responds to output price, however, the high variability of yield conceals the response. Thus, yield is often modelled as a function of weather and technology and not necessarily price. Total observed production is also another proxy used in literature to estimate output supply response. However, since external factors (such as weather and pest shocks) which usually happen after planting-influence observed production, the estimated supply response may not reflect how farmers respond to prices. Some studies estimated both acreage and yield responses (Weersink *et al,* 2010; Yu *et al,* 2012). Generally, acreage is the common measure of desired output in many agricultural supply response studies.

3.9. Price expectations

Alternative mechanisms of forming price expectations represent decision making in farming. Producers must make optimal production choices (such as what crops to grow and on how much land) subject to output prices that are not known when planting decisions are made. Thus, expected rather than observed output prices are used for decision making. Many researchers such as (Nerlove, 1958; Seale and Shonkwiler,1987) have focused on the classification of expectations in agricultural markets. Dechow and Sloan (1997) proposed the naïve expectation hypothesis, whereby expected prices are assumed to be equal to the latest observed prices. Nerlove (1958) developed a supply response model that estimates farmers' response to price under the adaptive expectations' hypothesis. The adaptive expectations hypothesis assumes that farmers make production decisions based on past experiences. This approach dominated supply response literature for many years. The naïve and adaptive expectation hypothesis has been criticised for ignoring that decision-makers' dynamics of price expectations can influence future prices (Nickell, 1985).

Previous studies have adopted the rational expectations hypothesis (REH) proposed by Muth (1961). This hypothesis has played a significant role in modelling agricultural markets and assumes that producers use all the available information to form their expectations for future production decisions. Rational expectations allow producers to form expectations for a subsequent period conditional upon current information contained in all exogenous variables and the structural relationships in the market (Seale and Shonkwiler, 1987). Other research has focused on modelling supply response using future prices as a proxy for price expectations (Gardner, 1976). Holt and McKenzie (2003) applied the quasi-rational expectations consistent with price prediction from a reduced-form dynamic regression equation. Representation of price expectation is often a challenge for many researchers. This is because empirical literature does not provide clear-cut evidence on which expectation approach to use for empirical agricultural supply response estimation.

3.10. Price risk as a determinant of agricultural supply response

Agricultural producers are subject to many uncertainties where future outcomes cannot be predicted with complete accuracy. The inherent biological lags that describe most physical agricultural production processes represents a superior form of risk. Also, the agricultural sector's reliance on highly volatile international markets has also added to the instability in agriculture markets (Chavas and Holt, 1990). Therefore, the study of decision makers' behaviour toward risk and uncertainty is highly important. Hardaker *et al,* (2004) defined risk as a situation characterised by a range of possible outcomes, where each outcome has some chance of occurring. Farmers face some risks which are common with other businesses. However, others are unique to farming. The most important risks in farming can be classified as follows; yield, weather and price risks. The inclusion of risk variables in econometric commodity models is very common in many agricultural supply response studies and is the focus of this study.

The potential role of price risk is relevant to agricultural production, where prices are typically more volatile than in other sectors, and where producers are price takers due to the competitive structure of the industry. Thus, if producers are risk-averse, their behaviour may be significantly affected by price variability. Hence, the analysis of price risk effects on producer behaviour has continued to be an important area of applied research. Several researchers have investigated the role of risk in farmers' production decisions (Berman, 1968; Just, 1974; Trail, 1978; Chavas and Holt, 1990; Lin and

Dismukes, 2005). Most of these studies measured risk in terms of variance, standard or absolute deviation of commodity prices or net returns.

3.11. Short-run and Long-run elasticities for agriculture products

Many supply response studies have recorded low short-run elasticities for agriculture production supply response (Askari and Cummings, 1977; Rao, 1989; Schiff and Montenegro, 1997; Muchapondwa, 2009; Leaver, 2004; Shoko *et al,* 2016). The main reason for the low elasticities is that most factors of agricultural production are fixed in the short run. The amount of available land cannot change without considerable investment; capital increases over time and labour in agriculture can change only through population growth or migration between production enterprises, sectors, regions etc. Collectively, land, labour, and capital account for about 70 to 85 percent of the cost of agricultural production (Binswanger, 1989). Hence, to get a large response, more of these resources must be devoted to agriculture something difficult in a short period of time. The only factors that can be changed quickly are variable inputs, such as fertilizers and pesticides, and they account for less than 15 to 30 percent of the cost of production.

Supply tends to be more elastic in the long run because given more time, farmers more easily adapt to price changes. Within short periods of time, farmers cannot easily change production (since changes often require land adjustments, labourers, and so forth). Figure 3.4 demonstrates how the supply of a grain crop, just like many other agricultural products, is more elastic in the long run. At the original price P_1, the supply of grain crop is Q_1. As the price for grain increases to P_2, farmers can only respond to the price increase by producing up to Q_2. The insignificant increase of supply in response to a rise in price is represented in the “1 season” supply curve A. Within two seasons, however, farmers have enough time to produce more. Hence, the 2 seasons supply curve B shows how, given more time, farmers can better respond to a change in price by producing up to Q_3.

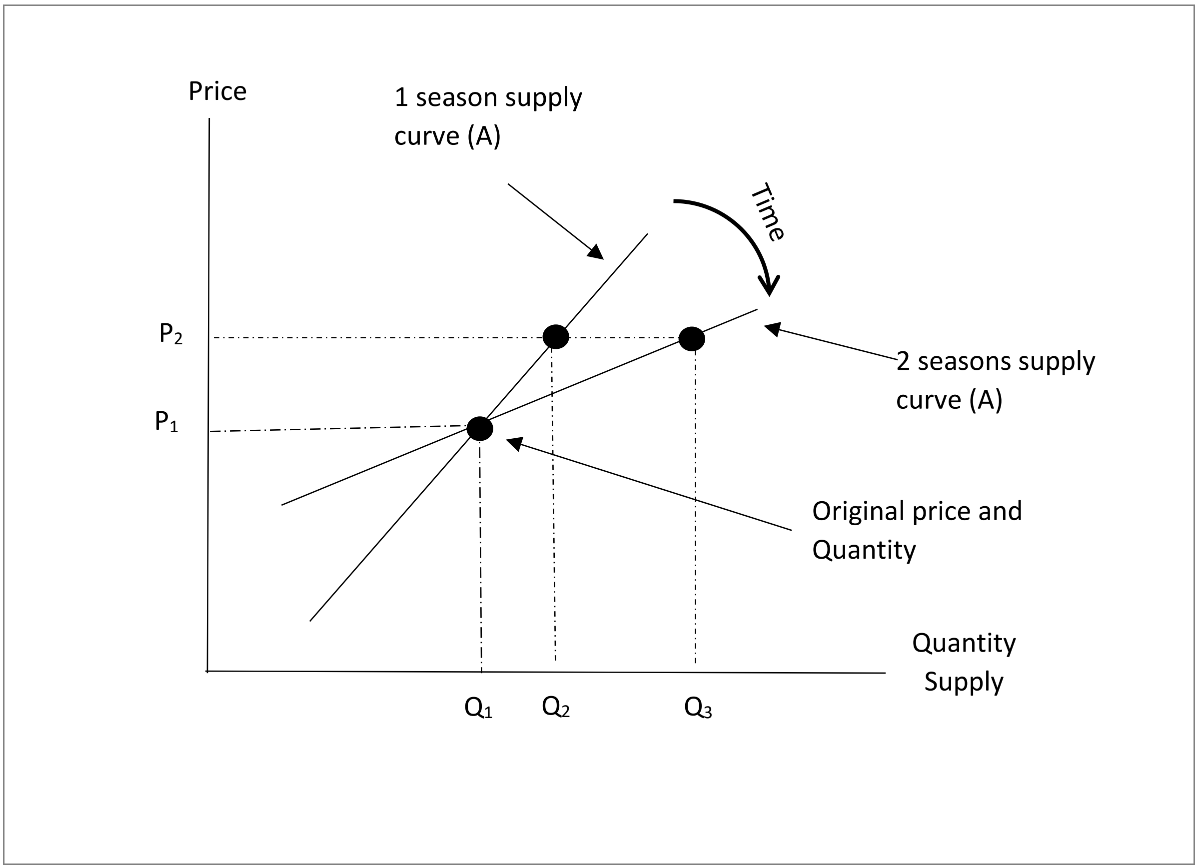

Figure 3.4: The short and Long run supply response

3.12. Concluding remarks

This chapter began with introducing the theory of supply, which is the foundation of this study, followed by a brief discussion of the critical determinants of agricultural supply. The concepts of price expectations and short and long-run supply response have also been discussed. Thus, in light of the discussions made in this chapter, the following conclusions are drawn;

- A competitive producer takes the given inputs and output prices and chooses a production plan (a set of technologically viable inputs and outputs) to maximize profits
- The relationship between the level of output and output price represents the supply curve
- Elasticity of supply is the basis of agricultural supply response and measures how much producers of a product change the quantities they are willing to sell in response to a change in price

- Farm prices provide the primary incentive for agricultural producers. However, adjusting prices may be a necessary condition for restoring incomes, but may not be sufficient when trying to increase producers' output and incomes.
- Rural infrastructure coupled with improved social factors is very important for agricultural growth and its deficiency can negatively affect agricultural production.
- Risk is an important feature of agricultural production and its inclusion in supply response studies may improve the supply estimates.
- Models of Agricultural supply response can be expressed in the form of area planted (acreage), yield, or production response of individual crops.
- Supply tends to be more elastic in the long run because given more time, farmers easily adapt to price changes. Within short periods of time, farmers cannot easily change production (since changes often require land adjustments, labourers, and so forth).

CHAPTER 4: OVERVIEW OF THE SOUTH AFRICAN GRAIN INDUSTRY

4.1. Introduction

This chapter gives an overview of the South African agricultural sector, with a focus on the grain industry, particularly the 4 major grain crops (maize, wheat, barley, sorghum) selected for this study. The chapter is organized as follows; the first section begins by giving insight into South African agriculture and its contribution to the overall GDP, employment and foreign exchange. The second section discusses each of the chosen 4 grain crops in detail, looking at production regions, historical production trends and planted area. Key information and facts about these grain crops are also included in this section. The last section provides a brief discussion about the movement of grain prices in South Africa. Price risk mitigation mechanisms, such as the future markets are also included in the section. The chapter concludes by examining the grain value chain, most importantly, the key players who are responsible for adding value to a product before it reaches the end user.

4.2. South African Agriculture sector

South Africa's agricultural sector is highly diversified, consisting of intensive and extensive crop farming systems, including vegetable, fruit, sugarcane, nuts and grain production. Livestock production includes cattle, dairy, sheep, goats, and well-established poultry and egg industry. Value-adding activities in different sub-sectors of the industry includes, but are not limited to;

- Slaughtering, processing and preserving of meat;
- Processing and preserving dairy products, fruits and vegetable, grain mill products;
- Crushing of oil seeds;
- Processing and preserving animal feeds
- Sugar refining and sugar confectionery

The well-established commercial farming in South Africa is the mainstay of the country's agricultural sector and plays a vital role in the economy by providing food security, employment, foreign exchange and raw materials. As shown in Figure 4.1, the country is divided into distinct farming regions ranging from subtropical to

Mediterranean, allowing for a variety of farming opportunities. Farming activities range from intensive crop production in winter rainfall and high summer rainfall areas to cattle ranching in the bushveld and sheep farming in the more arid regions. About 13.5% of land can be used for crop production and only 3% is considered high potential land (Najma, 2000). Most grain crops are produced in the Free state, Northwest, Western Cape and Mpumalanga provinces. These four provinces accounted for about 83% percent of South Africa's grain production in 2013 (Agricultural statistics, 2018)

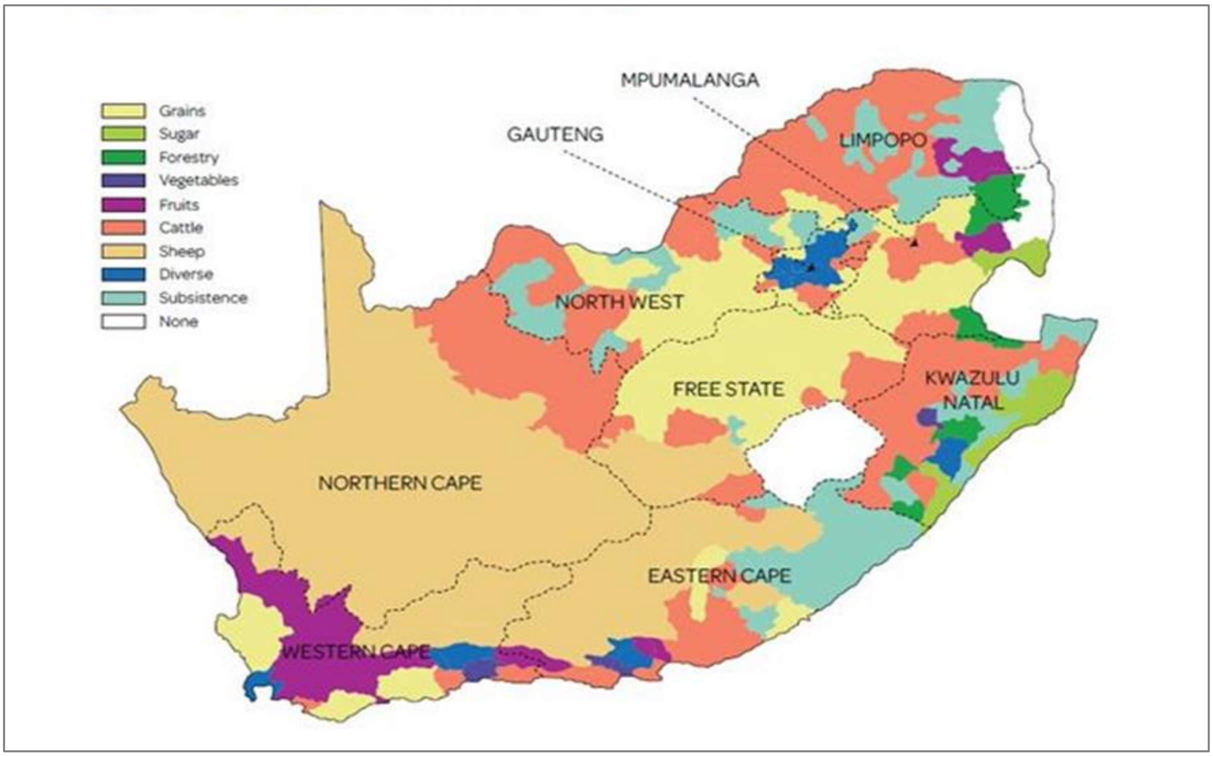

Figure 4.1: South African agricultural regions

Source: (Waldner, *et al,* 2017)

4.3. Agriculture contribution to the Economy

The agricultural sector represents about 2.5% of the South African economy's GDP and contributes about 10% of formal employment, which is relatively low compared to other African countries (DAFF, 2017d). Although the sector contributes a small share to the total GDP, it is a big foreign exchange earner and also provides raw materials for the manufacturing industry. Therefore, if we consider the whole agricultural value chain, the sector is estimated to contribute about 12% of the national GDP (DAFF 2017d). Figure 4.2 represents the quarterly performance of the agricultural sector over a 5-year period from 2014 to 2019. Fluctuations in GDP from agriculture are primarily attributed to various external forces, predominantly adverse climatic conditions. Recurring drought conditions are posing a serious threat to agricultural output in South Africa. In 2015 and 2016, drought conditions across all major grain-producing areas in the country affected the sector's output. The lowest GDP from agriculture in the 5-year period was recorded in the 4th quarter of 2016. Following the drop, the sector recovered well and reached an all-time high in the fourth quarter of 2017.

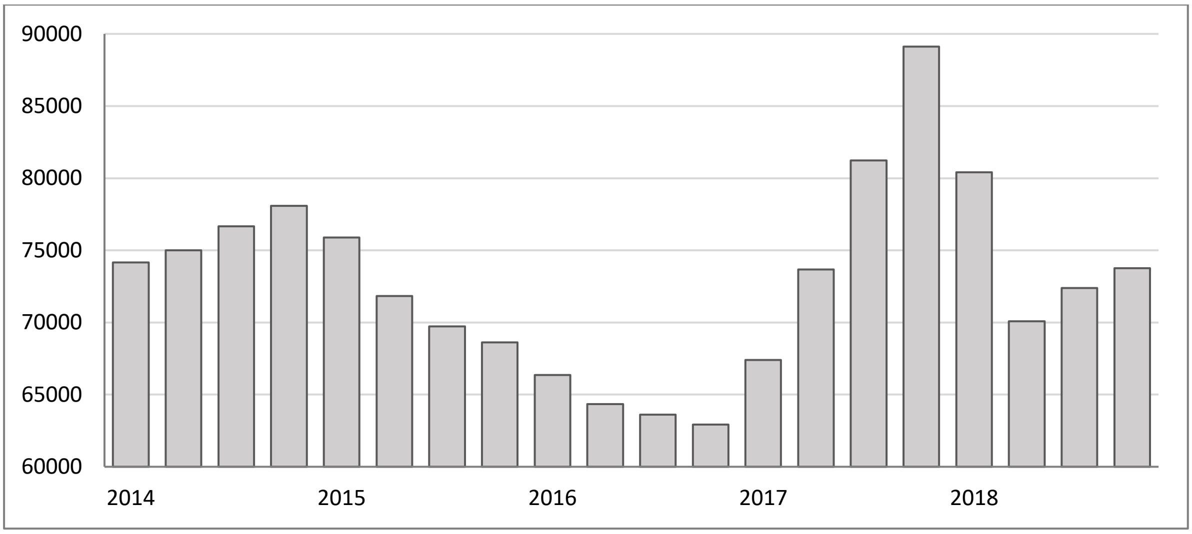

Figure 4.2: South African GDP from agriculture (ZAR million per quarter)

Source: (Stats SA, 2019)

As shown in the chart, agriculture output decreased in the second quarter of 2018 which contributed to overall GDP decline for South Africa in that same period by 0.08 percentage points. A large portion of agricultural output is used as raw materials in other sectors of the economy, e.g. food and beverages. Hence, a decline in agriculture spills over to other sectors of the economy, thereby affecting the overall GDP. The sector recovered in the third quarter and recorded a 6.5% increase (Stats SA, 2019).

The South African agriculture sector is a major foreign currency earner. During the 2018 financial year, the sector contributed about 10 percent to South Africa's total export earnings at a value of R170.3 billion Rands. Wine, table grapes, wool, citrus and maize accounted for the largest exports by value. During the same financial year, South Africa also imported agricultural and food products valued at 118.1 billion rands. The major products imported were rice, wheat, maize, soybean meal, chicken cuts and offal, and palm oil (Stats SA, 2019)

4.4. The South African grain industry

The South African Grain Industry (barley, maize, oats, sorghum and wheat) is one of the largest agricultural industries in South Africa, contributing more than 30% of the total gross value of agricultural production. The sector is also referred to as the grain and oilseed (canola, groundnuts, soybeans and sunflower) industry. However, this study will only focus on grains and cereals since they are the most important crops in South Africa, occupying more than 60 percent of total area under cultivation. Due to the high variation in climatic conditions, field crop production in South Africa is divided into two distinct categories, namely summer crops and winter cereals.

The most important summer grains are maize and sorghum, which are produced in the summer rainfall regions. The most important winter cereals are wheat and barley. Wheat is produced throughout the country, but the Western Cape accounts for the bulk of production since it falls in the winter rainfall region. Production of grain crops in South Africa fluctuates due to weather conditions and the number of hectares planted. Four major grain crops have been selected for this study; Maize, wheat, sorghum, barley. The selection of these crops is justified because many hectares are devoted to the production of these crops. Also, these crops contribute substantially to the food and beverage sectors and directly impact rural food security. These crops are discussed in detail below.

4.4.1. Maize

Maize (*Zea mays*) is the most important crop in South Africa and a staple diet, a source of livestock feed, and an export crop. Maize is produced in most parts of South Africa, but the most significant producing regions are the Free State, Gauteng, Mpumalanga and the North-West provinces, accounting for roughly 87% of overall production (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. Maize production generates at least 150,000 jobs in years with good rainfall and uses almost 50% of the modern agricultural sector's inputs. South Africa is the major maize producer in the SADC region (DAFF, 2017b), with an average production of about 12 million tons per year.

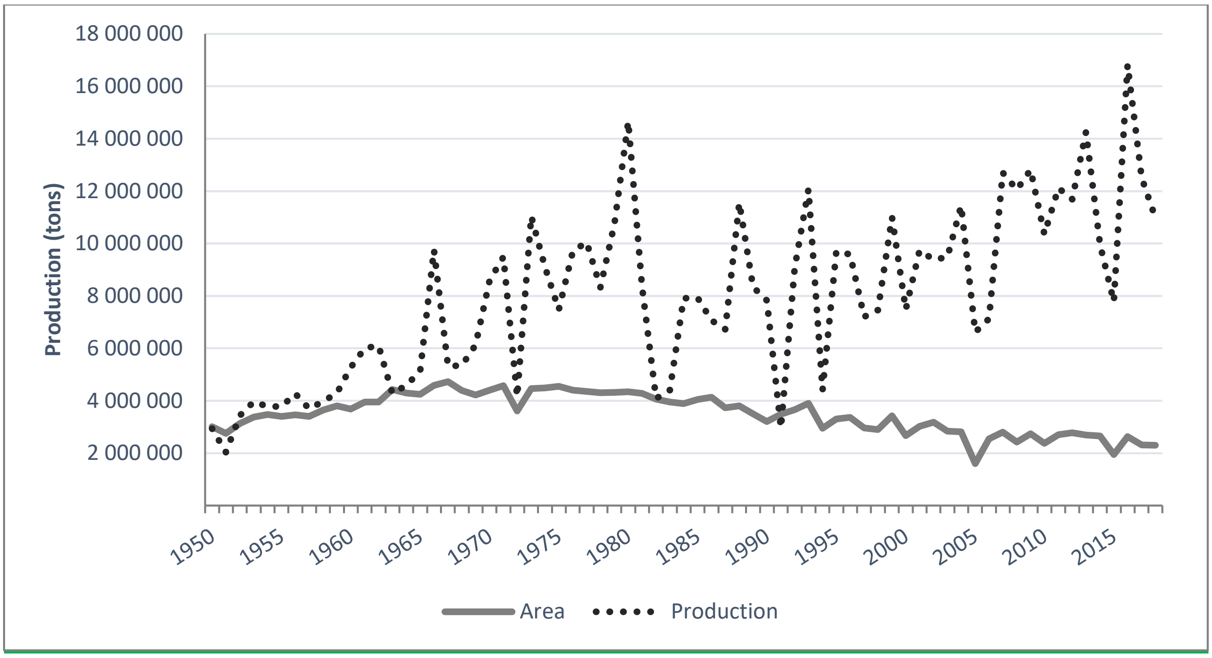

Figure 4.3: Maize production and area planted

Source: Abstract of Agricultural Statistics

The maize's local commercial consumption accounts for about 10 million metric tons, and the surplus maize is normally exported. Figure 4.3 above represents maize production and area planted with maize between 1950 and 2019. The area planted per year varies between 3.8 and 4.8 million hectares, which represents approximately 25% of the country's total arable land. The large fluctuations in production is attributed to poor climatic conditions which have strained the maize sector in the past three decades (DAFF, 2019).

The growing gap between area planted and production clearly represents the effects of technological change in the form of high yielding varieties introduced in the maize sector in recent years. As shown in Figure 4.3, In thw 1950 production season, South African farmers planted 2.9 million hectares of commercial maize, which is 20% below the area planted in 2018/19 production season. The output that season was roughly 2.5 million tons, which equates to a yield of about 1.0 tonne per hectare. However, in 2018/19 production season, average yield of 4.7 tons per hectare was recorded, hence production reached 10.9 million tons. This clearly shows the benefits of technological advancement and improved farming practices. Overall, maize production in South Africa has improved drastically over the years (DAFF, 2019).

4.4.2. Sorghum

Sorghum (*Sorghum bicolour*) is an indigenous crop to 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. Annual production of sorghum in South Africa varies from 100 000 tons to 180 000 tons and area planted of 130 00 ha and 150 000 ha respectively. For the past five seasons South Africa has produced on average 225 000 tons of sorghum per annum, which is only about 3% and 12% of the size of the average domestic maize and wheat crops, respectively. The Free State and Mpumalanga provinces are the largest contributors to the area planted to sorghum and sorghum production (DAFF, 2017a).

There has been a shift in sorghum production from the drier western production areas to the wetter eastern areas in recent years. This change in production area has resulted in the identification and development of new cultivars, which are more tolerant to lower temperatures. The market for sorghum consists of the food market, the animal feed market and exports. South Africa processes commercially on average 200 000 tons of sorghum per annum (five-year average). Virtually all sorghum processed is purchased from the commercial farming sector. About 90% is used for food production and 10% for animal feed (DAFF, 2017a).

Figure 4.4 shows fluctuations in production and area planted with sorghum from 1950 to 2019. Although area planted fluctuated steadily, from the lowest area planted (28 800Ha recorded in 2017/18), to the highest area planted (640 000 in 1966/67), production volumes fluctuated drastically. The highest production volumes were recorded in 1967 when 728 000 tons of sorghum were produced under 640 000Ha of land, with an average yield of 1.137 tons per hectare. Area planted and production levels then declined in the subsequent years.

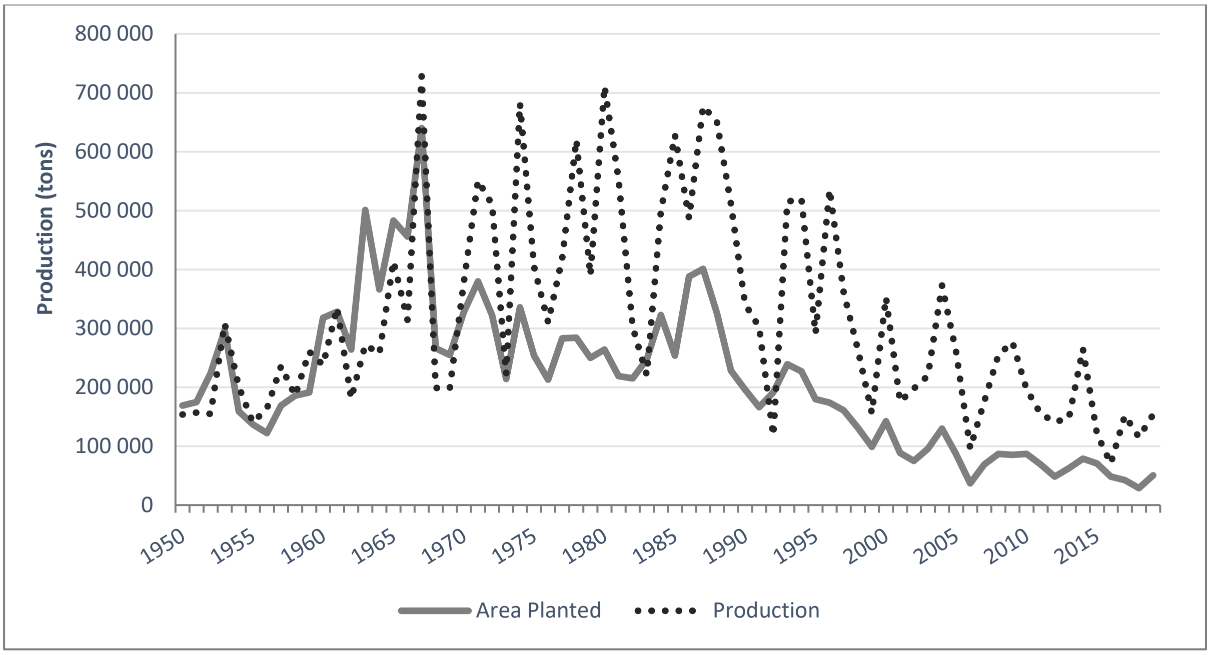

Figure 4.4: Sorghum production and area planted

Source: Abstract of Agricultural Statistics

Production peaked again in the 1980s, reaching an average production volume of 350 000 tons in that decade. However, production has declined significantly since then, with the all-time lowest production and planted area recorded in 2016 and 2018, respectively. The drastic decline in sorghum production in South Africa is largely attributed to the fact that producers now prefer crops that are more profitable such as maize and oilseeds (DAFF, 2019).

4.4.3. Wheat

Wheat (*Triticum aestivum*) is a staple crop and the second most important crop in South Africa after maize in terms of the area planted and production. Wheat is produced mostly in the winter-rainfall areas of the Western Cape and the eastern parts of the Free State province, with a substantial annual fluctuation in production. About 75% of wheat is produced under dry-land conditions and 25% under irrigation. Winter wheat produced under dry land in the Western Cape accounts for about 50% of South Africa's total wheat production (DAFF, 2017d). Local wheat production averages 1.8 million tons a year, and the local demand is approximately 3.3 million. Hence, South Africa has become increasingly reliant on imports in order to meet the growing demand (DAFF, 2019)

As shown in Figure 4.5, South Africa has witnessed a distinct downward trend in the area planted with wheat over the past few years. The significant decline in winter wheat plantings is attributed to the deteriorating profitability of growing wheat. However, according to Gouws (2018) high production costs, fluctuating commodity prices, climate change and outbreaks of pests and diseases are responsible for the significant drop in wheat production in South Africa. Production has decreased by almost half since reaching an all-time high of 3.9 million tons in 1988/1989. Consumption has doubled, thus necessitating imports of approximately half of the domestic demand for wheat. The situation is also worsened by large international transfer stocks of wheat that further suppress local prices. Also, the demand for meat products is growing locally and internationally, and grains that can be used as silage, enjoy priority over crops such as wheat. There is also an increasing demand for maize and vegetable oils to produce biofuels, pushing wheat even further into the background.

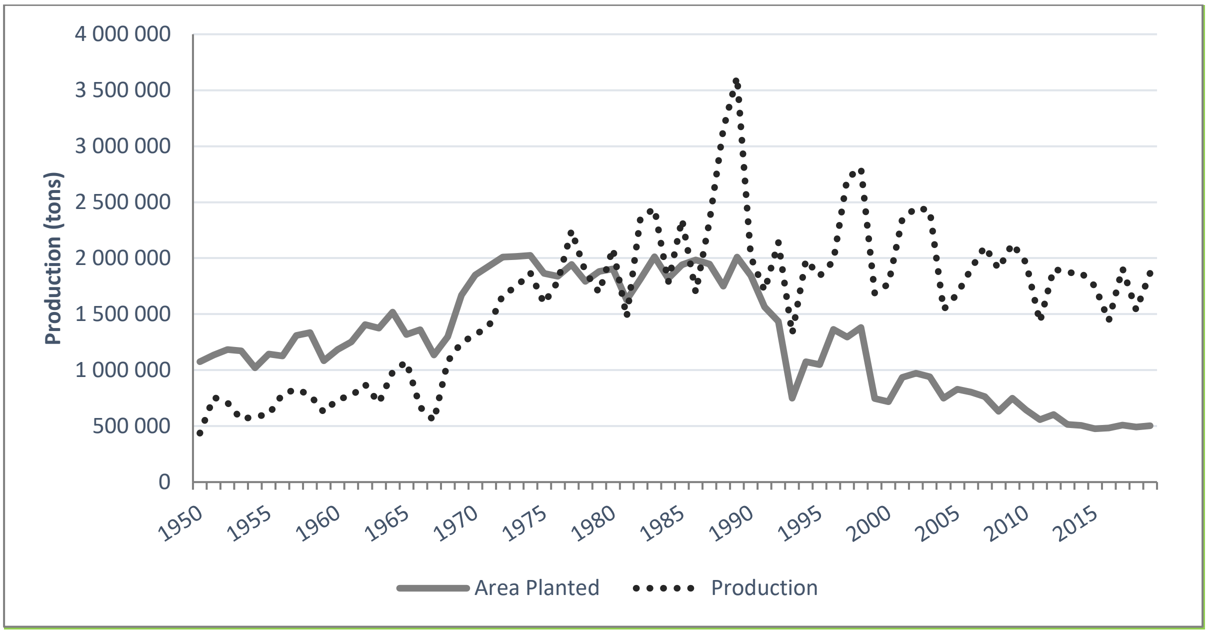

Figure 4.5: Wheat production and area planted

Source: Abstract of Agricultural Statistics

As shown in Figure 4.5, in 2018/19 South Africa recorded the lowest area planted with wheat in 50 years a situation that further pushed production levels down. At this rate, it is estimated that wheat production volumes and area will further plummet in the subsequent years (Gouws, 2018). This is a grave concern for South Africa given the role of the sector as a primary food source and the rise to prominence of concerns over food security. “Bread is a staple food and if wheat is to be mostly imported, the country will become dependent on its global availability as well as a market in which good quality wheat is very expensive" (Gouws, 2018). Technological change (through the introduction of high yielding varieties) has had major impacts on the wheat sector, particularly during the 90's and 2000's. Average yields between 1950 and 1990 were very low at 0.9 tons/ha, and there was a drastic change between 1990 and 2019 as average yields increased to 2.1tons/ha. Hence, if technical change has had so much impact on the grain sector in the past 3 decades, plant breeders and seed companies have a huge role to play in the wheat sector through breeding cultivars with better yield potential.

4.4.4. Barley

Barley *(Hordeum vulgare)* is not as popular as maize, wheat and sorghum, but it is a major cereal grain crop in South Africa and contributes significantly to gross value of agriculture production (DAFF, 2017c). Barley is a winter crop and is produced mostly in the Western Cape and Northern Cape, as well as the North West. It is adaptable to a greater range of climate than any other cereal, and it also adapts to a high variety of soils and is less sensitive than wheat to dryness or poor soil quality (FAO, 2007). On average, South Africa produces 272 300 tons of barley per annum while the local consumption requirements for the product is around 295 576tons per year. Hence, Imports vary according to local deficit and quality requirements. Barley is mainly produced for malt, which is used for brewing of beer. Most beer is made from malted barley, which is also used in distilled beverages. A small part of barley crop produced in South Africa that is generally less suitable for malting purposes is used for animal feed (DAFF, 2017c)

Unlike other agricultural commodities, there is one major barley buyer in South Africa, the SA Maltsters, which supplies South African Breweries (SAB) with malted barley (DAFF, 2017c). This is good for producers since the market for their barley is guaranteed. However, recently, producers are exposed to price risk as barley's price is now linked to wheat price. At present SAB sources, about 65% of its barley locally (Grain SA, 2013), and the rest is imported mainly from Canada. However, imports could reduce significantly in future since SAB has invested in new malting plants which will be expected to source raw materials locally. Heineken South Africa also intends to significantly reduce their malt imports by 2021, which means that all barley requirements for Heineken brewery will be sourced from local producers through the company's Barley Emerging Farmers Economic Development (BE-FED) project. In light of these developments, the future for the South African barley sector looks bright. Figure 4.6 shows barley production and area planted in South Africa from 1950 to 2019. As shown in the chart, local barley production volumes have drastically improved during the past 4 decades. In 1950, South Africa recorded the lowest production levels of 27 000 (yield at 0.5tons/ha) which is 55% below the production levels recorded in 2019. However, due to technological changes and better farming practices, South Africa has averaged 2.36 tons per hectare since 2002. Area planted has also improved significantly. In 1950, South African farmers planted 53 000ha of barley, which is 55% below the area planted in 2018/19 production season.

Production levels and area planted remained somewhat steady until the 1970s when production levels picked up for a few years, but then dropped in 1981. As from 1982, production began to increase gradually but fluctuated widely until the late 1990s and early 2000s. Today, the barley sector is regarded as a major industry in South Africa agriculture with improved production levels and yields. Hence, barley can be used as an alternative crop or leverage to improve farm profits, especially when other farm enterprises are struggling. The South African wheat industry has been in decline for more than a decade, and hence, production of barley could be an alternative to those producers who would like to diversify.

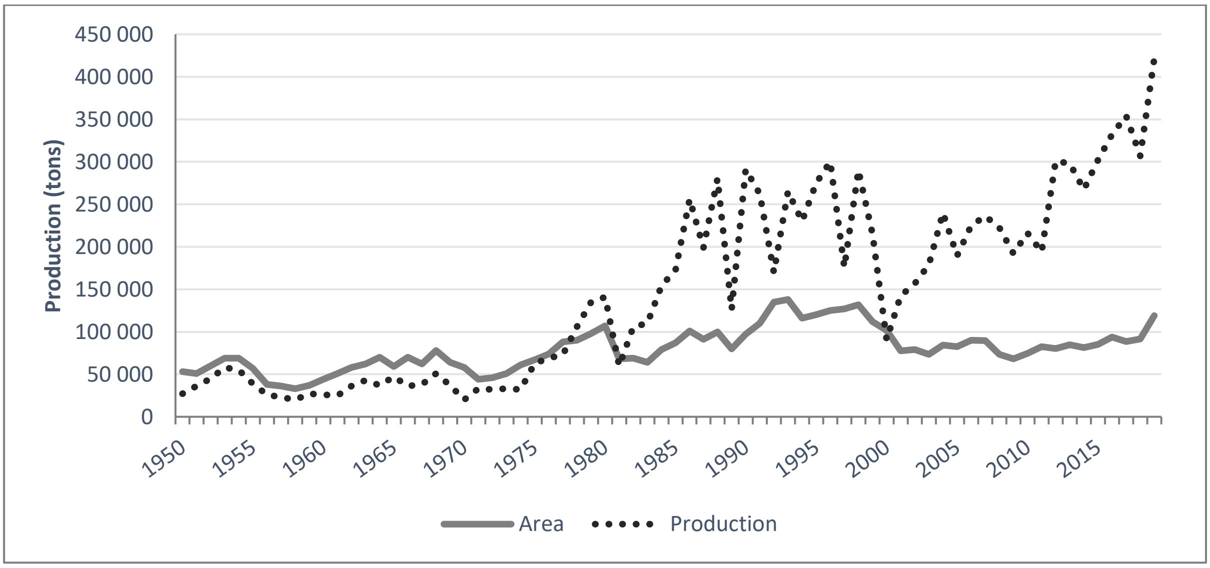

Figure 4.6: Barley production and area planted

Source: Abstract of Agricultural Statistics

4.5. Producer prices

One major incentive to produce is the price of the product. Economic theory suggests that favourable prices usually attract the decision to produce. Hence, prices play a huge role in determining production decisions in the agricultural sector. In South Africa, grain prices are determined by the interplay of supply and demand. This came about in 1997 when the Marketing of Agricultural Products Act (no 47 of 1996) was introduced, and all agricultural markets were deregulated. Since the reform process, the level of volatility has changed dramatically (see Figure 4.7). Producers now must establish their own selling prices, whereas previously the various agricultural boards were responsible for executing the task.

Figure 4.7 shows the movement of grain prices (yellow maize, white maize, wheat, barley, sorghum) since 1950, before the reform process. The Figure indicates that there was a steady rise in prices received for these commodities from the late 1950's to 1995/1996. It is important to note that before the marketing reforms, prices were fixed throughout the marketing year. The government-controlled the marketing of agricultural products, hence producer prices used to vary very little, except for the normal increases. Producers and processors knew exactly what the price of a commodity would be for the rest of the marketing season. Although the prices changed yearly, the prices were constant throughout a given marketing season. It is clear from the Figure that since 1995/96 grain crops experienced frequent price movements, resulting in high price volatility. The greater the price changes, the greater the price risk for both producers and processors.

In a deregulated market environment and against the background of international trade liberalisation, the prices of grain in the local market are influenced to a large extent by international prices and the Rand-dollar exchange rate. Therefore, if the value of the Rand declines in relation to the US dollar, the cost of the import of maize and wheat increases proportionally. This increase is equal to the depreciation of the Rand, which in a deregulated market exerts upward pressure on domestic prices.

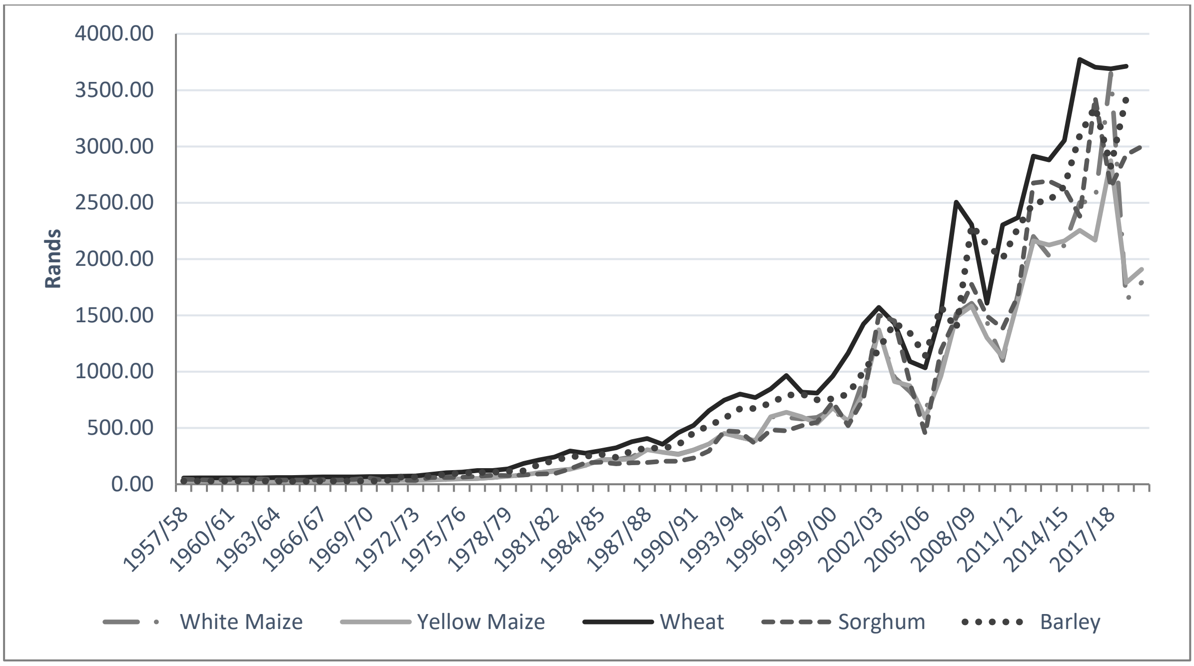

Figure 4.7: Grain price movements

Source: Abstract of Agricultural Statistics

The spillover of US maize price increases into the domestic maize market is a notable example of how international prices affect South African grain markets. It is estimated that US maize production will likely decline during the 2019/2020 production season, which could boost local prices since the US is the world market leader for maize (McCormick, 2020). It is evident that local producers will in future have to pay attention to production, consumption and closing stocks of grains on the world market, because these factors eventually determine the prices that producers receive in South Africa

4.6. Price risk management

In light of the discussion above, grain prices, are subject to significant fluctuations on both the international and domestic markets. These price changes create price risk against which those engaged in agriculture seek protection. In an attempt to reduce these risks, merchandising contracts known as forward contracts were developed. From these contracts, exchange-traded futures and option contracts were introduced.

4.6.1. Futures contract

Sehrawat (2015) defined a 'futures contract' as an agreement to buy or sell a certain quantity of an underlying asset, at a certain time in the future, at a predetermined price. It is a standardised financial contract traded in a recognised commodity exchange. The price at which the contract is traded in the futures market is called the futures price. The Johannesburg Stock Exchange (JSE) currently offers futures and options on white maize, yellow maize, wheat, soya beans, sorghum and sunflower seed. Contracts are priced and traded in rands per ton and can be physically settled should the futures position be held on until last trading day.

4.6.2. Options contract

An option contract can be defined as the right, but not obligation, to buy or sell a futures contract at some predetermined price within a specified time period. Basically, commodity options grant the opportunity, but not the obligation to sell or buy a commodity at a certain price. In the case of options on futures contracts, the underlying commodity is a futures contract and not the physical commodity. If the futures price changes in favour of the option holder, a profit may be realised either by exercising the option or selling the option at price higher than originally paid. If prices move so that exercising the option is unfavourable, then the option may be allowed to expire. There are two kinds of option contracts: puts and calls. Both futures and option contracts are traded on the futures market.

4.7. Futures market

JSE (2019) defined a futures market as a trading operation that provides market participants with a price determination mechanism and a price risk management facility through which they can manage their exposure to adverse price movements on the underlying physical market and where performance by both counterparties to the contract is guaranteed. There are three types of participants in the futures market: (1) Speculators, who bet on the future movement of the price of an asset, (2) Hedgers, who try to eliminate the risks involved in the price fluctuations of an asset by entering into the futures contract, and (3) Arbitrageurs, who try to take advantage of the discrepancy between the prices in different markets. While hedgers participate in the market to offset the risk, speculators make it possible for hedgers to do so by assuming the risk. Arbitrageurs ensure that the futures and the cash markets move in the same direction. The risks of physical commodity losses due to fire, theft, accidents, etc., are covered by insurance. However, the risk of value deprecation resulting from adverse price variations is covered by insurance.

4.7.1. South African Futures Exchange (SAFEX)

The collapse of agricultural marketing control boards in South Africa during the early 1990s and extensive deregulation was the circumstance that stimulated the formation of South African Futures Exchange's Agricultural product division to trade agricultural products. Presently, grain products are formally traded on SAFEX where the producer price (also known as the farm gate price) is derived from the SAFEX spot price minus the average transport differential and the handling costs. The price for futures and options contracts are generated on the exchange market through 'bids' and 'offers' and reflect the views of market participants on the prices of the specific products at different dates in the future. SAFEX is recognised as the price discovery facility for grains in South and Southern Africa and presently trade maize, wheat, sunflower seeds, sorghum and soya bean futures and options contracts (JSE, 2019).

Using the futures market individuals, companies or countries selling or buying grain can protect themselves against price movements in the underlying physical market. This is achieved by selling or buying futures or options contracts through a broker who is a member of the futures exchange (JSE, 2019). Consequently, futures markets allow grain producers and users of the grain products to hedge their price risk, thereby limiting their exposure to adverse price movements. This encourages increased productivity in the agricultural sector as farmers and users are able to concentrate their efforts on managing production risks.

4.8. Key players in grain value chains

The South African grain industry has various players responsible for moving a grain product from farmers until it reaches the consumer as a finished product. The movement of these products occurs along chains. These can be referred to as value chains because as the product moves from one chain player to another chain actor (for example, from wholesalers to consumers) it gains value. Hellin and Meijer (2006) defined a value chain as the full range of activities which are required to bring a product or service from conception, through the different phases of production (involving a combination of physical transformation and the input of various producer services), delivery to final consumers, and disposal after use.

Grain crops (maize, wheat, sorghum, barley) have different value chain players, some players are product specific (e.g. SA breweries for barley), and some players are common to all products. The typical chain players who transact grain products as they move through the value chain include input (e.g. seed suppliers), farmers, traders, wholesalers, retailers and final consumers. The structure of the value chain is usually determined by the needs of the consumer/final user. A simplified version of the grain value chain is shown in Figure 4.8.

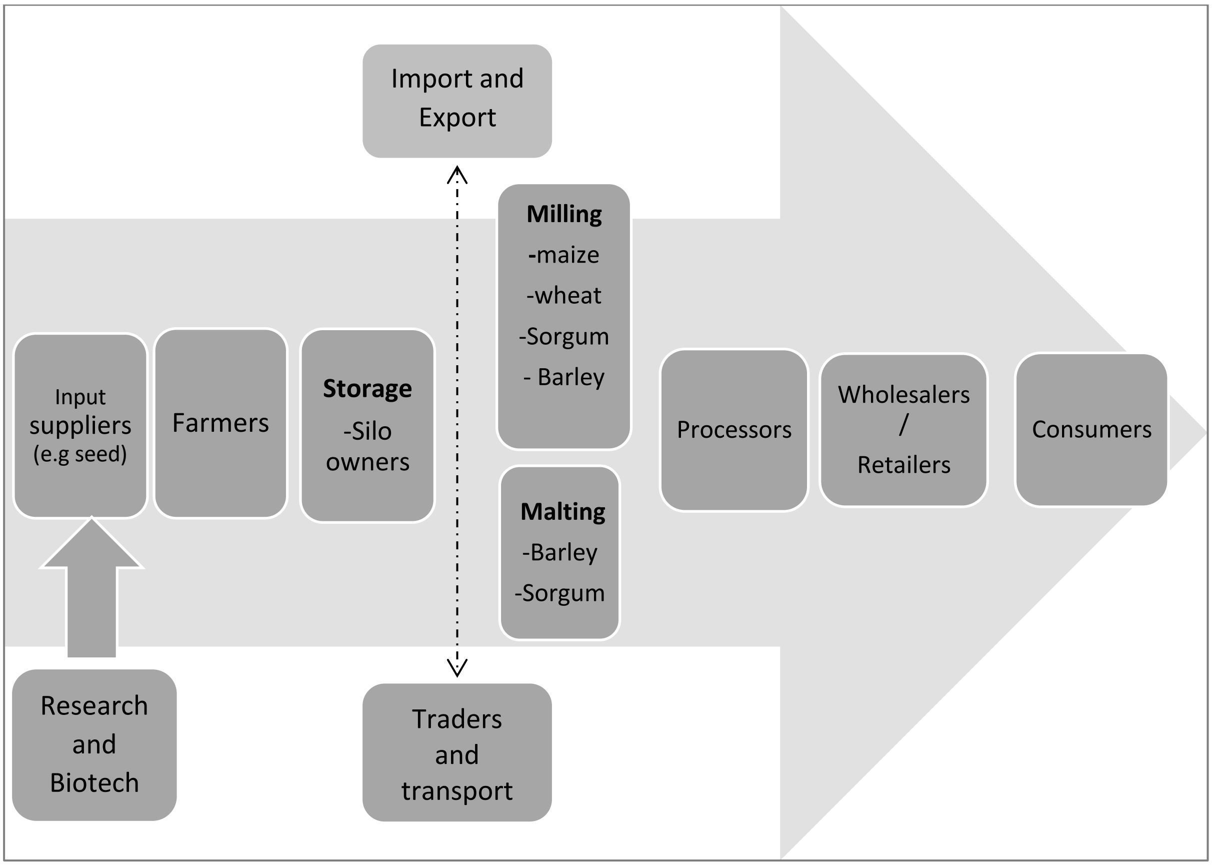

Figure 4.8: A simplified grain value chain

Source: Own elaboration

In reality, value chains are more complex and dynamic than the above illustration. In many cases, the input and output chains comprise more than one channel and these channels can also supply more than one final market. However, the diagram depicts a simplified value chain common to the 4 grain crops under study. The various value chain players involved in moving grain crops through the value chain are discussed in summary below;

- Research and Biotech - like universities investigate all aspects of the value chain.
- Input suppliers - produce inputs such as fertiliser, seeds, pesticides, packaging, and machinery.
- Farmers - produce commodities and, in most cases, do their own harvesting, and have their own transport.
- Storage/silo owners – offer storage facilities for harvested grain, including imported grain, e.g. AFGRI
- Milling– involves crushing the seed kernel and separating the bran from the endosperm. The endosperm is then ground to make flour, mealie meal and so forth, depending on the type of the grain crop.
- Malting – barley/sorghum is saturated and left to germinate, and after germination, it is then dried to a certain level and the malt is then used to make beer e.g. SAB Malting/breweries, Heineken beer company.
- Processors – manufacturing of grain-based goods, e.g. four is processed into bread, malted barley is processed into beer and so forth. Some examples of milling companies in South African are NWK, VKB, African Star, Western Cape milling, SA rice mills etc.
- Wholesalers/ Retailers – prepare and distribute the final product before it reaches the end user. They are also involved in packaging, branding etc.
- Consumers – are the end users of a product
- Technology suppliers are found across the value chain, from inputs, production, harvesting processing, logistics, and waste processing,
- Financiers – provide finance to value chain players and are found across the value chain.

4.9. Concluding remarks

The South African agriculture industry is very diverse, consisting of intensive and extensive crop farming systems. The industry contributes substantially to the economy through employment, foreign exchange, food security and so forth. The most important summer grains are maize and sorghum, which are produced in the summer rainfall regions. The most important winter cereals are wheat and barley. Production of grain crops in South Africa fluctuates due to weather conditions and the number of hectares planted. There is a distinct downward trend in the area planted to wheat and sorghum over the past few years. This is a serious concern for South Africa given the importance of these crops to the food, beverage and animal feed sectors. Maize is the most important crop in South Africa and its production generates at least 150,000 jobs in years with good rainfall and uses almost 50% of the inputs of the modern agricultural sector. Grain prices are subject to significant fluctuations on both the international and domestic markets. These price changes create price risk against which those engaged in agriculture seek protection. Hedging mechanisms such as futures and options contracts protect farmers and users of grain products from price risks. The grain industry comprises of various market players responsible for transforming raw agricultural products (through value-adding activities) into finished goods. The common chain players who transact grain products as they move through the value chain include input (e.g. seed suppliers), farmers, traders, wholesalers, retailers and final consumers. This chapter has discussed in detail each the major grain crops in South Africa, focusing on production regions, trends and area planted. This chapter is very important to this study as it brings into light some important concepts about the grain industry and grain production in South Africa.

CHAPTER 5: RESEARCH METHODOLOGY

5.1. Introduction

Modelling supply response and price risk is an essential issue in the analysis of agricultural supply response. This chapter provides details of the study area, nature and sources of data and analysis techniques employed in this study. The chapter also discusses procedures that were used to analyse the supply response of grain crops to changes in price, price risk and non-price factors. The study adopts methods that are documented in econometrics literature and other agricultural supply response studies.

The Autoregressive Distributed Lag Model (ARDL) approach to cointegration was used to determine the short and long-run price elasticities of supply for each of the selected grain crops. A detailed discussion of the model is given in section 5.7.1. Price risk measures are discussed in detail in the last section of the chapter.

5.2. General description of the study area

The present study focuses on South Africa, officially the Republic of South Africa, which is a country located at the southern tip of Africa. It is divided into nine provinces, with 2,798 kilometres of coastline on the Atlantic and Indian oceans. To the north of the country lie the neighbouring territories of Namibia, Botswana and Zimbabwe, to the east are Mozambique and Swaziland, while Lesotho is an enclave surrounded by South African territory. As discussed in Chapter 4, grain crops are produced throughout the country with Free State, Mpumalanga, Western cape and North West provinces being the largest producers.

5.3. Data sources

Annual historical time series data of 49 observations for the period 1970 to 2018 from secondary sources were used in this study. State-level data pertaining to the planted area (measured in hectares) for each individual grain crop were extracted from the records maintained by the Department of Agricultural Forestry and Fisheries (DAFF) and the Government of South Africa. In addition, 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). Data on the prices of sunflower and soybeans (measured in ZAR/Rands), the main competitors of grain crops based on planted area were collected from the same source. Time series data on the producer price index were obtained from the Abstract of Agricultural Statistics, (DAFF, 2019). Fertiliser consumption data was obtained from 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).

5.4. Data analysis and description of variables

Using the time series data specified above, four supply models were estimated, each representing one of the selected grain crops. The use of four different supply models was justified by the fact that each crop is affected by different economic and non-economic factors such as prices, climatic conditions, production costs and so forth. The general relationship between the dependent variable for each individual grain crop under study (maize/wheat/sorghum/barley) and its associated explanatory variables can be expressed in the form of a simple supply function which is specified as;

$$PD_t = f(P_t, PS_t, PR_t, PC_t, RF_t, FC_t, Dm) \qquad 5.1$$

Where:

PD_t = Supply variable measured by production volumes in tons.

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 index 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 = Dummy variable for years before and after liberalisation of the grain industry (period 1: 1970 – 1997; period 2; 1998 – 2018). Periods 1 and 2 take the value of 0 and 1, respectively. The variable was used to measure the impact of the Agricultural marketing policy (Act No 47 of 1996) that was introduced in 1997.

Finding a good price deflator in supply response analysis is of paramount importance. Most economic time series data such as prices are subjected to inflation and hence, a good deflator is necessary to convert nominal data to real one. Many studies have used either the consumer price index (CPI), GDP deflator or the producer price index (PPI), depending on data availability and choice of the analyst. Similarly, this study used the producer price index (PPI) of prices received by farmers to correct the effects of inflation using the following formula;

$$Real\,price = \frac{Norminal\,price}{PPI}\ X\ 100$$

The PPI for summer crops was used to adjust prices of maize and sorghum, whereas the prices of barley and wheat were adjusted by the PPI for winter crops.

The rainfall variable was included in the analysis to capture variations in weather. It was not the total annual rainfall that was important, but the rainfall received during the production months was relevant. This was so because, it was felt that favourable moisture conditions during production period would improve production (Singh and Bhatnagar, 1983). Therefore, 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 intermediate costs of fuel was used to measure 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. Also, price data for fuel and fertiliser could not be obtained for the sampled period. High production/fuel costs signify technical change which in turn stimulates production output. In other words, high fuel costs could imply growth in mechanisation, which is important in boosting production volumes.

5.5. Framework for selecting the analytical method

Wrong specification of a time series model could lead to estimation bias and unreliable results (Shrestha and Bhatta, 1989). Thus, it is important to choose the appropriate methodology that best suits the properties of the data. Figure 5.1 represents the basic framework/criteria that was used to select the most appropriate time series method for this study. The model selection criteria were adopted from Shrestha and Bhatta (1989) and it is based on the unit root test results which determine the stationarity of the variables.

Shrestha and Bhatta argued that methods commonly used to analyse stationary time series cannot be used to analyse non-stationary series. However, if all the variables of interest are stationary, ordinary least square (OLS) or vector autoregressive (VAR) models can provide unbiased estimates. Consequently, if all the variables are non-stationary, OLS or VAR models may not be appropriate. Similarly, additional problems arise when variables used in the analysis are of mixed order of integration, that is, some are stationary, and others are non-stationary then as illustrated in Figure 5.1 the ARDL model becomes a suitable approach to handle time series data with such properties.

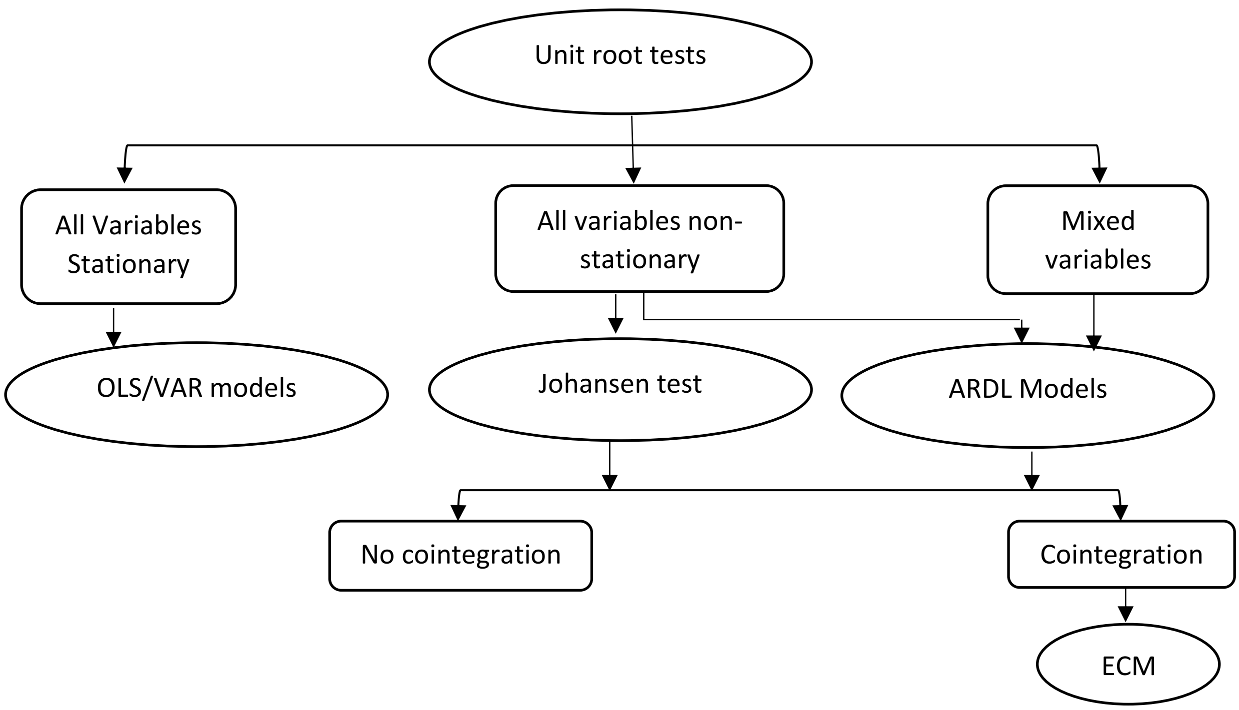

Figure 5.1: Model selection framework

Source: (Shrestha and Bhatta, 2017)

5.6. Unit root tests

In time series analysis the variables must be tested for stationarity before conducting any estimation. Majority of time-series studies apply the Augmented Dickey-Fuller test (ADF) which involves the fitting of a regression of the form;

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta_t + \varphi_1 \Delta y_{t-1} + \cdots + \varphi_k \Delta y_{t-k} + u_t \qquad 5.2$$

Where; β is the coefficient of y_{t-1}

Δy_t is the first difference operator of y_t, y_{t-1}

The ADF method tests the null hypothesis $H_0\!: \beta = 0$ against the alternative hypothesis of $H_1\!: \beta < 0$.

Similarly, this study used the ADF test and the Dickey-Fuller generalised least square (DF-GLS) de-trending test proposed by Elliot *et al,* (1996). 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. In particular, Elliot *et al,* (1996) found out that the DF-GLS test has substantially improved power when an unknown mean or trend is present. The ARDL method is based on the assumption that the variables are integrated of order 0 or 1 (I(0) or I(1)). Hence, before applying this method the order of integration of all the variables is determined using the unit root tests. The objective is to ensure that none of the variables are I(2) so as to avoid spurious results or a crush of the ARDL procedure.

5.7. Model specification

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 exogenous variables other than price. However, a lot of methodological questions have been raised on the model and the estimation techniques applied. These questions range from the reliability of the estimates for forecasting supply response to the validity of the estimates (Muchapondwa, 2009). Over the years, researchers have come up with alternative methods for measuring supply response. Majority of these models are based on the basic supply function (see equation 5.1).

According to Haile *et al,* (2016), the basic econometric supply model explaining acreage of a certain crop is formulated as a function of its own and competing crops' harvest time prices, input prices, and other exogenous factors. Likewise, Muchapondwa (2009) asserted that 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. The producer makes his or her crop acreage choices subject to output prices that are not known at the time of planting. Thus, the expected rather than realised output prices are used for decision making. According to Braulke (1982), the basic supply response function is specified by expressing desired output PD_t^* as a function of price expectations P_t^e and several exogenous factors.

$$PD_t^* = \beta_0 + \beta_1 P_t^e + \beta_2 Z_{t-k} + \varepsilon_t \qquad 5.2$$

where P_t^e represents a vector of the expected price of the crop and other competing crops; Z_{t-k} is a set of other exogenous variables including fixed and variable input prices, climate variables, technological change and so forth; ε_t accounts for the unobserved random factors affecting crop production. However, A_t^* and P_t^e are unobserved at the time of planting hence appropriate proxy variables are required to measure desired output A_t^* and expected price P_t^e.

In this study, production volume (PD_t) was used as a proxy for output and introduced as a dependent variable in supply response functions for all the grain crops considered in this study. The use of production volume as a proxy for 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 planted area. Leaver (2004) argued that farmers may respond to price incentives by using either more intensive or more extensive farming. Several other supply response studies have used production volume (measured in tons) as a proxy for output (Leaver, 2004; Muchapondwa, 2009; Haile *et al*, 2016; Shahzad *et al,* 2018)

The adaptive expectations hypothesis by Nerlove (1958) dominated the supply response analysis of agricultural products for many years. However, this study employed the distributed lag expectations as a proxy for expected price as suggested by (Pesando, 1976). The standard distributed lag expectations proxy is written as;

$$P_t^e = \sum_{i=0}^{k} \beta_i P_{t-i} \quad where\ 0 < k \leq \infty \qquad 5.3$$

The proxy assumes that economic behaviour in any one period is to a great extend determined by past experience and past patterns of behaviour.

In deciding how much of the crop to produce, farmers also consider the opportunity cost of producing that crop. Thus, the higher the price of the competing crop to those of main crop, ceteris paribus, the smaller would be the supply of the main crop. Thus, prices of competing/or substitutable crops were included in the supply models to measure the cross-price elasticities of supply.

5.7.1. The ARDL Model

The autoregressive distributed lag (ARDL) approach to cointegration is an effective approach to econometrics developed by Pesaran *et al,* (2001). The model has been used successfully in various studies to estimate supply parameters in agriculture, see (Amponsah, *et al,* 2015; Sarkodie, 2016, Ayinde *et al,* 2017; Shahzad *et al,* 2018). Similarly, this study relies on this approach to estimate the supply response of the selected individual grain crops to price and non-price changes.

The ARDL model provides an efficient platform for testing and estimating 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 major advantage of the ARDL model is its flexibility to analyze variables of different orders of integration. The cointegration test approach based on Johansen (1991) necessitates that all the variables be integrated of the same order. The general function of a simple ARDL (1,1) model is specified as;

$$A_t = m + \varphi_1 A_{t-1} + \emptyset_0 x_t + \emptyset_1 x_{t-1} + u_t \qquad 5.4$$

t = 1, 2,..T

u_t~i.i.d {0,σ^2}

A_t and x_t are stationary variables, and u_t is a white noise.

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

The sequence $\{u_t\}$ is a white noise processed for each period t,

$E(u_t) = E(u_{t-1}) = \cdots = 0$

$E(u_t^2) = E(u_{t-1}^2) = \cdots = 0$

$E(u_t u_{t-s}) = E(u_{t-j} u_{t-j-s} = 0$, for all u

The model can be estimated with OLS if the values of x_t are treated as given, as being uncorrelated with u_t. However, if X_t is simultaneously determined with A_t and $E(x_t u_t) \neq 0$, OLS would be inconsistent.

In order to interpret the dynamic effect of the model, equation 5.3 can be inverted as the lag polynomial in A as,

$$A_t = (1 + \alpha_1 + \alpha_1^2 + \cdots)m + (1 + \alpha_1 L + \alpha_1^2 L^2 + \cdots)(\beta_0 x_t + \beta_1 x_{t-1} + u_t) \quad 5.5$$

The current value of A depends on the current and all previous values of x and u.

$$\frac{\partial y_t}{\partial x_t} = \beta_0 \quad 5.6$$

This is referred to as the multiplier effect which measures the change in A as a result of a change in x. The effect after one period is presented as follows;

$$\frac{\partial y_{t+1}}{\partial x_t} = \beta_1 + \alpha_1 \beta_0 \quad 5.7$$

The effect after two periods

$$\frac{\partial y_{t+2}}{\partial x_t} = \alpha_1 \beta_1 + \alpha_1^2 \beta_0 \quad 5.8$$

The long run multiplier (long run effect) is $\frac{\beta_0 + \beta_1}{1 - \alpha_1}$ if $|\alpha_1| < 1$.

The ECM version of the selected ARDL model can be obtained by substituting A_t and x_t with $A_{t-1} + \Delta A_t$ and $x_{t-1} + \Delta x_t$ as follows;

$$\Delta y_t = m + \beta_0 \Delta x_t - (1 - \alpha_1) y_{t-1} + (\beta_0 + \beta_1) x_{t-1} + u_t \quad 5.9$$

$$\Delta A_t = \beta_0 \Delta x_t - (1-\alpha_1)\left[y_{t-1} - \frac{m}{1-\alpha_1} - \frac{\beta_0+\beta_1}{1-\alpha_1}x_{t-1}\right] + u_t \quad 5.10$$

This is called the error correction model (ECM).

The current change in A_t is the sum of two components. The first is proportional to the current change in x. The second is a partial correction for the extent to which A_{t-1} deviated from the equilibrium value corresponding to x_{t-1} (the equilibrium error).

5.8. Empirical estimation

Using the ARDL model specified above, four supply models were estimated to determine the production response of maize, sorghum, wheat and barley to price risk price and non-price factors. The models were applied in two steps. The existence of a long run relationship amongst the variables was determined in the first step, and the short-term and long-term coefficients of the model were estimated in the second step using the error correction model. Thus, evidence of cointegration among the variables suggests the existence of an error correction representation.

E-views 10 econometric software was used to carry out the analysis, with the optimum lag lengths 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 log transformation is employed to obtain a more homogeneous variance of a series (Luetkepohl and Xu, 2009). The transformation is also justified by the fact that it allows the coefficient of each explanatory variable to be interpreted directly as short run elasticities. The four supply models for the grain categories under study are specified below.

5.8.1. Maize supply response function

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

$$LnMPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, LnMPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, LnMP_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, LnMPR_{t-i}$$
$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, LnFC_{t-i} + \sum_{i-1}^{P_4} \alpha_{5i}\, LnWP_{t-i} + \sum_{i-1}^{P_5} \alpha_{6i}\, LnPC_{t-i} + \sum_{i-1}^{P_6} \alpha_{7i}\, LnRF_{t-i} \qquad 5.11$$
$$+ \sum_{i-1}^{P_7} \alpha_{8i}\, Dm + u_t$$

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

Where; $LnMPD_t$ is the natural logarithm of maize production, $LnMPD_{t-i}$ represents the natural logarithm of maize production in the previous period. $LnMP_{t-i}$, is the natural logarithm of maize real price, $LnMPR_{t-i}$ represents the natural logarithm of the price risk variable for maize. $LnFC_{t-i}$ represents the natural logarithm of fertiliser consumption variable, $LnPC_{t-i}$ represents natural logarithm of production costs, Dm represents the policy variable. Also $LnRF_{t-i}$ is the natural logarithm of average annual rainfall and $LnWP_{t-i}$ represents the natural logarithm of wheat price a close substitute of maize. Breitenbach and Fenyes (2000) asserts that there has been a gradual substitution of wheat for white maize in recent years.

The short run coefficients were estimated by the error correction term (ECT) in the following error correction model;

$$\Delta LnMPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, \Delta LnMPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, \Delta LnMP_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, \Delta LnMPR_{t-i}$$
$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, \Delta LnFC_{t-i} + \sum_{i-1}^{q} \alpha_{5i}\, \Delta LnWP_{t-i} + \sum_{i-1}^{q} \alpha_{6i}\, \Delta LnPC_{t-i} + \sum_{i-1}^{q} \alpha_{7i}\, \Delta LnRF_{t-i} \qquad 5.12$$
$$+ \sum_{i-1}^{q} \alpha_{8i}\, Dm + \alpha_{9i} ECT + u_t$$

Where Δ is the difference operator, α_{9i} represents the coefficient of the ECT which provides the speed of adjustment (ECM term), which measures the deviation of MPD_t from the long run equilibrium level.

5.8.2. Sorghum supply response function

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

$$LnSPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, LnSPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, LnSP_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, LnSPR_{t-i}$$
$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, LnSA_{t-i} + \sum_{i-1}^{P_4} \alpha_{5i}\, LnWP_{\ t-i} + \sum_{i-1}^{P_5} \alpha_{6i}\, LnPC_{t-i} + \sum_{i-1}^{P_6} \alpha_{7i}\, LnRF_{t-i} \qquad 5.13$$
$$+ \sum_{i-1}^{P_7} \alpha_{8i}\, Dm + \mathrm{u_t}$$

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

Where; $LnSPD_t$ is the natural logarithm of sorghum production, $LnSPD_{t-i}$ represents the natural logarithm of sorghum acreage in the previous period $LnSP_{t-i}$, is the natural logarithm of sorghum real price, $LnSPR_{t-i}$ is the natural logarithm of the price risk variable for sorghum. $LnSA_{t-i}$ is the natural logarithm of sorghum acreage, $LnPC_{t-i}$ represents the natural logarithm of the production cost variable, Dm represents the policy variable, $LnRF_{t-i}$ is the natural logarithm of average annual rainfall, and $LnWP_{\ t-i}$ represents the natural logarithm of real wheat price a close competitor of sorghum in terms of planted area.

The short run coefficients were estimated by the following error correction model;

$$\Delta LnSPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, \Delta LnSPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, \Delta SP_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, \Delta LnSPR_{t-i}$$
$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, \Delta LnSA_{t-i} + \sum_{i-1}^{q} \alpha_{5i}\, \Delta LnWP_{t-i} + \sum_{i-1}^{q} \alpha_{6i}\, \Delta LnPC_{t-i} + \sum_{i-1}^{q} \alpha_{7i}\, \Delta LnRF_{t-i} \qquad 5.14$$

$$+\sum_{i-1}^{q}\alpha_{8i}\,Dm+\alpha_{9i}ECT+u_t$$

Where Δ is the difference operator, α_{9i} represents the coefficient of the ECT which provides the speed of adjustment (ECM term), which measures the deviation of SPD_t from the long run equilibrium level.

5.8.3. Wheat supply response function

The wheat supply model that was used to measure the long run relationship among the variables is specified as;

$$LnWPD_t=\alpha_0+\sum_{i-1}^{q}\alpha_{1i}\,LnWPD_{t-i}+\sum_{i-1}^{P_1}\alpha_{2i}\,LnWP_{t-i}+\sum_{i-1}^{P_2}\alpha_{3i}\,LnWPR_{t-i}$$
$$+\sum_{i-1}^{P_3}\alpha_{4i}\,LnWA_{t-i}+\sum_{i-1}^{P_4}\alpha_{5i}\,LnSYP_{\ t-i}+\sum_{i-1}^{P_5}\alpha_{6i}\,LnPC_{t-i}+\sum_{i-1}^{P_6}\alpha_{7i}\,LnWRF_{t-i} \qquad 5.15$$
$$+\sum_{i-1}^{P_7}\alpha_{8i}\,Dm+u_t$$

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

Where; $LnWPD_t$ is the natural logarithm of wheat production, $LnWPD_{t-i}$ represents the natural logarithm of wheat production in the previous period. $LnWP_{t-i}$ is the natural logarithm of wheat price, $LnWPR_{t-i}$ is the natural logarithm of the price risk variable for wheat, and $LnWA_{t-i}$ represents the natural logarithm of wheat acreage. Also $LnPC$ represents the natural logarithm of production costs, and $LnRF_{t-i}$ is the natural logarithm of average annual rainfall. Annual rainfall figures for wheat were calculated from average monthly rainfall recorded in the free state and western cape provinces during the production months of the sampled period. Dm represents the policy variable. Soybeans and wheat compete for farm resources (Azzam, 1991). Thus, the natural logarithm of soybeans price, $LnSYP_{t-i}$ was introduced in the wheat acreage equation. The short-run coefficients were estimated by the following error correction model;

$$\Delta LnWPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, \Delta LnWPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, \Delta LnWP_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, \Delta LnWPR_{t-i}$$

$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, \Delta LnWA_{t-i} + \sum_{i-1}^{q} \alpha_{5i}\, \Delta LnSYP_{t-i} + \sum_{i-1}^{q} \alpha_{6i}\, \Delta LnPC_{t-i} + \sum_{i-1}^{q} \alpha_{7i}\, \Delta LnWRF_{t-i} \qquad 5.16$$

$$+ \sum_{i-1}^{q} \alpha_{8i}\, Dm + \alpha_{9i} ECT + u_t$$

Where Δ is the difference operator, α_9 represents the coefficient of the Error Correction Term (ECT) which provides the speed of adjustment (ECM term), which measures the deviation of WPD_t from the long-run equilibrium level.

5.8.4. Barley supply response function

The barley supply model that was used to measure the long-run relationship among the variables is specified as;

$$LnBPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, LnBPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, LnRPBW_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, LnBPR_{t-i}$$

$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, LnFC_{t-i} + \sum_{i-1}^{P_4} \alpha_{5i}\, LnBRF_{\ t-i} + \sum_{i-1}^{P_6} \alpha_{7i}\, DM_{t-i} + \sum_{i-1}^{P_7} \alpha_{8i}\, LnPC_{t-i} + u_t \qquad 5.17$$

$$\forall i = 1,2, \ldots K$$

Where; $LnBPD_t$ is the natural logarithm of barley production, $LnBPD_{t-i}$ represents the natural logarithm of barley production in the previous period, $LnBPBW_{t-i}$, is the natural logarithm of the ratio of relative prices of barley to wheat. $LnBPR_{t-i}$ represents the natural logarithm of the price risk variable for barley, $LnFC_{t-i}$ represents the natural logarithm of fertiliser consumption. $LnPC_{t-i}$ represents the natural logarithm of the production cost variable. $LnBRF_{t-i}$ is the natural logarithm of average annual rainfall. Annual rainfall figures for barley were calculated from average monthly rainfall recorded in the Western Cape province during the production months of the sampled period, Dm represents a policy variable. The short run coefficients were estimated by the following error correction model;

$$\Delta LnBPD_t = \alpha_0 + \sum_{i-1}^{q} \alpha_{1i}\, \Delta LnBPD_{t-i} + \sum_{i-1}^{P_1} \alpha_{2i}\, \Delta LRBPBW_{t-i} + \sum_{i-1}^{P_2} \alpha_{3i}\, \Delta LBPR_{t-i}$$
$$+ \sum_{i-1}^{P_3} \alpha_{4i}\, \Delta LnFC_{t-i} + \sum_{i-1}^{q} \alpha_{5i}\, \Delta LnBRF_{t-i} + \sum_{i-1}^{q} \alpha_{6i}\, Dm + \sum_{i-1}^{q} \alpha_{7i}\, LnPC_{t-i} \qquad 5.18$$
$$+ \alpha_{8i} ECT + u_t$$

Where Δ is the difference operator, α_7 represents the coefficient of the ECT which provides the speed of adjustment (ECM term), which measures the deviation of BPD_t from the long-run equilibrium level.

5.9. Diagnostic tests

The consequences of model misspecification in regression analysis can be severe in terms of the adverse effects on the sampling properties of both estimators and tests (Green, 1990). Thus, to validate the goodness of fit of the ARDL models, the relevant diagnostic tests such as the Jarque Bera test for normality, Breusch-Godfrey LM test for serial correlation were applied. The White test was used to test for heteroscedasticity within the model. Table 5.1 below summarises relevant diagnostic tests that were used in this study.

Table 5.1: Diagnostic tests employed in the study

Test	**Method**	**Hypothesis**
Heteroskedasticity	White test	H_0 :Homoskedastic
Serial correlation	Breusch -Godfrey test	H_0 :Serial correlation
Normality	Jarque-Bera test	H_0 :Not normally distributed

5.10. Stability tests

The Cumulative Sum (CUSUM) and CUSUM Squared tests were used to test for model stability. Several authors have utilised these tests such as Janjuaa (2014) to examine whether the parameters of a model are stable across various subsamples of the data.

5.11. Measuring price risk

As discussed in Chapter 3, several studies have found that including risk variables in supply response improves the supply estimates (Seal and Shonkwiler, 1987, Holt and Aradhyula 1990; Lin and Dismukes, 2005). Ryan (1977) observed that the risk models outperform the non-risk models and omitting risk response significantly biases the supply response. The idea in dealing with risk responsiveness is to add additional explanatory variables that capture the lack of uncertainty involved in forming expectations about unknown prices. Therefore, the inclusion of price risk variables in supply response functions is valuable for this study.

Since expected price risk is unobservable, price volatility was used as a proxy for expected price risk in this study. There are two kinds of volatility that are found in literature: historical (realised) volatility and implied volatility. Historical volatility is based on observed past prices. It reveals how volatile prices have been in the past. Implied volatility is focused on how volatile prices will be in the future as measured by the value of the price of an option. This study is focused on only the realised volatility based on observed grain prices. There are several realised volatility measures which 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 third and fourth objectives of the study, volatility in the prices of wheat, maize, sorghum and barley were computed using two distinct methods. In the first method, volatility was measured by the standard deviation (SD) of annual logarithmic returns as adopted from Haile *et al,* (2013). This method was selected because it is more relevant in an analysis conducted over a long period of price changes. In the econometric models, volatility is captured by standard deviation σ_n, and the square of volatility σ_n^2 is the variance rate (Hull, 2002). Thus, the standard deviation σ_n was calculated from historical prices of the grain commodities under study. First the log returns were computed as follows;

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

Where $P_t\ and\ P_{t-1}$ represents prices in the current and previous period, respectively.

$\therefore$

$$Volatility = \sigma_n = \sqrt{\frac{1}{m}\sum_{i-1}^{m}(u_i - \bar{u})^2} \quad 5.19$$

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

A 5-year moving average was used to conduct the statistical analysis as proposed by Huchet-Bourdon (2011). The volatility values generated using this method were then included in the production response functions in section 5.8 to estimate the effect of price risk on grain production. The second method is based on a framework that was proposed by Moledina *et al,* (2003) to measure conditional volatility in the prices. The same framework was adopted and used in this study to measure volatility in the prices of maize, sorghum, wheat and barley.

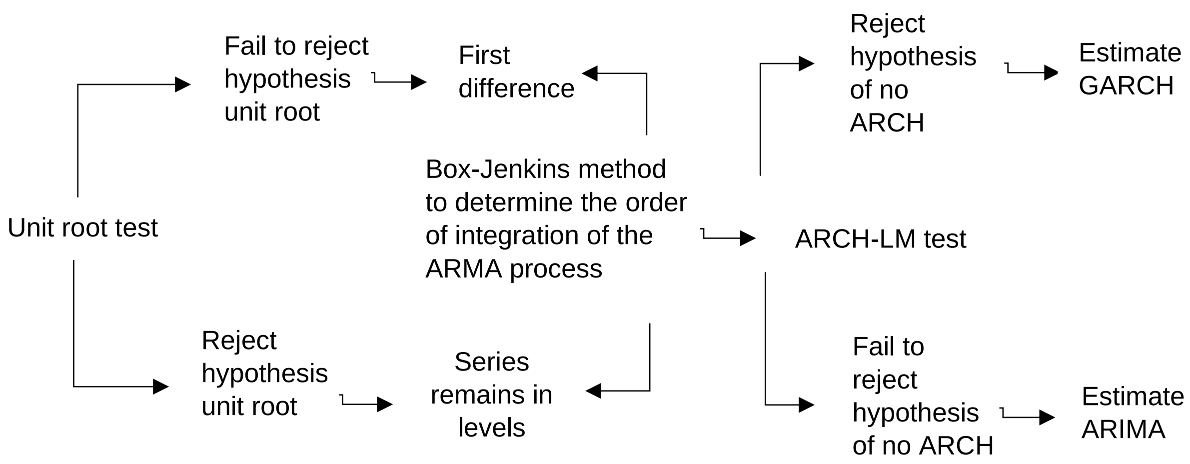

Figure 5.2: Flowchart of methodology to model conditional volatility

Source: Moledina *et al,* 2003

As demonstrated in the flow chart, the variables were first tested for unit roots before employing the Box-Jenkins method to determine the order of integration of the Autoregressive Moving Average (ARIMA) process. However, Moledina *et al,* (2003) proposed that, before performing unit root tests, the data should be treated for inflation, trends and seasonality. Therefore, as mentioned on page 63 of this chapter, PPI was used to convert nominal time series to real data. The ADF test and the DF-GLS were used to test for stationarity of the time series data in order to determine the order of integration (see on page 65).

5.11.1. Application of the Box-Jenkins approach

The development of the ARIMA models is based on the methodology quantified in Box and Jenkins's classic work. The ARIMA (*p, d, q*) model is given by;

$$\Delta^d y_t = \delta + \alpha_1 \Delta^d y_{t-1} + \alpha_2 \Delta^d y_{t-2} + .. + \alpha_p y_{t-p} + e_t - \varphi_1 e_{t-1} - \cdots - \varphi_q e_{t-q} \qquad (5.19)$$

or equivalently by

$$\omega(B)(\Delta^d y_t - \mu) = \theta(B)\varepsilon_t \qquad (5.20)$$

where;

y_t, y_{t-1} signifies the observed sorghum series at time *t*, e_t, e_{t-1} is a sequence of uncorrelated random variables having zero mean, $\alpha_1, .., \alpha_q, \varphi_1, .., \varphi_q$ are parameters of the model, *μ* is the mean of $\Delta^d y_t$, ω(B) is $1 - \omega_1 \mathrm{B} - \cdots - \omega_p \mathrm{B}_p$, *θ(B)* is $1 - \theta_1 B - \cdots - \theta_q B^q$ signifies the moving average parameter, *Δ* and *B* denote the difference and back-shift operators, respectively, ω denotes the autoregressive parameter *p, q,* and *d* denote the autoregressive, moving average and difference orders of the process, respectively (Awal and Siddique, 2011). The AIC and BIC values were used for parameter estimation. A model with the smallest values of AIC, BIC and Q-statistics and with high R-square may be considered as an appropriate model for forecasting (Biswas and Bhattacharyya, 2013).

After having selected the values of *p* and *q*, the next step was to test whether or not the volatility is time varying through identification of significant Autoregressive Conditional Heteroskedasticity (ARCH) effect.

5.11.2. Test for the presence of the ARCH effect

The rejection of the null hypothesis of no ARCH effect indicates that the series varies over time suggesting that the GARCH approach should be used instead. The Box-Jenkins method assumes that the residuals are homoscedastic (remain constant over time). Hence, this assumption was tested by fitting ARCH equation. The ARCH model was first suggested by Engle (1982). The estimate of the variance is based on a long-run average variance and *m* observations. The older the observation, the less weight it is given. The ARCH (1,1) model is given by;

$$\sigma_n^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{n-1}^2 \qquad 5.21$$

The model states that σ_n^2 depends on the squared error in the preceding time. When fitting ARCH equations, Lagrange Multiplier (LM) and tests are used to test the null hypothesis of no ARCH effect.

5.11.3. Application of the GARCH approach

The rejection of the hypothesis of no ARCH effect leads to the application of the GARCH approach. The GARCH (1,1) model as adopted from Holt and Aradhyula (1990) is presented as;

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-1} \qquad 5.22$$

and

$\sigma_t^2 = var(P_t|\Omega_{t-1}) = h_t$

Where h_t is the conditional variance of innovation ε_t and Ω_{t-1} is the information set available at time *t-1*. Among other things, the information set Ω_t would include, but is not limited to, past realisations of P_t and h_{t-1}. The model was first proposed by Bollersev (1986), and it states that conditional variance is a function of past innovations and past realisations of the variance.

Substituting h_t with σ_t^2 , the model in 5.22 can be rewritten as;

$$\sigma_n^2 = \omega + \alpha_i u_{n-1}^2 + \beta_i \sigma_{n-1}^2 \qquad 5.23$$

and

$\omega = \gamma V_L$

Where; γ is the weight assigned to V_L, α is the weight assigned to u_{n-1}^2, β is the weight assigned to σ_{n-1}^2. Since the weights must sum up to one,

$$\gamma + \alpha + \beta = 1$$

The GARCH (1,1) model indicates that σ_n^2 is based on the most recent observations of u^2 and the most recent estimate of the variance rate σ_{n-1}^2.

The parameters (γ, α, β) of the GARCH model are estimated using maximum likelihood method based on the historical price data. The approach involves choosing values for the parameters that maximise the chance (or likelihood) of the data occurring (Hull, 2002). Firstly, u_i is defined as v_i as the variance estimated for year i. The probability distribution of u_i conditional on the variance is assumed to be normal. Thus, the best parameters are the ones that maximise

$$\prod_{i=1}^{m}\left[\frac{1}{\sqrt{2\pi v_i}} exp\left(\frac{u_i^2}{2v_i}\right)\right] \qquad 5.24$$

Taking logarithms of the expression in equation (5.27) and ignoring constant multiplicative factors, is equivalent to maximising;

$$\sum_{i=1}^{m}\left[-In(v_i) - \frac{u_i^2}{v_i}\right] \qquad 5.25$$

The parameters in the GARCH (1,1) model that maximizes the expression in equation 5.25 are searched iteratively as suggested by (Hull, 2002). The Ljung-box statistic is used to test whether the GARCH (1,1) is of good fit and explains the data well.

5.11.4. Estimating ARIMA

Failure to reject the null hypothesis of no ARCH effect necessitates that an alternative model be used to compute the values of price volatility. Hull 2002 argued that if the ARCH effect does not exist, GARCH will not be the appropriate model to measure volatility. Thus, standard errors of the ARMA process estimated in section 5.11.1 were used to measure volatility as suggested by Jordaan *et al,* (2007). As already discussed earlier in the chapter the study follows the work of Haile, (2013) who used the standard deviation of the log returns of the price data to measure price volatility.

5.12. Summary

In summary, this chapter focused on discussing the research methods that were used to address each one of the research objectives of this study. Analytical techniques and measures followed during data analysis were discussed in detail. The Chapter also revealed the research area, sampled period and data sources.

CHAPTER 6: RESULTS AND DISCUSSION: ANALYSIS OF PRICE RISK F OR MAJOR GRAIN CROPS

6.1. Introduction

It is well documented that in many agricultural markets, output prices are important source for risk and uncertainty (Ullah *et al*, 2016). Price risk has been perceived and discussed as an area of considerable importance in agricultural economics literature. Thus, this chapter provides the results of an analysis that was carried to determine the level of price risk for maize, wheat, barley and sorghum in South Africa. Since risk is unobservable, price volatility was used as a proxy for expected price risk. The chapter is organized into 2 sections; the first section presents the summary statistics and analysis of grain price behaviour for the period between 1970 and 2018. The second section provides the results and analysis of price volatility/risk for all the grain crops considered in the study. Two measures of price volatility were used; (a) standard deviation of log returns and (b) standard error of ARIMA model.

6.2. Summary statistics

The basic statistics characterising the analysed price behaviour are included in Table 6.1. The data is presented in real form after having been corrected by producer price indices. In this data series, there are 49 observations ranging between 1970 to 2018. From the output, the study can infer that the average prices for wheat and barley are higher than average prices recorded for maize and sorghum. Also, the median values for barley and wheat are much closer to the mean as compared to the median values for maize and sorghum. This may suggest that the distribution of barley and wheat price series is close to normal.

Table 6.1: Summary statistics of price series for grain crops (1970-2018)

Statistical option	MP	SP	WP	BP
Mean	845.661	866.8574	1777.455	1516.692
Median	751.321	759.0769	1785.714	1540.041
Maximum	2369.5	1978.335	2366.626	2494.981
Minimum	527.027	460.1408	1208.644	525.0909
Range	1842.47	1518.1942	1157.982	1969.8901
Std. Dev.	328.316	359.3223	258.5558	365.5734
Skewness	2.39506	1.258068	-0.31241	-0.080461
Kurtosis	10.836	3.839408	2.967336	4.553433

Note: MP, SP, WP and BP are maize price, sorghum price, wheat price and barley price respectively. For more information regarding variable descriptions see appendix A.

The standard deviations of sorghum and barley are much higher than that of maize and wheat. This reflects greater variation in the prices of sorghum and barley. At the same time, maize and sorghum prices have a moderate positive skewness which demonstrates a long distribution tail on the right. The same variables also recorded high positive kurtosis, reflecting a leptokurtic distribution in the price series. Barley and wheat series have low negative skewness reflecting an approximately symmetric distribution. Consequently, positive kurtosis was estimated in the same variables, reflecting a leptokurtic distribution. Sorghum and maize price series may be seen as highly variable as the distance between mean and median is higher as compared to other crops.

6.3. Analysis of grain price behaviour

Figures 6.1 to 6.2 present the behaviour of maize, wheat, sorghum and barley prices between 1970 and 2018. The prices are presented in nominal and real values. In all the grain price series displayed in the chart, real and nominal values moved steadily between 1970 and 2000 and spiked significantly between 2000 and 2018. This realisation might be an indication that price variability in all price series increased with time.

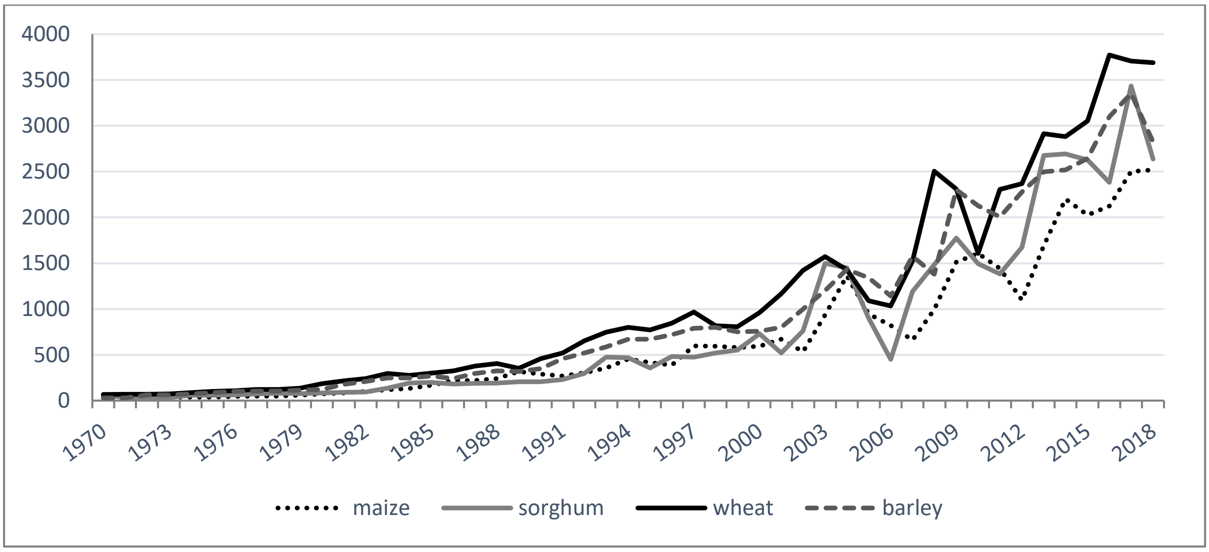

Figure 6.1: Nominal grain prices from 1970 to 2018

It is evident that the nominal prices show a positive linear trend during the period considered in the analysis. This is a sign of inflation which was corrected by the PPI. Thus, nominal prices were converted to real prices (see Figure 6.2). It should be noted that real values reflect a truer picture of grain price behaviour as compared to nominal prices. Real values show moderate price variability between the 1970 and 2000 and high price variability between 2000 and 2018. During the period under study, the real maize prices fluctuated between R527.0270/ton and R2369.500/ton and peaked in 2003 reaching an all-time high in 2018 for the sampled period. Real wheat prices fluctuated between 1208.644 and 2366.626 during the same period. Real prices of barley peaked during the 1970s and 1980s and this was followed by a slight dip in prices during the late 1990's. For all the grain crops under study, a significant drop in grain prices was recorded between 2006 and 2007. This slump in prices may have been caused by economic recession that hit South Africa during that period.

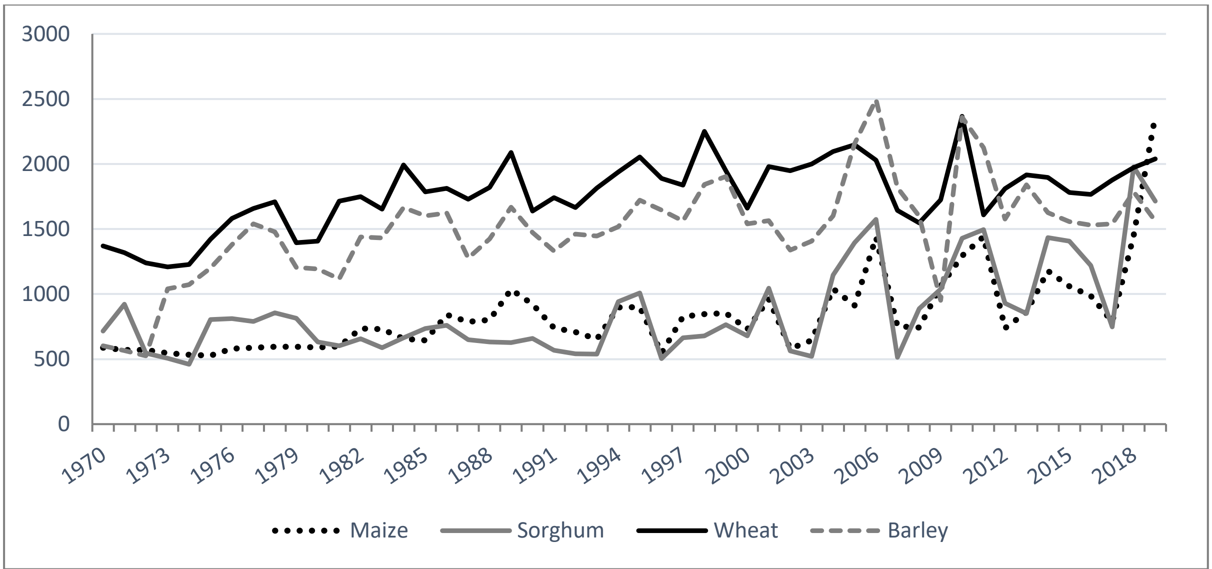

Figure 6.2: Real grain prices from 1970 to 2018

It is evident that the displayed movement in grain prices changed considerably during the period considered in the analysis with high grain prices being recorded after the year 2000. This may have been caused by, among other things, economic reforms introduced in the 1990's, particularly the Agricultural Market Act introduced in 1997. Before South Africa's democratic dispensation and the introduction of agricultural policies (i.e. prior to 2000) prices were less variable and low as compared to years after the economic reforms. It should also be noted that, after the democratic dispensation, the South African economy experienced drastic transformation characterised by rapid urbanisation and increased incomes. As a result, the overall demand grew as well, and therefore grain prices went up.

Log returns of grain prices calculated according to equation 5.6 (in Chapter 5) are plotted in Figures 6.4 to 6.7. It is a common practice in finance variables to use log returns to analyse the variability of an asset (Hull, 2002; Haile *et al,* 2016). Similarly, this study used log returns to analyse the behaviour of grain prices during the period considered in the analysis. Before calculating the log returns, price data were first converted to natural logarithms since the series exhibited high levels of skewness and kurtosis, particularly maize and sorghum prices (see Table 6.1). Log returns were then calculated from transformed real price data. It is evident that the plotted series between 1970 and the mid 1990's appears to be less variable as compared to the late 1990's and 2000's (see Figures 6.4 to 6.7 below). A visual inspection of the plotted log returns series also show that maize and sorghum series appear to be more variable as compared to barley and wheat series.

6.4. Analysis of price risk

Moving the discussion from trends to price volatility, Table 6.2 shows a common measure of price volatility based on standard deviation (σ) of a series calculated per each decade of the period considered in the analysis. By splitting the entire period into sub-periods of ten years, it provides a relatively crude visual indication of whether volatilities have been changing. Since price volatility is associated with price risk, the standard deviation of log returns was also used to measure price risk in this study. Thus, higher standard deviation values indicate greater price risk.

Table 6.2: Split sample standard deviation of log returns

Period	Maize	Sorghum	Barley	Wheat
1970-1979	0.03592	0.27168	0.09151	0.22779
1980-1989	0.13748	0.08746	0.13062	0.14118
1990-1999	0.24454	0.30423	0.10816	0.10746
2000-2009	0.38774	0.53643	0.13633	0.36725
2010-2018	0.39143	0.43847	0.13975	0.13435
1970 - 2018	0.26487	0.36123	0.12349	0.22200

All the four variables show that volatility was moderately high for wheat and sorghum in the1970s and low in the 1980s for all crops. Volatility increased after the economic reforms in the 1990s and became higher in the 2000s, and then marginally declined in the 2010s. The standard deviation figures are showing high price volatility for maize and sorghum. This finding suggests that the two crops experienced greater price risk as compared to barley and wheat.

Figure 6.3 represents the price volatility of grain prices computed by the standard deviation of log returns. The calculated volatility figures were used in the supply response model to determine whether price risk influences production changes in South Africa. It is evident from this figure that high volatility levels were recorded in recent years; between 2000 to 2010 there was an increase in volatility for all the crops. In contrast, when the period between 2010-2017 is compared with other sub-periods, a decline in volatility can be seen for most grain crops, particularly wheat and barley. These results are consistent with Gilbert (2006) who showed that agricultural price volatility was moderately high in the 1970s and low in the 1980s and the early 1990s. Similarly, Huchet-Bourdon (2011), found that price volatility levels for wheat and maize were higher in the 1970's and second half of the 2000s.

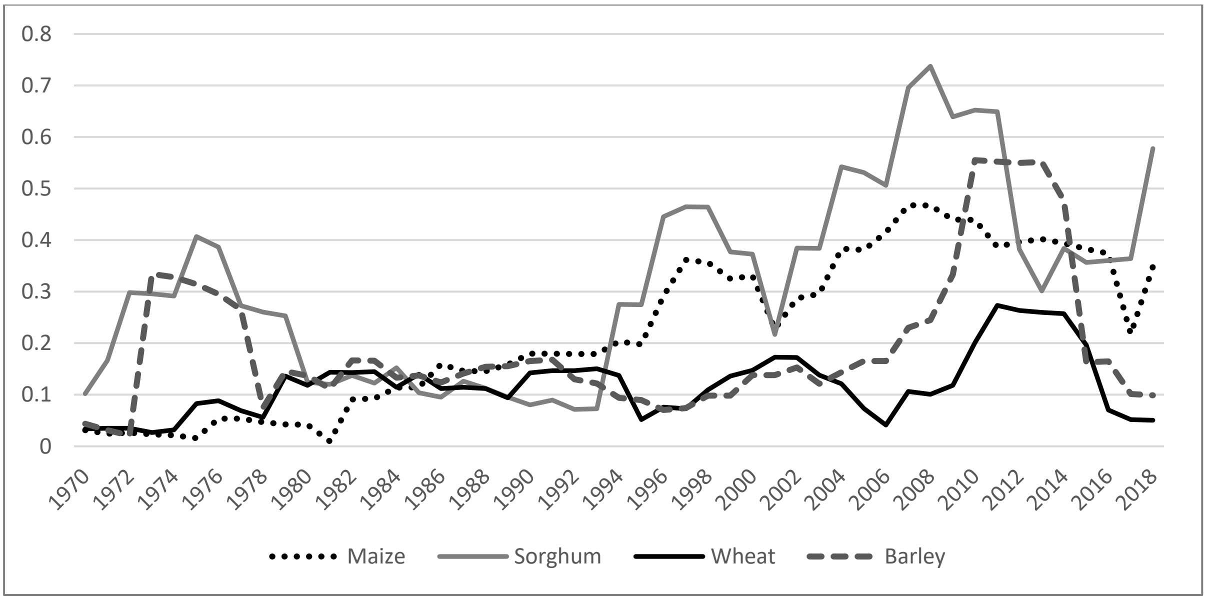

Figure 6.3: Price volatility of grain crops from 1970 to 2018

The results obtained from this analysis suggest that in recent years' wheat and barley presented less price risk for farmers as compared to maize and sorghum. It is, however, difficult to judge whether the volatility is time varying with such a simple analysis. Hence, the next section presents the results of an analysis that was carried out to ascertain whether the volatility in grain prices is time varying.

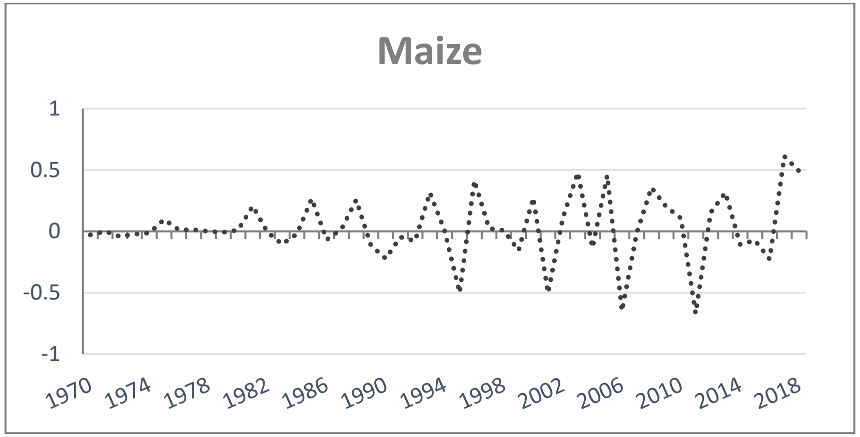

Figure 6.4:Log returns of maize series (1970 to 2018)

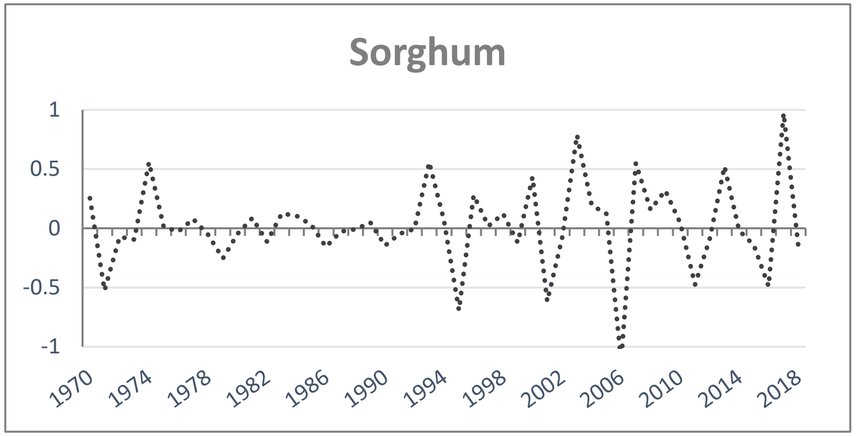

Figure 6.5: Log returns of sorghum series (1970 to 2018)

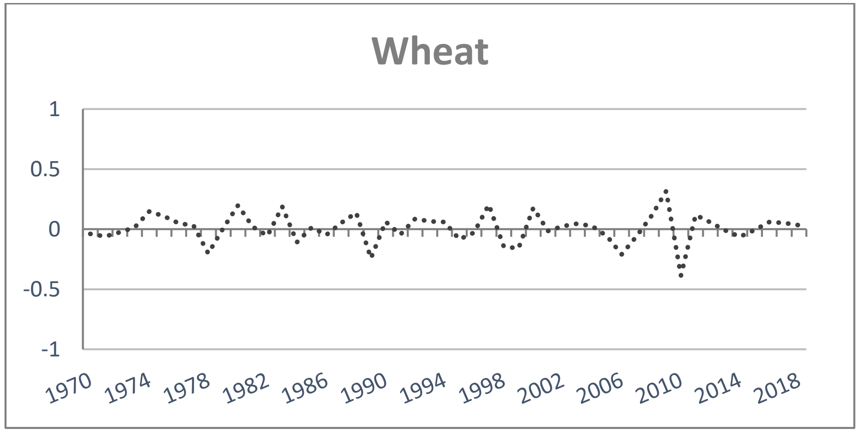

Figure 6.6: Log returns of wheat series (1970 to 2018)

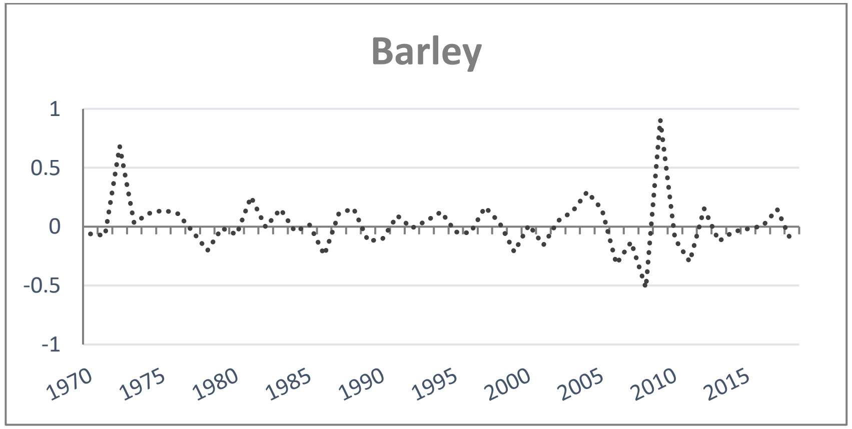

Figure 6.7: Log returns of barley series (1970 to 2018)

6.5. Unit root test results

Box Jenkins analysis can only be applied on stationary time series. Thus, all the grain price series were tested for unit root first before conducting the analysis. Table 6.3 presents the results of the ADF and DF-GLS unit root tests. The test results show that all price variables are stationary at levels. These results demonstrate that the variables are integrated of order zero I(0) and need no differencing.

Table 6.3: 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%
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	-4.0390	-3.1900	-6.5483	-3.1900
LNBP	-3.8218	-3.5063	-8.3259	-3.5085	-3.3067	-3.1900	-8.3158	-3.1900

- Analysis includes trend and intercept
- The model includes constant and trend
- All variables are in natural logarithmic form

6.6. Results of the Box Jenkins analysis

The Box Jenkins approach was applied to determine the mean equation. The results of the box Jenkins analysis for all the crops considered in the study are presented in Tables 6.4 to Table 6.7 below. The best model should have significant coefficients and yield lowest information criterion values of AIC, SC, HQ and largest value of Log likelihood. Based on these criterions, the selected model is ARMA (1,1) for maize, sorghum wheat and AR (1) for barley.

Table 6.4: Box Jenkins results for maize analysis

Model	Coefficients		LogL	AIC	SC	HQ
ARMA(1,1)	0.97689 (11.5287)	-0.6953** (-4.4637)	-0.7450	0.19367	0.34811	0.2522
AR(1)	0.66884 (5.83658)		-2.4609	0.2229	0.33872	0.2668
MA(1)	0.64401 (6.41485)		-4.1991	0.29384	0.40967	0.3377

<u>Note</u>
- ** Denotes coefficient of MA(1) coefficient
- Figures in parenthesis are t-ratios

Table 6.5: Box Jenkins results for sorghum analysis

Model	Coefficients		LogL	AIC	SC	HQ
ARMA (1,1)	0.967605 (15.0115)	-0.75932** (-6.4208)	-12.1127	0.65767	0.8121	0.71626
AR(1)	0.50731 (3.58803)		-13.5227	0.6744	0.7902	0.71834
MA(1)	0.449888 (3.13348)		-14.3714	0.70904	0.8248	0.75298

Note
- ** Denotes coefficient of MA (1) coefficient
- Figures in parenthesis are t-ratios

Table 6.6: Box Jenkins results for wheat analysis

Model	Coefficients		LogL	AIC	SC	HQC
ARMA(1,1)	0.949141 (18.5424)	-0.5592** (-3.9217)	37.2917	-1.3588	-1.2044	-1.3003
AR(1)	0.66763 (11.5287)		36.1934	-1.3548	-1.239	-1.3109
MA(1)	0.55110 (4.45694)		32.2996	-1.1959	-1.0801	-1.152

Note
- ** Denotes coefficient of MA (1) coefficient
- Figures in parenthesis are t-ratios

Unlike other grain crops, results of the Box Jenkins analysis for barley show that AR (1) is the best model based on significant coefficients and low information criterion values of AIC, SC, HQ (see Table 6.7). ARMA (1,1) model has good statistical properties, however, the coefficient of the MA (1) term is insignificant at 5% level. Thus, AR (1) becomes the ideal model based on significant coefficients.

Table 6.7: Box Jenkins results for barley analysis

Model	Coefficients		LogL	AIC	SC	HQC
ARMA(1,1)	0.7701 (7.0940)	-0.07933** (-0.3637)	5.9221	-0.0785	0.07598	-0.0199
AR(1)	0.7171 (8.8838)		5.8816	-0.1176	-0.0018	-0.0737
MA(1)	0.58201 (4.9723)		2.5519	0.01829	0.13411	0.06223

Note
- ** Denotes coefficient of MA (1) coefficient
- Figures in parenthesis are t-ratios

After having selected the best models for the respective crops, and having estimated their parameters, the next step was to test whether volatility is time varying through the identification of significant ARCH effect.

6.7. Results of the ARCH Effect test

The results of the ARCH-LM test are presented in Table 6.8. The selected ARCH models have the lowest information criterion values of AIC, SC and HQ. The probability values for all grain crops considered in the analysis are greater than 0.05 indicating that the null hypothesis of no ARCH effect is not rejected at 5 percent level of significance. Thus, the test for the presence of ARCH effect confirmed the absence of ARCH effects in the errors of ARMA (1,1) models for maize, sorghum, wheat and AR (1) for barley.

Table 6.8: ARCH-LM test results

Crop	Model	Test statistic	Probability
Maize	(ARCH1)	6.712341	0.3281
Sorghum	(ARCH1)	16.56284	0.0823
Wheat	(ARCH1)	0.128568	0.7216
Barley	(ARCH1)	3.872434	0.0551

Note:

H_0: No ARCH effect

The confirmation of the absence of the ARCH effect suggests that volatility in the prices of these crops is not time varying and hence, conditional volatility does not exist. Thus, the GARCH model cannot be used to model price volatility in these prices. However, according to Figiel and Hamulczuk (2012), the absence of ARCH effects is not a confirmation of the lack of conditional volatility. But it simply means that GARCH (1,1) model does not properly describe the data and there may exist other models which are more appropriate.

It should however be noted that the price series analysed were annual whereas GARCH models are usually used to examine behaviour of daily or hourly financial market price series. Thus, GARCH may not be the most appropriate method to use when measuring conditional volatility in annual grain prices. Thus, it would be important to analyse data of another type of frequency (e.g., daily and monthly data).

As a result, the alternative methods of measuring price volatility were used since GARCH cannot be applied. Thus, standard errors of the ARMA process were used to measure volatility in grain prices as suggested by Jordaan *et al,* (2007). The results of the analysis are presented in Table 6.9 below. High standard errors indicate greater price volatility which is interpreted as increased price risk in this study.

Table 6.9: Standard errors of the estimated ARMA models

Crop	Model	R-squared	LogL	AIC	Standard error
Sorghum	ARMA(1,1)	0.296356	-12.1127	0.65767	0.32016
Maize	ARMA(1,1)	0.402706	-0.7450	0.19367	0.25254
Wheat	ARMA(1,1)	0.454735	37.2917	-1.3588	0.11656
Barley	AR(1)	0.415328	5.8816	-0.1176	0.21986

When comparing the standard errors of sorghum (0.32016), maize (0.2525), wheat (0.11655) and barley (0.21986) over the period considered in the analysis, the prices of sorghum were found to be the most volatile, followed by maize, barley and wheat. The varying standard errors suggest that there is greater risk associated with the prices of sorghum and maize as compared to the prices of wheat and barley. These findings coincide with the results obtained in the analysis of the standard deviation of log-returns discussed earlier in the chapter. Interestingly, all the volatility measures utilised in this study indicate that price risk associated with wheat is the lowest of all the crops and higher risk is associated with the price of sorghum. Therefore, based on this analysis, sorghum and maize producers may face greater price risk which can adversely affect farm profits. This shows the need for produces and traders to use different marketing/hedging strategies in order to take account of the different risk levels to which they are exposed.

6.8. Concluding remarks

The aim of this chapter was to analyse the price behaviour and price risk of maize, wheat, sorghum, barley for the period between 1970 to 2018. The study questions how volatility has evolved in recent years as compared with previous decades. The two measures of price volatility were used; namely, the standard deviation of log returns and the standard error of ARMA model. The ARCH effect test was also utilised to check whether the price data for grain crops is time varying. Based on the results reported in the chapter, prices of sorghum were found to be the most volatile, followed by maize, barley and wheat. The results suggest that there is greater risk associated with the prices of sorghum and maize as compared to the prices of wheat and barley. A comparison of the risk associated with the prices of these crops allow decision makers to make well-informed decisions regarding the choice of which of these crops to produce, given their risk characteristics.

CHAPTER 7: RESULTS AND DISCUSSION: PRODUCTION RESPONSE TO PRICE RISK, PRICE AND NON-PRICE FACTORS

7.1. Introduction

This study argues that price-incentives, non-price incentives and price risk may have an effect on supply response of grain producers in South Africa. Four ARDL models were estimated, each representing one of the selected grain crops. The chapter presents the empirical results of each analysis. This chapter is divided into three sections and the first section provides a summary of the variables used in the study, descriptive statistics and unit root tests are used. The second section presents the empirical results. for sorghum and maize supply models and the empirical results for wheat and barley are presented in section three. The reason for presenting results for maize and sorghum in one section is that both grain crops are grown predominantly in the same geographical regions during summer. Hence, their empirical results are comparable. Similarly, wheat and barley are both winter cereal crops that are grown largely in the western cape and share similar biological characteristics.

7.2. Descriptive statistics

Understanding the properties of the variables involved in the analysis is an essential prerequisite for modelling time series data. Thus, various descriptive statistics including mean, standard deviation, kurtosis, skewness, minimum and maximum for all variables involved in the maize, sorghum, wheat and barley analysis are summarized in Table 7.1. On average, 9 699 775 tons of maize, 344 406 tons of sorghum, 1 971 711 tons of wheat and 183 145 tons of barley are produced at national level in South Africa. The amount of grain produced varies by crop with maize being the most produced crop, occupying more land than any other grain crop. The mean planted area of maize (MA) is higher in comparison with Sorghum (SA), wheat (WA) and barley (BA) put together. The mean values of maize price (MP) and sorghum price (SP) are similar but lower than wheat and barley mean values. For the sampled period, maize production has the highest maximum value of 17 551 000 tons, followed by wheat production with 3620000 tons. Sorghum and barley production have maximum values of 711000 and 354065, respectively. The standard deviation represents the deviation of the data variables from the series mean. The price variables (maize price, wheat price) show relatively high standard deviation values indicating that the data points are spread out over a large range of values. This is also an indication of high price variability in grain products. The sample kurtosis and skewness values signify non-normality in some of the variables. This was corrected by logarithmic transformation and first differencing.

Table 7.1: Summary statistics for variables used in the supply models

Variable	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
MPD	9699775	2952901	0.254398	0.12587	3244000	17551000
SA	182151	105542	-0.97247	0.33777	28800	401000
SPD	344406	180885	-0.95334	0.42857	70500	711000
WA	1292511	583246	-1.72888	-0.07302	476570	2025000
MA	3910490	833726	-0.9442	-0.22495	2032446	5172370
WPD	1971711	457095	2.85350	1.38397	131600	3620000
BPD	183145	93903	-1.07885	-0.17224	20000	354065
SYP	3701.78	905.841	0.105877	-0.04053	1286.650	5549.81
MP	845.661	328.316	10.836	2.39506	527.027	2369.50
SP	866.8574	359.3223	3.839408	1.258068	460.1408	1978.335
WP	1777.455	258.5558	2.967336	-0.31241	1208.644	2366.626
BP	1516.692	365.5734	4.553433	-0.080461	525.0909	2494.981
RPBW	0.84917	0.1553	3.004821	-0.00390	0.423647	1.322348
SPR	0.28042	0.1250	-0.0759	0.95104	0.072817	0.586478
MPR	0.24349	0.0600	2.80546	1.76922	0.17559	0.438355
WPR	0.16227	0.0494	-0.06205	0.15106	0.080551	0.298661
BPR	0.25388	0.0864	10.55799	3.02037	0.150359	0.657255
PC	42.6408	48.918	-0.12567	1.13820	1.6000	156.300
FC	380142	70368	1.157312	-1.05799	180685	517269
RF	84.6365	16.724	-0.22377	-0.00464	47.29	121.650
WRF	39.6079	7.2948	0.046731	0.28157	26.1075	58.9500
BRF	60.7705	10.523	0.201690	0.28030	42.1987	89.6833

Note: Definition of variables;

a) MP, MPD, SA, SPD, WA, MA, WPD, BPD are maize price, maize production, sorghum acreage, sorghum production, wheat acreage, maize acreage, wheat production, barley production, respectively.

b) SYP, MP, SP, WP, BP, RPBW are soybean price, maize price, sorgum price, wheat price, barley price, ratio of barley price to wheat price

c) SPR, MPR, WPR, BPR are sorghum price risk, maize price risk, wheat price risk, barley price risk.

d) PC, FC, RF, WRF, BRF are production cost, fertiliser consumption, weather variable, weather variable with respect to wheat, weather variable with respect to barley. **For more information regarding variable descriptions see appendix A.**

7.3. Unit root test results

The results of the ADF and DF-GLS unit root tests are presented in Table 7.2. All variables that were involved in the maize, sorghum, wheat and barley supply equations were tested for their levels and first differences in order to determine the degree of integration. The test results show that wheat price risk variable and fertiliser consumption are non-stationary at levels. As expected, the variables became stationary after first differences. All other variables used in the supply models of the grain crops under study are stationary at levels.

Table 7.2: 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%
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
LNWPD	-4.7232	-3.5063	-7.4346	-3.5107	-4.3778	-3.1900	-7.5306	-3.1900
LNBPD	-4.1197	-3.5063	-11.705	-3.5085	-2.4731	-3.1900	-11.763	-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
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
LNRPBW	-5.1933	-2.9237	-6.1612	-2.9297	-2.5861	-1.9478	-6.0798	-1.9484
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
LNBPR	-3.8423	-2.9237	-7.8157	-2.9251	-3.1932	-1.9478	-7.6680	-7.6680
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
LNWRF	-5.9955	-2.9251	-6.1136	-2.9314	-5.7960	-1.9479	-8.1249	-1.9483
LNBRF	-5.9474	-2.9237	-6.7449	-2.9281	-5.3058	-1.9478	-9.7517	-1.9479
LNPC	-0.4249	-3.5064	-5.9957	-3.5131	-0.2845	0.7773	-7.9636	-3.1900

Note: Analysis includes trend and intercept

a) The model includes constant and trend and all variables are in natural logarithmic form
b) LNMPD, LNSA, LNSPD, LNWA, LNMA, LNWPD, LNBPD are natural logarithm of maize price, maize production, sorghum acreage, sorghum production, wheat acreage, maize acreage, wheat production, barley production, respectively.
c) LNSYP, LNMP, LNSP, LNWP, LNBP, LNRPBW are natural logarithm of soybean price, maize price, wheat price, barley price, ratio of barley price to wheat price
d) LNSPR, LNMPR, LNWPR, LNBPR are natural logarithm sorghum price risk, maize price risk, wheat price risk, barley price risk.
e) LNPC, LNFC, LNRF, LNWRF, LNBRF are natural logarithm of production cost, fertiliser consumption, weather variable, weather variable with respect to wheat, weather variable with respect to barley.

The ADF and the DF-GLS method test the hypothesis that H_0: X~ I(1), that is, has unit root (non-stationary) against H_1: X~I(0), that is, no unit root (stationary). However, the null hypothesis of unit root cannot be rejected at levels since not all variables were stationary at levels. However, the hypothesis of unit root in all series was rejected at (5%) level of significance for all series after first difference. These results 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.

7.4. ARDL bounds test for cointegration results

This section presents the results of the ARDL supply analysis for maize, sorghum, wheat and barley. The results of this section seek to address the first and the second research objectives of the study.

7.4.1. Cointegration test results

ARDL Bounds test was used to determine the existence of long run relationship among variables involved in the maize, sorghum, wheat and barley supply models. The results of the bounds test for each grain crop model are presented in Table 7.3. The F-statistic values of 19.45 for maize and 27.14 for sorghum are greater than the upper bound critical value at 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 conclude that there exists a long run relationship among the estimated variables for maize, sorghum, wheat and barley supply models.

Table 7.3: F-Bounds test for cointegration results

Variables	F-Statistic value	Lower bound value 1(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
Wheat	8.23	2.45	3.61	Cointegration
Barley	6.18	2.86	4.01	Cointegration

The presence 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.

7.4.2. Long and short results of maize and sorghum

Long run elasticities are presented and discussed first followed by short run parameters. Diagnostics test results for model potency are discussed later in the section.

7.4.2.1. Long run elasticities of maize and sorghum

The results of long run elasticities for maize and sorghum analysis are presented in Table 7.4. The dependent variables are maize production (MPD) and sorghum production (SPD) volumes measured in tons. The results show that production responses for both maize and sorghum with respect to price are positive and significant at 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 5 percent level for maize and sorghum, respectively. This is acceptable to show overall fitness of the model.

Table 7.4: ARDL model long run equilibrium estimates

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
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

Note

- * ** *** Represents the 1%, 5% and 10% level of significance, respectively.
- All variables are in logarithmic form

The results indicate that maize has larger production responses to own price as compared to sorghum. The coefficient of the own price variable for maize is positive and significant at the 1 percent level, indicating that a 10 percent increase in price of maize will be followed by an increase in maize production of about 7.5 percent in the long run. Likewise, the own price elasticity of sorghum is also positive and significant at 5 percent level, suggesting that a 10 percent increase in sorghum prices will induce an increase in sorghum production by 5.1 percent in the long run. The long run parameters obtained in this study are also comparable to Alemu *et al,* (2003) who recorded long run price elasticities of 0.51 for maize in Ethiopia. Townsend *et al,* (1997) obtained higher long run price elasticities for maize with a magnitude of 1.76.

The price risk variable for maize measured by the standard deviation of log returns is significant at 1 percent level with a long run parameter of -0.39. The sign of the estimated coefficient is negative, as expected, and this effect of price risk is similar to the findings of Just (1974), Seal and Shonkwiler (1987) and Holt and Aradhyula (1990). The results suggest that greater expected price risk leads to decreased maize production volumes. Specifically, the estimated results suggest 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 5 percent 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. This means that sorgum producers may be willing and able to accept price risks in the long run. This result is consistent with other related studies that found positive effects of price risk on crop output (e.g. Haile *et al,* 2016; Assoutoa *et al*, 2020). The statistically significant long run cross-price elasticities have negative signs in both maize and sorghum models, and this is consistent with economic theory. The results indicate that higher wheat prices are negatively correlated with maize and sorghum production, meaning, maize and sorghum producers respond to higher wheat prices by lowering maize and sorghum production.

The empirical results also reveal that 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 percent increase in wheat price leads to a decrease in maize production by 2.5 percent. The cross-price elasticity for sorghum is 0.57 and higher than that for maize. The finding suggests that a 10 percent increase in wheat price decreases sorghum production by 5.7 percent. 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 of Shahzad *et al,* (2018) who obtained a long run cross price elasticity of -0.79 for tobacco. Haile *et al,* (2016) recorded much lower cross price elasticities of -0.015 and -0.205 for maize and soybeans, respectively.

The estimated long run elasticity of supply for maize with respect to rainfall variable is close to unitary with a value of 0.91. The results suggest that a 10 percent increase in rainfall increases maize production by 9.1 percent in the long run. Moreover, the implied long run elasticity for sorghum with respect to rainfall is 0.75 suggesting that a 10% increase in rainfall will boost sorghum production by 7.5 percent. The results suggest a strong effect of rainfall on maize and sorghum production in the long run. In South Africa, grain production is still largely rain-fed and hence rainfall still plays a huge role in determining maize and sorghum production. Thus, encouraging the adoption of drought resistant varieties and enhancement of irrigation facilities in water stressed regions is critical. 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).

With regard to the sorghum model, the long run elasticity for fertilizer 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 fertilizer consumption. The positive coefficient suggests that an increase in fertilizer use by 10% will be followed by an increase in sorghum production by 8.3 percent in the long run. Janjua *et al,* (2014) argued that in the long run fertilizer enhances land fertility causing an increase in agricultural production. Thus, the results validate the importance of fertilizer use on sorghum production in the South African grain industry. The coefficient of sorghum area is positive and significant at 1 percent level. This finding indicates that sorghum production could rise by 8.08 percent every time planted area is increased by 10 percent 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 results are similar to those obtained by Shahzad *et al,* (2018) but, higher than those obtained by Muchapondwa (2009).

The long run coefficient of production costs for maize measured by the fuel cost index is positive and significant at 1 percent level indicating that a 10 percent increase in production costs increases maize production by 8.8 percent. These findings imply that high production/fuel costs signify resource intensification 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 fertilizer consumption explain sorghum production better than production costs. The policy variables (Dm) were not included in the discussion as they were not significant in both the maize and sorghum equations. Dropping the variables during the analysis improved the quality of the supply estimates of the other variables.

7.4.2.2. Short run equilibrium elasticities of maize and sorghum

The results of the ECMs for sorghum and maize are reported in Table 7.5. 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. As discussed in Chapter 5, the ECT shows 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 error correction term further confirms the existence of a stable long run relationship. With regard to the maize model, the ECT demonstrates that after 10 percent shock to the system, the long run equilibrium relationship of maize production is quickly re-established at the rate of about 90 percent per annum. Similarly, the ECT for the sorghum model implies that change in sorghum production from short run to long run length of time is corrected by about 97 percent per year. Thus, disequilibrium occurring due to a shock will take slightly more than a year to correct.

Table 7.5: 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

<u>Notes</u>

- All variables are significant at 1% level.
- The maize model includes trend and intercept

7.4.2.3. Diagnostic test results of maize and sorghum

Misspecification in the regression is possible and therefore it is important to confirm the validity of the estimated maize and sorghum ARDL models by utilising relevant diagnostic tests. The tests include the Jarque-Bera test for normality, the Breusch-Godfrey test for serial correlation, the white test for heteroskedasticity as shown in Table 7.6. Both the sorghum and the maize models passed all diagnostic tests. The values of the F-statistics 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 then conclude that the estimated supply models are adequate in terms of their specifications.

Table 7.6: Diagnostic test results

Diagnostic	**Serial Correlation Test**		**Heteroskedasticity Test**		**Normality Test**	
Method	Breusch-Godfrey H_o: Serial correlation		Breusch-Pagan-Godfrey H_o: Homoscedastic		Jarque-Bera H_o: 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

7.4.2.4. Stability test results of maize and sorghum

When analysing the stability of the long run parameters together with the short run dynamics, the cumulative sum (CUSUM) and the cumulative sum of squares are applied. The results of the tests are presented in graphical form (see Figure 7.1 for the maize model results and 7.2 for the sorghum model results). The output shows that the CUSUM lines in all figures are positioned between the critical bound of 5% significance level over time, indicating that both models are largely stable throughout the entire period of study.

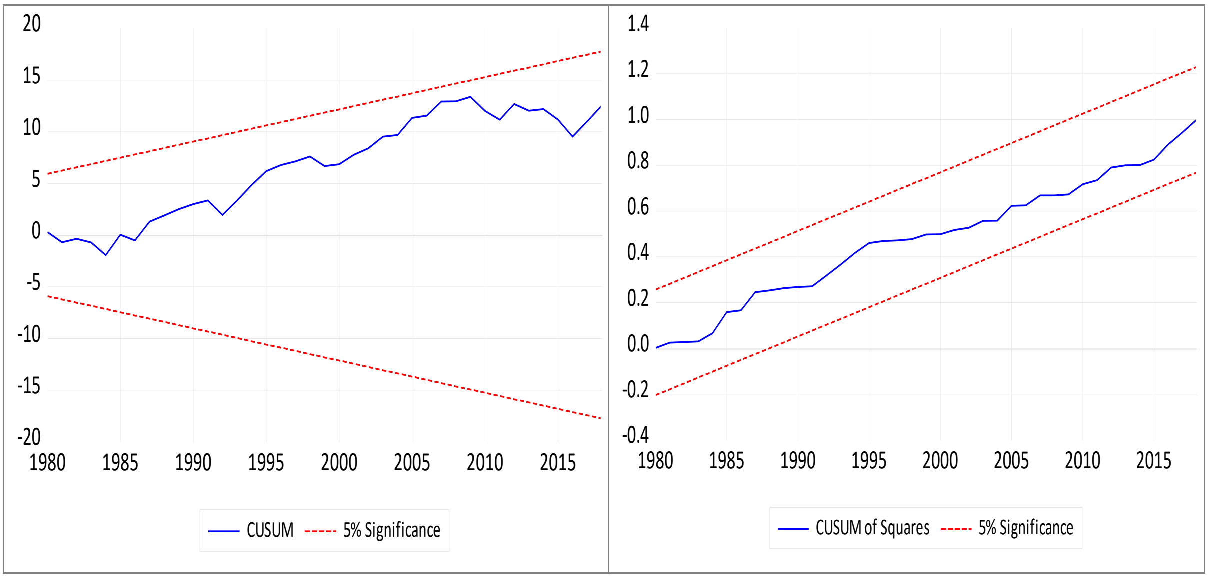

Figure 7.1: CUSUM and CUSUM of Squares test results for maize model

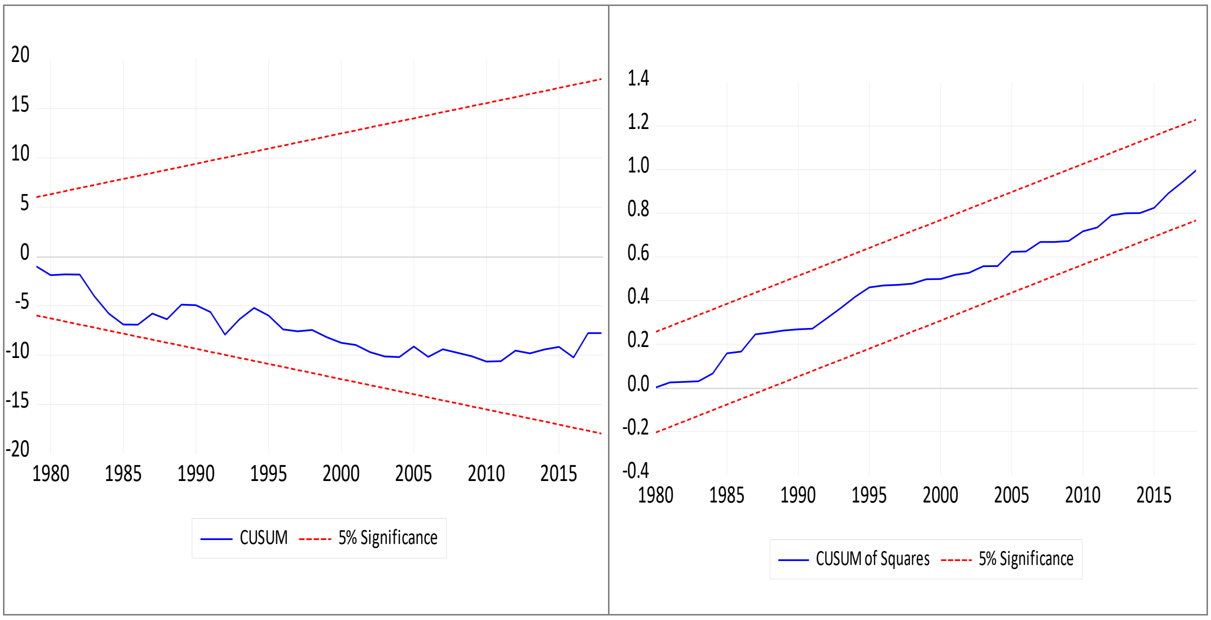

Figure 7.2: CUSUM and CUSUM of Squares test for sorghum model

7.4.3. Long and short results of wheat and barley

The estimated models behave quite well yielding significant elasticities. In order to derive a conclusion from the estimated supply models, one needs to determine to what magnitude the independent variables, specifically price and price risk, affect crop output.

7.4.3.1. Long run elasticities of wheat and barley

Table 7.7 presents the long run parameters for barley and wheat ARDL supply models. The depended variables are barley production (BPD) and wheat production (WPD) volumes measured in tonnes. The results are as expected and consistent with economic theory. The first thing to note is the high explanatory power of the estimated supply functions. Although this does not necessarily imply that all suitable variables have been included in the supply model, it is, nevertheless, a useful feature to show overall fitness of the model. The estimated parameters are as expected and have the correct algebraic sign, although some of the coefficients are not statistically significant.

Table 7.7: Long run elasticities for Barley and wheat

Barley Long run parameters				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(RPBW)	0.644559	0.232084	2.697515	0.0126**
LN(BPR)	-0.675777	0.28254	-2.391793	0.0250**
LN(BRF)	1.754611	0.832031	2.10883	0.0456**
LN(FC)	0.76286	0.536203	1.422707	0.1677
Wheat Long run parameters				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN(WP)	0.247969	0.141006	1.758573	0.0882***
LN(WRF)	0.423114	0.235244	1.798616	0.0815***
LN(WPR)	-0.171636	0.153386	-1.118984	0.2715
LN(WA)	0.452711	0.19187	2.359464	0.0246**
LN(SYP)	-0.347515	0.16852	-2.062166	0.0474**
LN(PC)	0.061477	0.135447	0.453878	0.6530

Note

- ** *** Represents the 5% and 10% level of significance, respectively.
- All variables are in logarithmic form

With regard to the supply function for barley, the coefficient of ratio of relative prices of barley to wheat is positive and significant at 5 percent level. The parameter is inelastic with a value of 0.64 and the sign is as expected. The results suggest that a 1 percent increase in the ratio of relative prices of barley to wheat lead to an increase in barley production by 0.64 percent. These findings are much lower as compared to results obtained by Baltas (1986) who recorded long run elasticities of 3.26 for barley in Greece. Barley and wheat are potential substitute crops, although wheat production has been given priority, this being reflected in more favourable prices (Dawson, 2006). Thus, Barley adjusts to compensate for any exogenously induced shortfall in wheat production. In South Africa, barley is mainly used for brewing beer, however, its use could be extended to animal feed.

The coefficient of price risk measured by the standard deviation of log returns for barley is negative and significant at 5 percent level, indicating that as price risk increases, quantity supplied by producers' decreases. The results demonstrate an aversive reaction by barley farmers towards price risk and uncertainty. In South Africa, barley prices are linked to wheat prices which exposes barley farmers to adverse price risk (Grain SA, 2013). Thus, an alternative pricing system for barley is needed to mitigate the effects of adverse price risk for barley producers.

As expected, the long run coefficient for rainfall is positive and significant at 5 percent level. The results suggest that an increase in rainfall by 1 percent lead to an increase in barley production by 1.75 percent in the long run. The value of the coefficient is elastic and within the range of long run elasticities obtained in by Mythili (2006). The findings show the importance of rainfall in determining barley production in South Africa where majority of grain crops are grown under rain-fed conditions. Thus, investment in irrigation infrastructure is critical if large barley production levels were to be achieved in the long run. Long run elasticity for barley with respect to fertilizer consumption is positive but insignificant in the long run. The results may suggest that famers could turn to alternative plant fertilizers (i.e manure, compost) to boost barley production in the long run.

Coming now to the empirical results for wheat, the own price elasticity is much lower compared to maize, sorghum and barley with a value of 0.24. The findings indicate that an increase in own price of wheat by 1 percent induces wheat production by 0.25 percent. The results suggest weak response to own prices by wheat producers. However, such a result is not unique to supply response literature as other studies such Alemu *et al,* (2003) and Ghatak *et al,* (1999) have recorded similar results. Interestingly, Foster and Mwaunauno (1995) recorded higher long run own price elasticity of 1.57 for wheat in Zambia. As discussed earlier in the study, wheat production in South Africa has been on a decline for the past decade (DAFF, 2019). Thus, given the low response of supply to own price, it means that price incentives may no-longer be good production triggers in South Africa. Thus, alterative incentives (such as investment in irrigation and infrastructure) could save the industry in the future. Mythili (2006) suggested non-price incentives such as better technology, use of better-quality inputs and intensive cultivation as potential production drivers in developing countries.

The coefficient of the rainfall variable for wheat is positive and significant at the 10 percent level indicating that an increase in rainfall by 10 percent will be followed by an increase in wheat production by about 4.2 percent. The sign is as expected, and the parameter is similar to the one recorded by Muchapondwa (2009) in Zimbabwe. Although the rainfall coefficient is low, the results show the importance of rainfall in determining wheat production in South Africa. However, in recent years South Africa has been experiencing more frequent occurrences of drought conditions, a situation which has caused production levels to decline. Therefore, it is imperative to improve farming technology by investing in shorter-season varieties and drought tolerant varieties. This will allow wheat production to thrive in a climate where rainfall patterns have shifted.

The coefficient of the area variable for wheat is positive and significant at 5 percent level. This finding is to be expected and indicates that wheat production will increase by 4.5 percent every time planted area is increased by 10 percent in the long run. The results are in the range of those obtained by Shahzad *et al,* (2018) and Muchapondwa (2009). The implication of the finding is that in the long run, expansion of planted area will still play an important role in determining wheat production in South Africa. Although South Africa has recorded a significant reduction in area planted with wheat during the past two decades (see chapter 4), the results suggest that area expansion is still an important grain production driver in South Africa.

The coefficient of the soybeans price variable is negative and significant at 5 percent level. The implication of the finding is that when soybean prices go up farmers shift production resources from wheat to soybean production. The results agree with the findings by Gouws (2018) who suggested that reduction of wheat production in South Africa has been increasing as a result of farmers switching land to other profitable crops. Haile *et al,* (2016) recorded much lower cross price elasticities of -0.015 and -0.205 for maize and soybeans, respectively. The price risk variable is negative and not significant, possibly suggesting that price risk will not adversely hurt wheat production in future. Thus, in the long run, farmers will adopt alternative risk coping measures (such as futures markets and production contracts). Surprisingly, the coefficient of production costs measured by intermediate fuel cost index is also not significant in the long run. The policy variables (Dm) were not included in the discussion as they were not significant in both the wheat and barley equations. Dropping the variables during the analysis emproved the quality of the supply estimates of the other variables.

7.4.3.2. Short run equilibrium elasticities of wheat and barley

The dynamic results of the error-correction models for wheat and barley are reported in Table 7.8 and 7.9 respectively. The values of the R-squared are relatively high in both supply models (0.81 for wheat and 0.74 for barley). This indicates that that 81 percent and 74 percent of the variation in the depended variables for wheat and barley, respectively is explained by the explanatory variables present in the model. The Durbin Watson (DW) statistic values of 1.89 for wheat and 1.96 for barley cannot be used to detect autocorrelation since the estimated model supply model is dynamic. However, a value that is close to 2 is commonly acceptable. As expected, the coefficient of production costs for maize measured by the fuel cost index introduced in the supply model to express technological advancements is positive and significant at 10 percent level. The results suggest that a 10% increase in the fuel cost index induces wheat production by 3.3 percent in the short run. Interestingly, this variable is not significant in the long run. The implication is that high production/fuel costs signify technical change which in turn stimulates maize production

The coefficient of the ECT (-1) is -0.90 and implies that the deviation from the long-term wheat production is corrected at a rate of about 90 percent per year. This represents a high adjustment process. As expected, the ECT is negative and highly significant. The estimated ECT for wheat is in the range of short run parameters for sorghum and maize reported earlier in this chapter. The present study's estimates are not too far away from those reported by Muchapondwa (2009) and Shahzad *et al,* (2018).

Table 7.8: Short run equilibrium elasticities for wheat supply model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	6.868761	0.828446	8.291142	0.0000*
DLN(WP)	0.188344	0.128302	1.467979	0.1519
DLN(WP(-1))	0.318391	0.150761	2.111894	0.0426**
DLN(WRF)	0.009402	0.080861	0.116269	0.9082
DLN(WA)	0.648024	0.109429	5.92189	0.0000*
DLN(SYP)	0.064935	0.110206	0.589217	0.5599
DLN(PC)	0.337394	0.180382	1.870443	0.0706***
DM	-0.251122	0.045107	-5.567224	0.0000*
ECT(-1)*	-0.904945	0.109407	-8.2714	0.0000*
R-squared	0.81293	Durbin-Watson statistic		1.893162

Note

- * ** *** Represents the 1%, 5% and 10% level of significance, respectively.

Table 7.9: Short run equilibrium elasticities for barley supply model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-16.74098	2.823288	-5.929606	0.0000
DLN(BPD(-1))	0.311659	0.126575	2.462243	0.0214
DLN(BPD(-2))	0.392986	0.119272	3.294876	0.003
DLN(RPBW)	0.061509	0.341255	0.180242	0.8585
DLN(RPBW(-1))	-0.576494	0.311855	-1.848599	0.0769
DLN(RPBW(-2))	-0.548952	0.268133	-2.04731	0.0517
DLN(RPBW(-3))	-0.554394	0.256597	-2.160567	0.0409
DLN(BRF)	0.239579	0.221075	1.083697	0.2893
DLN(BRF(-1))	-1.120088	0.256004	-4.375268	0.0002
DLN(BRF(-2))	-0.585042	0.271437	-2.155349	0.0414
DLN(BRF(-3))	-0.430276	0.212871	-2.021297	0.0545
DLN(FC)	1.05231	0.416196	2.5284	0.0184
DLN(FC(-1))	0.455662	0.414444	1.099453	0.2825
DLN(FC(-2))	0.253592	0.471584	0.537746	0.5957
DLN(FC(-3))	1.401093	0.557939	2.511195	0.0192
DM	0.950572	0.221517	4.291201	0.0003
ECT(-1)*	-0.684014	0.113897	-6.005541	0.0000
R-squared	0.741895	Durbin-Watson statistic		1.9632

Note

- * ** *** Represents the 1%, 5% and 10% level of significance, respectively.
- All variables are in logarithmic form

Turning now to the short run error correction results for barley, the parameters of the production variable lagged once and twice are positive and significant at 5 percent and 1 percent, respectively. The results suggest that an increase in production in one period will be followed by an increase in production in the following period. According to Leaver (2004) this is due to farmers' commitment to covering their fixed costs capital. The estimated coefficient of the ECT which measures the speed of adjustment is -0.67 and significant at 1 percent level. The sign of the ECT coefficient is negative as expected. It demonstrates that after 10 percent shock to the system, the long run equilibrium relationship of barley production is quickly re-established at the rate of about 68% per annum. The result demonstrates a normal adjustment process which is in the range of results obtained in other studies such as Leaver (2004) and Shahzad (2018). However, the estimated ECT for barley is low as compared to other estimated short run parameters for wheat, sorghum and maize. This indicates that in the event of a shock to the system barley will re-establish equilibrium at a slower rate as compared to maize, wheat and sorghum.

7.4.3.3. Diagnostic tests of wheat and barley

The results of diagnostic tests conducted for wheat and barley supply functions are presented in Table 7.10. The values of the F-statistics and their associated p-values for the completed tests demonstrate that again, the wheat and barley models are heteroskedastic, normally distributed and have no problems of serial correlation. By rejecting the Null Hypothesis for each test conducted, we then conclude that the estimated supply models are adequate in terms of their specifications.

Table 7.10: Diagnostic test results for wheat and barley function

Diagnostic	**Serial Correlation Test**		**Heteroskedasticity Test**		**Normality Test**	
Method	Breusch-Godfrey H_0: Serial correlation		Breusch-Pagan-Godfrey H_0: Homoscedastic		Jarque-Bera H_0: Not normally distributed	
	F-statistic	P-value	F-statistic	P-value	F-stat	P-value
Wheat	0.38793	0.9620	1.241774	0.2952	1.4044	0.4954
Barley	0.77096	0.4718	1.313409	0.2577	0.3982	0.8194

7.4.3.4. Stability test results of wheat and barley

The results of the CUSUM and CUSUM of squares tests are presented in graphical form (see Figure 6.3 for barley model results and 6.4 for wheat model results). The output shows that the CUSUM lines in all figures are positioned between the critical bound of 5% significance level over time, indicating that both models are largely stable throughout the entire period of study.

Figure 7.3: CUSUM and CUSUM of Squares test results for barley model

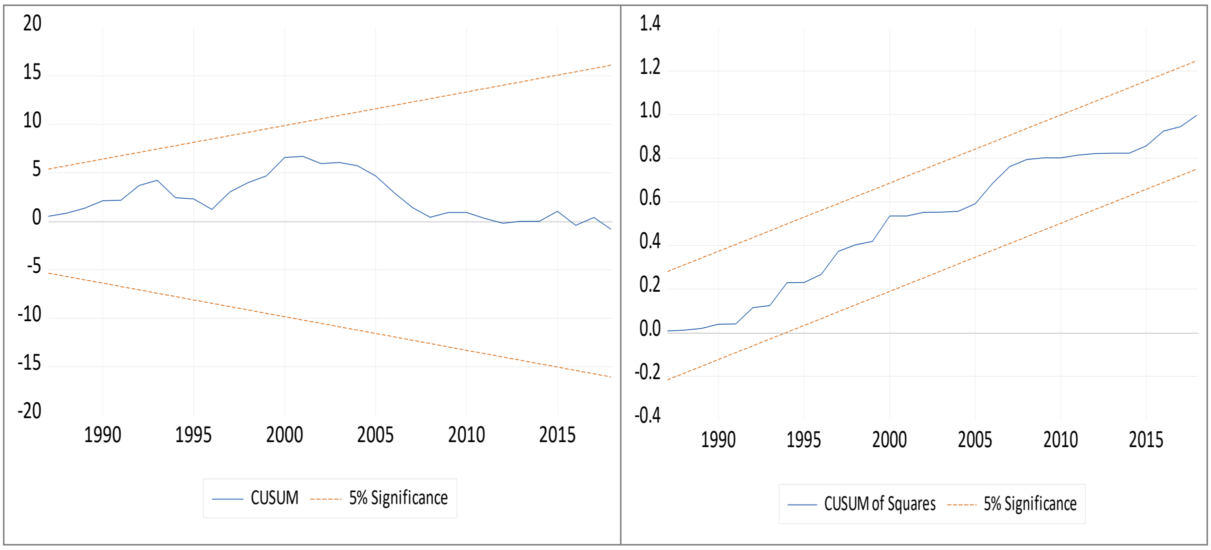

Figure 7.4: CUSUM and CUSUM of Squares test results for wheat model

7.5. Concluding remarks

This chapter illuminated some interesting findings within the area of agricultural supply response. First, the response of grain producers to price incentives in South Africa was revealed. The greater implication of this finding is that grain producers in South Africa do respond to price incentives, however, the response is weak. Second, it was revealed that grain crops demonstrate 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 study has also shown that grain producers respond to non-price incentives (such as rainfall, fertilizer) better than price incentives. The greater implication of the finding is that non-price incentives are better grain production drivers than price incentives in South Africa. The study has also shown that price risk negatively affects grain production, meaning greater price risk lead to reduced production levels, particularly for maize and barley.

CHAPTER 8: SUMMARY AND CONCLUDING REMARKS

This chapter summarises the findings of the thesis and their possible impact and it also discusses the limitations and important directions of future research.

8.1. Summary

The main argument in this thesis is that price-incentives, non-price incentives and price risk may have an effect on supply response of grain producers in South Africa. As a result, the four dynamic ADRL models were estimated, each representing one of the grain crops considered in the study (maize, sorghum, wheat, barley) by employing the annual time series data of 49 observations for the period 1970 to 2018.

The emphasis of the analysis was on two aspects of agricultural supply response modelling: Firstly, an attempt was made to determine the level of price risk among the selected grain crops using two price risk measures. Price risk variables were generated and included in the grain supply functions in order to measure the supply response of grain producers to price risk. Secondly, the study estimated the supply response of grain producers to their own price, price risk and non-price factors. To achieve this, four supply functions were developed and analysed. In such models, supply was expressed as a function of own price, price risk and non-price factors.

The empirical results show that grain supply in South Africa is reasonably responsive to changes in own prices. However, the degree of responsiveness is low and varies among different crops. The results of the study also showed that besides price incentives, non-price incentives (such as rainfall, fertilizer, technology) are better production drivers than price incentives in South Africa. The results underscored the relevance of price risk in determining production output. Therefore, given the results obtained in this study, the null hypothesis stated earlier in Chapter 1 was therefore rejected, and the inference is that prices, price risk and non-price factors affect grain supply in South Africa.

8.2. Conclusion

Based on the results obtained in this study, the following conclusions can be drawn:

- Price factors are not sufficient in accelerating production of grain crops. Non-price factors such as rainfall, advancements in technology, fertiliser and area expansion are more relevant explanatory variables. Similar results were obtained in other studies (Maming, 1996; Leaver, 2004; Rao, 2004 and Shoko, 2016; Shahzad *et al,* 2018).
- Price risk negatively affects grain production, meaning greater price risk leads to reduced production levels, particularly for maize and barley.
- Sorghum prices display high levels of volatility, followed by maize, barley and wheat. The results suggest that maize and sorghum producers face greater price risk than barley and wheat producers. Thus, grain producers need to take note of the high volatility in the prices especially for maize and sorghum. Hence, hedging strategies in the form of forward contracts may be the right tools that farmers can use to circumvent the negative impacts of price risk.
- High levels of volatility in grain prices were recorded between 2000 and 2010 as compared to other sub-periods. This may have been caused by, among other things, economic reforms introduced in the 1990's.
- Inclusion of price risk variables in supply functions is quantitatively important in the analysis of grain production. The finding is in agreement with other related studies (Just, 1974; Seal and Shonkwiler, 1987; Holt and Aradhyula, 1990).
- Grain crops demonstrate 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 results indicate that advanced methods in the econometrics literature may be successfully applied to agricultural data. This study applied some techniques that are popular in econometrics and finance literature (ARDL, ARIMA, ARCH). However, the results suggest that GARCH model may not be the most appropriate method to use when measuring conditional volatility in annual grain prices. Thus, it would be important to analyse data of another type of frequency (e.g., daily and monthly data)

8.3. Contribution

The inclusion of price risk variables in the supply functions increased the originality of this study. Although the concept is not new to supply response literature (Behrman, 1968; Just, 1974; Seal and Shonkwiler, 1987; Holt and Aradhyula, 1990), the concept is still unfamiliar to supply response literature for South African Agriculture. At the time of writing this thesis there have only been a handful of studies focusing on agricultural supply response for South Africa (Schimmelpfennig *et al,* 1996; Ogundeji *et al,* 2011; Shoko *et al,* 2016; Nhundu *et al,* 2018), and none of these studies included risk variables in the analysis. Thus, this study attempts to close that knowledge gap contributing towards the greater understanding of the South African grain industry.

8.4. Limitations and suggestions for future research

Although this study followed some of the best methods of measuring agricultural supply response and obtained meaningful results. It is however, important to document some of the notable limitations of this research:

1) The scope of this study was restricted to state level supply response. However, predicting supply response of grain crops focusing on provincial level data may improve the supply estimates. South Africa has 9 provinces and hence, focusing on provincial application of supply response will allow the analyst to compare results between different provinces. However, accurate provincial level data required to complete the analysis was not readily available for the sampled period.
2) Possible model misspecification challenges were encountered because it is impossible to account for all the model assumptions. Thus, the actual supply models may never be known. This is caused by a number of issues including variable selection, omitting relevant variables, function form misspecification, including irrelevant variables, missing data and incorrect specification of the model. Omitting relevant variables can potentially reduce the statistical power of the study and can produce biased estimates, leading to invalid conclusions.
3) It was a challenge to find appropriate proxy variable for expected price since it is unobservable at the time of planting. Also, it was not possible to include technology variables such as research and development and new crop varieties due to lack of data or lack of sufficient variation in the data. Thus, special attention is needed

when selecting proxy variables since wrong selection may lead to misspecification problems.

4) The analyst found it difficult to analyse price risk, particularly finding the correct measure of price risk. Advanced methods such as GARCH could not be applied. Thus, the process of selecting an alternative risk measure was challenging.

Based on the discussion above, further research can be expanded in the following several potential ways;

- Since the analysis was restricted to national level data, further research of this nature is required for provincial level data with different competing crops and agricultural climatic environment. The analysis can also be extended to other crops (i.e soybeans and sunflower).
- Since GARCH model was not applied in this study, future research could apply it to measure conditional volatility using monthly/or daily data. Focusing on price volatility using GARCH may also be another option for future research.
- Further research should also look into the factors influencing the levels of volatility in South Africa. Knowledge of these factors could help policy makers interested in mitigating the negative impacts of price volatility.

8.5. Policy implications

Agricultural price policies are important tools that might be used to accelerate production output. However, such policies cannot be designed fully unless the effects and implications of price and non-price changes are considered. Thus, the following are policy recommendations, which will favour increased growth in the South Africa grain industry.

Given the importance of grain crops in South Africa, the grain industry and policymakers should take these results into consideration and try to improve the industry’s performance. The study recommends that any policy initiatives undertaken to stabilise the grain industry (particularly for maize and sorghum) should provide vulnerable grain farmers with effective market-based risk management tools. Therefore, the government should look into proposing packages (such as futures contracts, forward contracts, contract farming) that can reduce the volatility in the prices of commodities. Future contracts and forward contracts cushion farmers from adverse price movements by guaranteeing the price of agricultural produce ahead of sale.

The government should also look into financing solutions (relief funds and loans) for grain farmers to provide immediate liquidity in the event of substantial income losses due to adverse price movements. This initiative can also be achieved by establishing risk financing partnerships between producers and banks.

Given the magnitude of the price and non-price factors obtained in this study. Policy measures should give more attention to non-price factors. This study underscored the importance of rainfall in accelerating grain production in South Africa. Thus, encouraging the adoption of drought resistant varieties and enhancement of irrigation facilities in water stressed regions is critical.

It should, however, be noted that mere reforms would not contribute to the improvement of production response unless adequately supported by improving the farmers' access to seasonal grain price information, expansion of irrigation and risk reducing tools. Thus, a package of both price and non-price factors will go a long way in ensuring the stability of the South African grain industry.

Below are policy implications and directions for each grain crop;

- **Barley:** The study found that barley prices are linked to wheat prices which exposes barley farmers to adverse price risk. Thus, an alternative pricing system for barley is needed to mitigate the effects of adverse price risk for barley producers in South Africa.
- **Wheat:** Given the low supply estimates of own price of wheat with respect to production, it means that price incentives may no-longer be good production triggers for wheat in South Africa. Therefore, alternative incentives such as drought resistant varieties could provide positive results to the wheat industry. Expansion of planted area could also play an important role in determining wheat production in the future. Invesment in irrigation equipment can also plan a huge role in stimulating wheat production partcicculary in drought prone areas of the countries.
- **Sorghum:** Results have showed that expansion of production area significantly increases production volumes. Although land for production expansion is limited in South Africa, land can be made available by shifting resources from other crops (such as maize and wheat) to sorghum in the long run. Consequently, given the high volatility in sorghum prices found in the study, farmers should look into using

various hedging mechanisms such as futures contracts, forward contracts and contract farming.

- **Maize:** Given the high supply parameters of own price and rainfall variables found in this study, adoption of price policies that favour maize farmers could go a long way in improving maize production in South Africa. In addition, policy initiatives should encourage the adoption of drought resistant varieties and enhancement of irrigation facilities in water stressed regions.

9.0. REFERENCES

Alemu, Z.G., Oosthuizen, K. & Schalkwyk, H. D. V. (2003). "Grain-Supply Response in Ethiopia: An Error-Correction Approach", Agrekon, Vol 42, No 4, 389-404.

Amponsah, L., Hoggar, K. G., Asuamah, S. Y. (2015). Climate change and agriculture: modelling the impact of carbon dioxide emission on cereal yield in Ghana. Agric. Food Sci. Res., 2(2): 32–38.

Anwarul, H., and Fatimah, M. A. (2010). Supply response of potato in Bangladesh: a vector error correction approach. Journal of Applied Sciences, 10(11): 895-902.

Arnade C and Kelch. D. (2007). Estimation of Area Elasticities from A Standard Profit Function. American Journal of Agricultural Economics. 89(3): 727–737.

Askari, H. and Cummings, J., 1977. Agricultural Supply Response: A Survey of Econometric Evidence. Praeger, New York.

Assoutoa, A.B., Houensou, D.A, Semedo, G. (2020). Price risk and farmers' decisions: A case study from Benin. Scientific African. Vol (8): 1 – 11.

Astover, A. and Motte, M. (2003) Price Risks in Estonian Agriculture. Economic science for Rural development. Jelgava: Maquette Ltd: 250-254.

Awal, M. A., and Siddique, M. A. B. (2011). Rice production in Bangladesh employing by ARIMA model. Bangl. J. Res., 36(1): 51–62.

Ayinde, E.O, Bessler D.A and Oni FE (2017) Analysis of supply response and price risk on rice production in Nigeria. Journal of Agribusiness and Rural Development. 1(43): 17-24.

Azzam, A. M. (1991). Food subsidies and market interdependence: the case of the Moroccan soft wheat subsidy. Agricultural Economics, 5(4): 325-339.

Ball, V.E. (1988). "Modelling Supply Response in a Multiproduct Framework." American Journal of Agricultural Economics 70(4): 813–825.

Baltas, N.C. (1986). European Review of Agricultural Economics, 14(2): 195–220, https://doi.org/10.1093/erae/14.2.195.

Banerjee, A., Dolado, J., Galbraith, J & Hendry, d. (1993). Co-Integration, Error Correction, And the Econometric Analysis of Non-Stationary Data. 10.1093/0198288107.001.0001.

Bapna, S, Binswanger, HP., and Quizon, J.B. (1984). “System of output supply and factor demand equations for the semiarid tropical India”, Indian Journal of Agricultural Economics 39(2): 179-213.

Batra, R. N., and Ullah, A. (1974). Competitive firm and the theory of input demand under price uncertainty. Journal of Political Economy, 82(3): 537-548.

Begum, M.A.A, Islam, S.M.F., Kamruzzaman, M., Kabir J.M and Shiblee, S.M.A, (2002). Supply Response of Wheat in Bangladesh: An Application of Partial Adjustment Model. Pakistan Journal of Biological Sciences, 5: 225-229.

Behrman, J.R. (1968). Supply Response in Underdeveloped Agriculture: A Case Study of Four Major Annual Crops in Thailand 1937-1963. Amsterdam: North-Holland.

Binswanger, H., Yang, M. C., Bowers, A., and Mundlak, Y. (1987). On the determinants of cross-country aggregate agricultural supply. Journal of Econometrics, 36(1-2): 111-131.

Bhagat L.N. (1989). Supply responses in backward agriculture, Ashok Kumar Mittal publishers, New Delhi, India.

Bloom, D.E., and Sachs, J. (1998). Geography, Demography, and Economic Growth in Africa. Brookings Papers on Economic Activity, 2: 207–273.

Boansi, D. (2014). Yield response of rice in Nigeria: A cointegration analysis. American Journal of Agriculture and Forestry, 2: 15-24. 10.11648/j.ajaf.20140202.11.

Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3): 307-327.

Bond, M.E. (1983). Agricultural responses to prices in Sub-Saharan Africa. International Monetary Fund Staff Papers, 30: 703-726.

Braulke, M. (1982). 'A note on the Nerlove model of agricultural supply response'. International economic review, 23(1): 241-246.

Breitenbach, M. C., & Fenyes, T. I. (2000). Maize and wheat production trends in South Africa in a deregulated environment/mielie en koring produksietendense in'n ge-dereguleerde markomgewing in Suid-Afrika. Agrekon, 39(3): 292-312.

Chambers, R. G., and Just, R. E. (1989). Estimating multioutput technologies. American Journal of Agricultural Economics, 71(4): 980-995.

Charemza, W.C. and Deadman, D.F. (1992) "New Directions in Econometric Practice: General to Specific Modelling. Cointegration and Vector Autoregression", Edward Elgar Publishing Limited.

Chavas, J.P and Holt, M.T. (1990). Acreage Decisions Under Risk: The Case of Corn and Soybeans. American Journal of Agricultural Economics, 72 (3): 529–538

Conteh, A.M.H., Yan, X., and Gborie, A.V. 2014. Using the Nerlovian Adjustment Model to Assess the Response of Farmers to Price and Other Related Factors: Evidence from Sierra Leone Rice Cultivation. World Academy of Science, Engineering and Technology International Journal of Agricultural and Biosystems Engineering Vol:8, No:3: 687 – 693.

DAFF (2016) Department of Agriculture; Trends in the Agricultural sector 2016. South Africa Available at: http://daff.gov.za (accessed 18 November 2017).

DAFF. (2017a). A profile for the South African Sorghum Market Value chain. Available online at www.nda.agric.za/doaDev/sideMenu/Marketing/Annual%20Publications.

DAFF. (2017b). A profile for the South African Maize Market Value chain. Available online at www.nda.agric.za/doaDev/sideMenu/Marketing/Annual%20Publications.

DAFF (2017c) A profile for the South African Barley Market Value chain. Available online at www.nda.agric.za/doaDev/sideMenu/Marketing/Annual%20Publications.

DAFF. (2017d). Economic Review of the South African Agriculture 2016/217, Pretoria: Department of Agriculture, Forestry and Fisheries.

DAFF (2018). Abstract of Agricultural statistics. South Africa. Retrieved Nov 11th, 2018.https://www.daff.gov.za/Daffweb3/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Abstract%202016%20.xls.

DAFF (2019). Abstract of Agricultural statistics. South Africa. Retrieved Dec 17th, 2019.https://www.daff.gov.za/Daffweb3/Portals/0/Statistics%20and%20Economic%20Analysis/Statistical%20Information/Abstract%202019.pdf.

Dawson, P. J., Sanjuán, A. I., and White, B. (2006). Structural breaks and the relationship between barley and wheat futures prices on the London International Financial Futures Exchange. Review of Agricultural Economics, 28(4): 585-594.

Dechow, P. M., and Sloan, R. G. (1997). Returns to contrarian investment strategies: Tests of naive expectations hypotheses. Journal of financial economics, 43(1), 3-27.

Demery, L and Addison, T. (1987) Stabilization policy and income distribution in developing countries. World Development, 15 (12): 1483-1498.

Díaz-Bonilla, Eugenio. (2016). Volatile volatility: Conceptual and measurement issues related to price trends and volatility. In Food price volatility and its implications for food security and policy, eds. Matthias Kalkuhl, Joachim von Braun, and Maximo Torero. Chapter 2, pp. 35 - 57. http://dx.doi.org/10.1007/978-3-319-28201-5_2

Filipe, M. D. (2008). Bean supply response for Mozambique (Doctoral dissertation, Purdue University).

Duasa, J. (2007). Determinants of Malaysian trade balance: An ARDL bound testing approach. Global Economic Review, 36(1): 89-102.

Elliott, G., Stock, J., and Rothenberg, T. (1996). Efficient Tests for an Autoregressive Unit Root. Econometrica, 64: 813-36. 10.2307/2171846.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the econometric society, 987-1007.

Engle, R.F and Granger, C.W.J. (1987). Cointegration and Error Correction: Representation, Estimation, and Testing. Econometrica, 55(2): 251-276

Ferjani, A., and Zimmermann, A. (2013). Estimating Agricultural Supply Response with the dynamic sectormodel SILAS-dyn. Journal of Socio-Economics in Agriculture (Until 2015: Yearbook of Socioeconomics in Agriculture), 6(1), 155-176.

Figiel and Hamulczuk, M. (2012). Price risk in the wheat market in Poland. Selected paper prepared for presentation at the International Association of Agricultural Economics (IAAE) Trinnial conference, Foz do Ignacu, Brasil, 18 – 24 August, 2012.

Flinn, J. C., Kalirajan, K. P., and Castillo, L. L. (1982). Supply responsiveness of rice farmers in Laguna, Philippines. Australian Journal of Agricultural Economics, 26(1), 39-48.

Ghatak, S., Manolas, G., and Vavouras, I. (1999). Wheat Supply Response in Greece and The European Union Policy. European Research Studies Journal, 2(1-4), 57-68.

Ghatak, S., and Seale, J. L. (2001). Rice, risk and rationality: supply response in West Bengal, India. European Research Studies Journal, 4(3-4): 155-169.

Gilbert, C. L. (2006). Trends and volatility in agricultural commodity prices. Agricultural commodity markets and trade: new approaches to analyzing market structure and instability, 31-60.

Goodwin, T. H., and Sheffrin, S. M. (1982). Testing the rational expectations hypothesis in an agricultural market. The Review of Economics and Statistics, 658-667.

Grain SA (2013). The relative value between barley and wheat from a production point of view: Northern Cape irrigation areas. December 2013. Available online at https://www.grainsa.co.za/the-relative-value-between-barley-and-wheat-from-a-production-point-of-view:-northern-cape-irrigation-areas.

Gardner, B. L. (1976). Futures prices in supply analysis. American Journal of Agricultural Economics, 58(1): 81-84.

Granger, C., and Newbold, P. (1974). Spurious regressions in economics. Journal of Econometrics, 2 (1): 227–238

Gulati, A., and Kelley, T. (1999). Trade Liberalization and Indian Agriculture, Oxford University Press, United Kingdom

Haile, M., Kalkuhl, M., & von Braun, J. (2013). Short-term global crop acreage response to international food prices and implications of volatility. ZEF-Discussion Papers on Development Policy, (175).

Haile, M. G., Kalkuhl, M., & von Braun, J. (2016). Worldwide acreage and yield response to international price change and volatility: a dynamic panel data analysis for wheat, rice, corn, and soybeans. American Journal of Agricultural Economics, 98(1): 172-190.

Hallam, M and Zanoli, D. (1993). European Review of Agricultural Economics, Vol 20(2): 151–166.

Hardaker, J.B., Huirne, R.B.M., Anderson, J. R. and Lien, G. (2004). Coping with Risk in Agriculture. 2nd ed. Oxfordshire: CABI Publishing.

Hassler, U., & Wolters, J. (2006). Autoregressive distributed lag models and cointegration. In Modern econometric analysis (pp. 57-72). Springer, Berlin, Heidelberg.

Hull, JC. (2002). Options, Futures and Other Derivatives, 5th Edition. Prentice Hall, New Jersey.

Hellin, J., and Meijer, M. (2006). Guidelines for value chain analysis. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Holt, M. T., and Aradhyula, S. V. (1990). Price risk in supply equations: An application of GARCH time-series models to the US broiler market. Southern Economic Journal, 230-242.

Holt, M.T., and Moschini, G. (1992). Alternative Measures of Risk in Commodity Supply Models: An Analysis of Sow Farrowing Decisions in the United States. Journal of Agricultural and Resource Economics, 17(1): 1-12.

Holt, M.T and Mckenzie, A. (2003). Quasi-rational and ex ante price expectations in commodity supply models: An empirical analysis of the US broiler market. Journal of Applied Econometrics, 18: 407-426

Huchet-Bourdon, M. (2011), "Agricultural Commodity PriceVolatility: An Overview", OECD Food, Agriculture andFisheries Working Papers, No. 52, OECD Publishing.http://dx.doi.org/10.1787/5kg0t00nrthc-enOECD Food, Agriculture and FisheriesWorking Papers No. 52Agricultural CommodityPrice VolatilityAN OVERVIEWMarilyne Huchet-Bourdon.

Iqbal J and Uddin, M.N. (2013) Forecasting Accuracy of Error Correction Models: International Evidence for Monetary Aggregate M2. Journal of International and global Economic Studies, 6(1): 14-32

Janjua, Z.P, Samad. G. and Khan. N. (2014). Climate Change and Wheat Production in Pakistan: An Autoregressive Distributed Lag. Wageningen Journal of Life Sciences, 68, 13–19.

Johansen, S. (1991). Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. Econometrica 59, 1550 – 1580.

Johannesburg Stock Exchange (2019). Grain Futures and Options. Available online https://www.jse.co.za/trade/derivative-market/commodity derivatives/agricultural-derivatives.

Jongeneel, R., and Gonzalez-Martinez, A. R. (2020). Estimating crop yield supply responses to be used for market outlook models: Application to major developed and developing countries. NJAS-Wageningen Journal of Life Sciences, 92, 100327.

Jordarn, H, Grove.,B, Jooste, A and Alemu Z.G.,(2007). Measuring the price volatility of certain field crops in South Africa using the ARCH/GARCH Approach. Agrekon, Vol 46, No 3: 306 – 322.

Junaid, S., Ullah, A., Zheng, S., Shah, S. N. M., Ali, S., and Khan, M. (2014). Supply response analysis of rice growers in district Gujranwala, Pakistan. Agricultural Sciences, 5(11): 1069-1076.

Just, R. E. (1974), "An Investigation of the Importance of Risk in Farmers' Decisions," American Journal of Agricultural Economics 56, 14–25.

Kalirajan., K and Flinn J.C. (1981). Allocative efficiency and Supply response in irrigated rice production. Indian Journal of Agricultural Economics, 36 (2): 16 – 24.

Kavinya, P., & Phiri, M. A. R. (2014). Maize hectarage response to price and non-price incentives in Malawi. Scholarly Journal of Agricultural Science, 4(3): 142-151.

Khan, S. U., Faisal, M. A., Haq, Z. U., Fahad, S., Ali, G., Khan, A. A., & Khan, I. (2019). Supply response of rice using time series data: Lessons from Khyber Pakhtunkhwa Province, Pakistan. Journal of the Saudi Society of Agricultural Sciences, 18(4): 458-461.

Kohli, D.S (1996). Supply response in Agriculture, A review of Methodologies. Working paper No. 63, National council of Applied Economic Research. Parisila Bhawan, 11 Indrastha estate, New Dehli, India.

Krautkraemer, J. A. (1994). Population growth, soil fertility, and agricultural intensification. Journal of Development Economics, 44(2): 403-428.

Krishna, R. (1982). Some aspects of agricultural growth, price policy and equity in developing countries. Food Research Institute Studies, 18(1387-2016-115920), 219-260.

Leaver, R. (2004). Measuring the supply response function of tobacco in Zimbabwe. Agrekon 43(1): 113-331.

Li, P., and Ouyang, Y. (2020). Technical Change and Green Productivity. Environmental and Resource Economics, 76: 271-298.

Lin, W. W., and Dismukes, R. (2005). Risk Considerations in Supply Response: Implications for Counter-Cyclical Payments' Production Impact (No. 378-2016-21441).

Liu, F., You, L. and Yu, B. (2010). Dynamic Agricultural supply response under economic transformation. A case study of Heran province. IFPRI discussion paper 00987.

Mamingi, N. (1996). How Prices and Macroeconomic Policies Affect Agricultural Supply and the Environment. World Bank Policy Research Working Paper No. 1645. Available at SSRN: https://ssrn.com/abstract=614957.

McCormick. (2020, May 14). All the latest data on maize production around the world. https://www.mccormick.it/za/all-the-latest-data-on-maize-production-around-the-world/

Mohammad, S., Javed, M.S., Ahmad, B and Khalid M. (2007). Price and Non-Price Factors Affecting Acreage Response of Wheat in Different Agro-Ecological Zones in Punjab: A Cointegration Analysis. Pakistan Journal of Agricultural Sciences, 44(2): 370 – 377.

Moledina, A.A., Roe, T.L and Shane, M. (2003). Measurement of commodity price volatility and the welfare consequences of eliminating volatility. Working Paper at the Economic Development Centre, University of Minnesota.

Muchapondwa, E. (2009). Supply response of Zimbabwean agriculture: 1970–1999. African Journal of Agricultural and Resource Economics, 3(311-2016-5512), 28-42.

Mushtaq, K. and Dawson, P.J. (2002). Acreage response in Pakistan: a cointegration approach. Agricultural Economics, 27,111-121.

Muth, J.F. (1961). Rational expectations and the theory of price movement. Econometrica, 29, 315-355.

Mythili, G. (2006). Supply Response of Indian Farmers: Pre and Post Reforms, India Gandhi Institute of Development Research, Mumbai.

Najma. M. (2000). "Greening Land and Agrarian Reform: A Case for Sustainable Agriculture", in at the Crossroads: Land and Agrarian Reform in South Africa into the 21st century, ed. Cousins, Ben. Bellville, School of Government, University of the Western Cape.

Narayana, N.S.S. and Parikh, K.S. (1981). Estimation of Farm Supply Response and Acreage Allocation: A Case Study of Indian Agriculture. Research Report–81-1, International Institute for Applied Systems Analysis.

Nerlove, M. (1958). The Dynamics of Supply: Estimation of Farmers' Response to Price. Johns Hopkins, Baltimore.

Nerlove, M. (1979) "The Dynamics of Agricultural Supply: Retrospect and Prospect", in American Journal of Agricultural Economics, 61(5): 867-888.

Nhundu, K., Gandidzanwa, C., Chaminuka, P., Mamabolo, M., Mahlangu, S., and Makhura, M. N. (2021). Agricultural supply response for sunflower in South Africa (1947–2016): The partial Nerlovian framework approach. African Journal of Science, Technology, Innovation and Development, 1-11.

Nichell, S. (1985). Error correction, partial adjustment and all that: an expository note. Oxford bulletin of economics and statistics, 47(2): 119-129.

Nowshirvani, V.F. (1971). American Journal of Agricultural Economics, 53(1): 116-119.

OECD, (2016). OECD Review of Agricultural Policies: South Africa, ISBN 92-64-036792

Ogazi, C.G. (2009). Rice output supply response to the changes in real prices in Nigeria: An autoregressive distributive lag model approach. Journal of sustainable Development in Africa,11 (4): 83-100.

Ogundeji, A. A., Jooste, A., & Oyewumi, O. A. (2011). An error correction approach to modelling beef supply response in South Africa. Agrekon, 50(2): 44-58.

Olwande, J., Ngigi, M., and Nguyo, W., (2009). "Supply Responsiveness of Maize Farmers in Kenya: A Farm-Level Analysis," 2009 Conference, August 16-22, 2009, Beijing, China 50786, International Association of Agricultural Economists.

Penson, J.B, Capps, O., Rosson, C.P., Woodward, R.T. (2015). Introduction to Agricultural Economics, Global Edition. 6th Edition, Pearson Education Limited. USA

Pesando, J. E. (1976). Rational expectations and distributed lag expectations proxies. Journal of the American Statistical Association, 71(353): 36-42.

Pesaran, M.H, Shin Y and Smith, R.J. (2001) Bounds Testing Approaches to the Analysis of Level Relationships. Journal of Applied Econometrics,16: 289-326.

Platteau, J. P. (1996). Physical infrastructure as a constraint on agricultural growth: The case of sub-Saharan Africa. Oxford Development Studies, 24(3), 189-219.

Rao, M.J. (1989). Agricultural Supply Response: A Survey. Agricultural Economics, 3 (1989) 1-22

Rao, N.C. (2004). “Aggregate agricultural supply response in Andhra Pradesh”, Indian Journal of Agricultural Economics, 59(1): 91-104.

Rao, B.B. (2007). Estimating short and long-run relationships: a guide for the applied economist. Applied Economics, 39(13), 1613-1625.

Rasmussen S., Production Economics. (2013). The Basic theory of Production Optimisation. Springer, Berlin.

Rezitis, A. N., and Stavropoulos, K. S. (2009). Modeling pork supply response and price volatility: the case of Greece. Journal of Agricultural and Applied Economics, 41(1): 1-18.

Sadoulet, E. and de Janvry, A. (1995) “Quantitative Development Policy Analysis”. The Johns Hopkins University Press.

Seale Jr, J. L., and Shonkwiler, J. S. (1987). Rationality, price risk, and response. Southern Journal of Agricultural Economics, 19(1378-2016-111223): 111-118.

Schiff, M. and Montenegro, C. (1997), Aggregate agricultural supply response in developing countries', Economic Development and Cultural Change 45 (2): 393-410.

Schimmelpfennig, D., Thirtle C. and Van Zyl, I. (1996). “Crop level supply response in South African agriculture: An error-correction approach”, Agrekon, 35(3): 111-22.

Sehrawat. S. (2015). Impact of Futures Contract on Agricultural Commodity Prices: An Indian Perspective. International Journal of Development Research, 5(3): 3740-3744.

Shahzad, M., Jan, A.U., Ali, S.S and Ullah, R. (2018). Supply response analysis of tobacco growers in Khyber Pakhtunkwa: An ARDL approach. Journal of field crops research, 218: 195 – 200.

Shrestha, M.B, and Bhatta, G.R. (2017). Selecting appropriate methodological framework for time series data analysis. The Journal of Finance and Data Science, (4): 72-89.

Singh, O. P. (1998). Growth and supply response of oilseeds in Uttar Pradesh. Agricultural Situation in India, 55(1), 3-8.

Shoko. R.R, Chaminuka. P and Belete. A. (2016) Estimating the Supply Response of Maize in South Africa: A Nerlovian Partial Adjustment Model Approach, Agrekon, 55(3): 237-253, DOI: 10.1080/03031853.2016.1203802.

Solomou, S., & Wu, W. (1999). Weather effects on European agricultural output, 1850–1913. European Review of Economic History, 3(3): 351-373.

Stats SA S.A. (2017) Statistics South Africa Mid-year population estimates pdf. Available at http://www.statssa.gov.za/publications/P0302/P03022017.pdf.(accessed 21 Feb 2018).

Stats SA (2019). Gross domestic product. Statistical release. 2019.

Steinfeld, H., Gerber, P., Wassenaar, T., Castel, V., Rosales, M., and de Haan, C. (2006). Livestock's long shadow, FAO, Rome: 7 – 10.

Suriagandhi. V. (2011). A Micro Level Study: Supply Responsiveness of Banana and Demand Inputs – Profit Function Approach – Vadipatti Block, Madurai District. Indian Journal of Agricultural Economics. 66(4): 676 – 686.

Tanko, M., & Alidu, A. F. (2016). Supply response of domestic rice and price risk in northern ghana. American International Journal of Social Science, 5(4): 107-115.

Tenaye, A. (2020). New Evidence Using a Dynamic Panel Data Approach: Cereal Supply Response in Smallholder Agriculture in Ethiopia. Economies, 8(3): 61.

Thiele, R. (2000). "Estimating the Aggregate agricultural supply response: A survey of techniques and results for developing countries", Working Paper 1016. Kiel Germany: Kiel Institute for World Economics.

Thiele, R. (2002). Price Incentives, Non-Price Factors, and Agricultural Production in Sub-Saharan Africa: A Cointegration Analysis, Kiel Institute for World Economics, Kiel, Working Paper 2002.

Townsend, R., Thirtle, C. and Revell, B.J. (1997). Dynamic acreage response: An error correction model for maize and tobacco in Zimbabwe. International Association of Agricultural Economists, Occasional Paper, 7: 198-209.

Traill, B. (1978). Risk variables in econometric supply response models. Journal of Agricultural Economics, 29(1): 53-62.

Triphati A. (2008). Estimated Agricultural supply response by co-intergration approach.pdf. Report submitted under visiting research scholar programme available at http://works, bepress.com.

Waldner, F., Hansen, C.M., Potapov, V.P., Löw, F., Newby, T., Ferreira, S. and Defourny, P. (2017). National-scale cropland mapping based on spectral-temporal features and outdated land cover information. PLOS ONE.12. e0181911. 10.1371/journal.pone.0181911.

Wall, C.A. and Fisher, B.S. (1987), Modelling a Multiple Output Production System: Supply Response in the Australian Sheep Industry, Research Report No. 11, Department of Agriculture Economics, University of Sydney, Sydney

Weersink, A., Cabas, J. H., & Olale, E. (2010). Acreage response to weather, yield, and price. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 58(1): 57-72.

Yu, B., Liu, F., and You, L. (2012). Dynamic agricultural supply response under economic transformation: a case study of Henan, China. American Journal of Agricultural Economics, 94(2): 370-376.

Ullah, R., Shivakoti, G. P., Zulfiqar, F., and Kamran, M. A. (2016). Farm risks and uncertainties: Sources, impacts and management. Outlook on Agriculture, 45(3): 199-205.

APPENDIX A

Appendix A: List and Definition of variables

Definition of the variables	
Symbol	**Description**
SUPPLY QUANTITIES	
MA	Acreage of maize measured in Hectares (Ha)
WA	Acreage of wheat measured in Hectares (Ha)
SA	Acreage of sorghum measured in Hectares (Ha)
BA	Acreage of Barley measured in Hectares (Ha)
MPD	Maize production volumes measured in tonnes
WPD	Wheat production volumes measured in tonnes
SPD	Sorghum production volumes measured in tonnes
BPD	Barley production volumes measured in tonnes
PRICE VARIABLES	
MP	Real price of maize measured in Rands
SNP	Real price of sunflower in Rands
WP	Real price of wheat measured in Rands
SP	Real price of sorghum measured in Rands
BP	Real price of barley measured in Rands
RPBW	Ratio of barley prices to the prices of wheat (P^i/P^i)
SYP	Real price of soya beans measured in Rands
RISK VARIABLES	
MPR	Price risk variable for maize
WPR	Price risk variable for wheat
BPR	Price risk variable for barley
SPR	Price risk variable for sorghum
TECHNOLOGY VARIABLES	
PC	Production costs variable measured by indices of intermediate cost of fuel.
FC	Fertiliser consumption
WEATHER VARIABLE	
RF	Weather variable measured by average rainfall (mm)
WRF	Weather variable for wheat model measured by mean rainfall (mm)
BRF	Weather variable for barley model measure by mean rainfall (mm)
POLICY VARIABLE	
DM	Dummy variable for policy changes

**All nominal prices were converted to real prices by the producer price index (PPI)

** Price, and price index data were obtained from the Abstract of Agricultural statistics which is maintained by DAFF

APPENDIX B

Appendix B: Research objectives and Methods Used

Objective		Methodology
i.	Estimate the supply response of the selected grain crops to changes in the price and non-price factors.	ARDL Model
ii.	Determine the short and long run price elasticities for the selected grain crops in South Africa.	ARDL Model
iii.	Determine the level of price risk among the selected grain crops in South Africa.	• Box Jenkins • ARCH LM test • Standard deviation of log returns
iv.	Estimate the effect of price risk on the output for the selected grain crops in South Africa.	ARDL Model

APPENDIX C

Appendix C: Time series of nominal prices for maize, sorghum, barley, wheat, soybeans and sunflower (1970 to 2018)

Years	MP	SP	WP	BP	RPWB	SYP	SNP	PPI
1970	34.78	56.202	67.250	28.880	0.429	20.998	75.210	1.632
1971	37.02	35.410	68.170	28.880	0.424	40.970	74.310	1.734
1972	37.68	34.930	71.310	61.400	0.861	60.345	78.610	1.835
1973	37.92	32.670	73.580	64.340	0.874	70.000	87.570	2.059
1974	39.00	59.460	88.090	74.340	0.844	128.478	96.750	2.448
1975	43.50	60.840	101.210	88.340	0.873	132.000	111.490	2.848
1976	47.00	63.210	107.800	100.080	0.928	137.000	143.600	3.227
1977	50.00	71.820	121.350	104.890	0.864	160.800	170.250	3.653
1978	59.00	80.500	121.350	104.890	0.864	181.730	178.780	4.033
1979	71.50	76.390	136.350	115.580	0.848	195.970	179.520	4.581
1980	83.10	83.730	185.210	120.540	0.651	227.070	218.510	5.275
1981	102.15	91.190	215.200	176.970	0.822	251.060	253.020	5.993
1982	118.25	94.970	241.400	209.020	0.866	294.130	265.470	6.836
1983	134.05	135.270	295.000	246.500	0.836	303.450	289.340	7.540
1984	167.55	191.330	275.000	246.500	0.896	340.100	306.200	8.170
1985	218.55	197.360	299.000	268.000	0.896	360.000	329.000	9.426
1986	218.60	180.520	325.000	240.000	0.738	404.310	417.640	11.197
1987	240.35	189.490	376.800	295.000	0.783	408.000	460.840	12.866
1988	318.00	192.400	405.000	323.500	0.799	524.550	564.500	14.674
1989	288.00	205.210	353.750	318.000	0.899	528.340	580.810	17.173
1990	268.00	205.470	458.250	350.000	0.764	589.870	683.910	19.232
1991	302.67	231.830	521.430	457.390	0.877	614.340	739.290	21.436
1992	357.62	295.000	653.320	520.180	0.796	723.280	736.400	22.973
1993	452.81	475.000	748.240	586.120	0.783	863.000	835.100	24.873
1994	417.00	466.370	801.480	671.290	0.838	843.000	845.000	27.118
1995	387.02	357.000	770.500	671.790	0.872	859.000	898.000	29.826
1996	598.62	482.000	846.780	720.110	0.850	930.000	980.000	32.203
1997	593.14	475.000	966.020	790.870	0.819	1200.000	870.000	34.526
1998	580.00	520.000	817.750	800.000	0.978	1391.460	1003.740	35.853
1999	593.00	550.000	808.190	750.000	0.928	1095.510	1364.170	37.739
2000	671.25	730.000	960.600	758.240	0.789	1202.650	1257.800	40.617
2001	535.10	520.000	1165.350	800.000	0.686	1285.540	915.700	43.515
2002	937.61	760.000	1421.610	1000.000	0.703	1242.540	1292.780	49.319
2003	1361.32	1500.000	1572.050	1200.000	0.763	2010.950	2238.040	51.564
2004	947.69	1450.000	1428.140	1433.000	1.003	2487.160	1977.720	52.613
2005	822.28	900.000	1091.430	1342.300	1.230	2134.740	1826.880	54.547
2006	659.66	450.000	1033.990	1142.800	1.105	1274.470	1579.780	58.027
2007	996.40	1191.410	1524.190	1576.420	1.034	1467.440	1866.650	63.695
2008	1513.18	1483.430	2505.580	1381.400	0.551	2343.310	2547.480	73.382
2009	1606.66	1774.430	2307.460	2300.310	0.997	4026.260	4271.880	73.917

Years	MP	SP	WP	BP	RPWB	SYP	SNP	PPI
2010	1440.96	1494.650	1607.670	2125.900	1.322	3187.390	2854.580	75.302
2011	1097.91	1383.500	2303.680	2006.340	0.871	2527.960	2953.460	79.585
2012	1691.66	1671.610	2369.080	2277.230	0.961	3176.390	3735.570	84.777
2013	2200.12	2675.010	2914.550	2498.990	0.857	3684.460	4396.900	89.860
2014	2026.56	2691.620	2880.310	2519.070	0.875	4691.650	4844.000	96.514
2015	2122.15	2626.780	3052.850	2644.290	0.866	5549.810	4435.470	100.000
2016	2502.41	2380.900	3772.440	3098.030	0.821	4731.870	4552.420	107.082
2017	2518.58	3434.390	3704.640	3352.150	0.905	6197.360	6064.020	112.303
2018	3649.03	2638.270	3689.870	2823.990	0.765	4844.020	4370.970	118.427

Source: (1) Abstract of Agricultural Statistics, (DAFF, 2019
(2) South African Grain Information services (SAGIS)

APPENDIX D

Appendix D: Time series of price risk variables for maize, sorghum, wheat and barley (1970 to 2018)

Years	MPR	SPR	WPR	BPR
1970	0.03127	0.10233	0.03408	0.04353
1971	0.02447	0.16650	0.03478	0.03140
1972	0.02630	0.29805	0.03502	0.02092
1973	0.02295	0.29581	0.02668	0.33428
1974	0.02166	0.29146	0.03222	0.32841
1975	0.01561	0.40723	0.08298	0.31448
1976	0.05375	0.38673	0.08833	0.29498
1977	0.05382	0.27313	0.06943	0.26534
1978	0.04662	0.26074	0.05591	0.07465
1979	0.04267	0.25272	0.13628	0.14535
1980	0.04173	0.12444	0.11830	0.13684
1981	0.00952	0.12039	0.14384	0.11218
1982	0.09077	0.13726	0.14286	0.16658
1983	0.09291	0.12271	0.14515	0.16586
1984	0.11401	0.15252	0.11472	0.13318
1985	0.11479	0.10425	0.14027	0.13770
1986	0.15927	0.09518	0.11206	0.12354
1987	0.14631	0.12649	0.11470	0.14130
1988	0.14587	0.11293	0.11211	0.15395
1989	0.15840	0.09537	0.09426	0.15539
1990	0.17949	0.08059	0.14256	0.16517
1991	0.17994	0.08994	0.14672	0.16776
1992	0.17899	0.07157	0.14657	0.13001
1993	0.17884	0.07302	0.15072	0.12169
1994	0.20362	0.27508	0.13724	0.09395
1995	0.19788	0.27463	0.05156	0.08996
1996	0.29165	0.44559	0.07575	0.07064
1997	0.36165	0.46468	0.07262	0.07443
1998	0.35676	0.46422	0.10938	0.09811
1999	0.32488	0.37719	0.13598	0.09836
2000	0.33090	0.37289	0.14743	0.13780
2001	0.22758	0.21677	0.17303	0.13798
2002	0.28697	0.38491	0.17249	0.15280
2003	0.29569	0.38405	0.13789	0.12105
2004	0.38336	0.54240	0.12132	0.14382
2005	0.38064	0.53124	0.07371	0.16561
2006	0.41523	0.50662	0.04144	0.16570
2007	0.46773	0.69564	0.10627	0.22973
2008	0.46739	0.73747	0.10105	0.24515
2009	0.43981	0.63915	0.11852	0.33281

Years	MPR	SPR	WPR	BPR
2010	0.43928	0.65196	0.20097	0.55521
2011	0.38735	0.64946	0.27336	0.55203
2012	0.39622	0.38236	0.26353	0.54967
2013	0.40226	0.30121	0.25973	0.55139
2014	0.39419	0.38418	0.25756	0.47638
2015	0.38301	0.35671	0.19667	0.16323
2016	0.37409	0.36028	0.07015	0.16505
2017	0.21786	0.36444	0.05153	0.10177
2018	0.34888	0.57768	0.05037	0.09913

APPENDIX E

Appendix E: Time series of production output for maize, sorghum, wheat and barley (1970 to 2018)

Years	MPD	MA	SPD	SA	WPD	WA	BPD	BA
1970	6278000	4497631	379000	328000	1 316 000	1 850 000	58000	20000
1971	8970000	4957458	551000	380000	1 396 000	1 930 000	44000	33000
1972	9863000	5112941	510000	322000	1 670 000	2 010 000	46000	32000
1973	4360000	4124523	222000	214000	1 746 000	2 017 000	51000	33000
1974	11464000	4961015	682000	336000	1 871 000	2 025 000	61000	32000
1975	9396000	4909768	405000	254000	1 596 000	1 865 000	67000	63000
1976	7820000	5172370	310000	213000	1 792 000	1 839 000	74000	69000
1977	9985000	5010876	419000	283000	2 248 000	1 944 000	88000	73000
1978	10306000	4959698	620000	284000	1 879 000	1 792 000	90000	106000
1979	8583000	4896010	390000	250000	1 692 000	1 880 000	98000	135000
1980	11061000	4915344	711000	264000	2 087 000	1 903 000	107000	141000
1981	15030000	4933540	553000	219000	1 472 000	1 627 000	68000	60000
1982	8820000	4865303	302000	215000	2 356 000	1 812 000	69000	106000
1983	4384000	4623062	221000	247000	2 444 000	2 013 000	64000	110000
1984	4843000	4495686	498000	323000	1 784 000	1 819 000	79000	154000
1985	8382000	4420625	628000	254000	2 346 000	1 942 000	87000	173000
1986	8567000	4599179	487000	388000	1 693 000	1 983 000	101000	256000
1987	7872000	4695848	677000	401000	2 333 000	1 946 000	91000	199000
1988	7646000	4239797	651000	326000	3 154 000	1 749 000	100000	280000
1989	12445000	4327368	511000	228000	3 620 000	2 009 000	80000	126000
1990	9134000	3983908	341000	196000	2 010 000	1 843 000	97000	291000
1991	8573000	3647272	302000	166000	1 709 000	1 563 000	110000	262000
1992	3244000	3965711	118000	191000	2 142 000	1 436 000	135000	170000
1993	9963000	4164736	515000	239000	1 324 000	750 000	138000	265000
1994	13245000	4442233	520000	227000	1 984 000	1 075 000	116000	230000
1995	4836000	3357264	291000	180000	1 840 000	1 048 000	120000	275000
1996	10138000	3761000	536000	174000	1 977 000	1 363 000	125000	300000
1997	10106008	4023065	361000	161000	2 712 000	1 294 000	127000	176000
1998	7664690	3559750	264600	131277	2 805 000	1 382 000	132000	290000
1999	7915615	3566683	155950	98900	1 687 500	745 000	112000	215100
2000	11422661	4012843	352450	142200	1 770 000	718 000	101700	90800
2001	7744964	3189215	175580	88300	2 348 550	934 000	77700	142350
2002	10048964	3533459	197525	75250	2 450 000	973 500	79190	156800
2003	9677504	3650904	219539	95497	2 427 000	941 100	73440	178900
2004	9710070	3204110	373000	130000	1 540 000	748 000	84220	240000
2005	11715948	3223440	260000	86500	1 680 000	830 000	82650	189365
2006	6935056	2032446	96000	37150	1 905 000	805 000	90000	225000
2007	7338738	2897066	176000	69000	2 105 000	764 800	89780	236000
2008	13164069	3296980	255000	86800	1 905 000	632 000	73360	222500
2009	12566633	2896683	276500	85500	2 130 000	748 000	68245	192000

Years	MPD	MA	SPD	SA	WPD	WA	BPD	BA
2010	13420864	3263340	196500	86675	1 958 000	642 500	74760	216000
2011	10924335	2858760	155000	69200	1 430 000	558 100	82670	194000
2012	12759119	3141114	141050	48550	1 905 280	604 700	80150	300910
2013	12485689	3238100	147200	62620	1 870 000	515 200	84940	298000
2014	14982050	3096000	265000	78850	1 870 000	505 500	81320	267500
2015	10628800	3048050	120500	70500	1 750 000	476 570	85125	302000
2016	8214240	2212880	70500	48500	1 440 000	482 150	93730	332000
2017	17551000	2995250	152000	42350	1 909 540	508 365	88695	354065
2018	13103975	2633685	115000	28800	1 535 000	491 600	91380	307000

Source: (1) Abstract of Agricultural Statistics, (DAFF, 2019

(2) South African Grain Information services (SAGIS)

APPENDIX F

Appendix F: Time series for production costs, fertiliser consumption, summer rainfall and winter rainfall variables (RF, WRF and BRF) and dummy variable (1970 to 2018)

Years	PC	FC	RF	WRF	BRF	Dm
1970	1.600	180685	47.288	37.266	51.931	0
1971	1.700	208527	85.047	38.525	56.450	0
1972	1.800	230464	105.352	27.642	47.083	0
1973	2.300	230104	68.398	33.792	43.333	0
1974	2.400	249716	108.371	46.233	71.250	0
1975	2.600	291875	103.917	40.417	60.883	0
1976	2.900	299660	120.718	43.583	63.867	0
1977	3.100	337619	92.767	53.933	89.683	0
1978	3.500	371730	100.176	34.492	45.150	0
1979	3.600	388498	61.608	43.083	53.617	0
1980	3.700	470124	83.473	32.992	50.100	0
1981	4.000	517269	97.310	47.383	72.633	0
1982	4.400	462731	67.502	41.125	58.517	0
1983	5.000	335927	59.316	46.317	75.867	0
1984	5.400	385767	83.681	38.408	58.800	0
1985	7.200	381996	76.529	34.000	62.850	0
1986	8.400	374279	77.363	45.817	70.200	0
1987	8.300	325200	80.683	58.950	76.233	0
1988	10.300	364298	102.160	43.875	59.000	0
1989	12.300	371909	96.864	40.692	64.817	0
1990	13.200	343689	87.930	43.242	67.067	0
1991	14.500	365035	89.810	37.551	65.307	0
1992	14.500	347525	53.648	37.299	65.265	0
1993	15.600	408459	77.110	46.224	81.796	0
1994	17.400	375066	91.595	34.530	61.518	0
1995	20.500	371491	67.004	34.389	56.590	0
1996	22.300	415084	121.651	44.207	61.804	0
1997	24.800	406914	96.616	45.170	56.299	0
1998	24.700	415521	78.602	30.079	54.113	1
1999	25.300	413045	86.367	26.108	43.272	1
2000	30.600	415933	105.308	32.508	42.758	1
2001	38.000	395813	79.115	52.463	71.758	1
2002	45.800	477072	89.507	49.902	68.396	1
2003	44.500	420827	63.394	27.039	45.591	1
2004	44.300	427571	80.482	31.535	48.974	1
2005	47.500	347260	78.993	37.243	60.132	1
2006	48.500	428719	104.902	51.078	78.196	1
2007	64.400	439480	57.848	43.526	68.188	1
2008	76.100	424123	90.733	40.813	67.038	1
2009	85.400	453777	83.705	36.444	57.541	1

Years	PC	FC	RF	WRF	BRF	Dm
2010	100.000	395000	97.204	26.377	42.199	1
2011	108.900	419000	104.877	44.300	57.160	1
2012	115.400	430000	62.285	40.452	64.601	1
2013	121.500	416500	78.600	37.168	65.153	1
2014	124.600	437325	90.520	30.701	54.388	1
2015	127.500	393593	68.562	39.217	60.324	1
2016	131.400	413272	83.679	38.238	61.356	1
2017	136.700	421538	80.920	37.724	60.497	1
2018	138.400	429968	77.721	36.736	58.210	1

Source: (1) Abstract of Agricultural Statistics, (DAFF, 2019
(2) South African Grain Information services (SAGIS)
(3) South African Weather services (SAWS)
(4) Fertiliser Association of Southern Africa