MEASURING ASYMMETRIC PRICE AND VOLATILITY SPILLOVER IN THE SOUTH AFRICAN POULTRY MARKET

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DECLARATION

I, David Ifeanyi Uchezuba hereby declare that this thesis work submitted for the degree of Philosophiae Doctor in the Faculty of Natural and Agricultural Sciences, Department of Agricultural Economics at the University of the Free State, is my own independent work, conducted under the supervision of Prof. A Jooste.

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ABSTRACT

Over the last decade South Africa experienced two events during which food prices increased significantly. The periods of high food prices were also characterised by a high degree of volatility in prices. The result of the aforementioned events were that food security in South Africa was threatened, but at the same time evidence emerged that due to the current market structure in the agricultural industry certain role players used their market power to manipulate food prices. In an effort to better understand pricing behaviour in the food industry it is necessary to investigate the nature of price transmission in different agro-food chains. It is furthermore important to understand the nature of price volatility and the degree to which such volatility spillover from one level of a value chain to the next.

The primary objective of this study is to measure asymmetric price and volatility spillover in the broiler value chain. The poultry (broiler) industry was chosen as a case study because there is an increasing demand for broiler meat in South Africa, culminating in increased per capita consumption compared to other meat categories such as the red meats. It is estimated that the per capita consumption of broiler meat increased steadily from 2001 to 2009. The sector is one of largest and fastest growing agricultural sectors in the country, contributing significantly to the total gross production value of agriculture. The specific issues addressed in measuring asymmetric price and volatility spillover in the broiler value chain includes: (i) the identification of the direction of flow of information (causality) between producers and retailers, (ii) examining the degree of asymmetric price transmission across the farm-retail value chain, (iii) quantifying volatility and volatility spillover across farm and retail prices, and (iv) investigating volatility spillover from feed materials to farm and retail market prices.

The data used for this study include farm and retail poultry prices, as well as the daily near-market monthly spot prices for yellow maize, sunflower seed and soybeans. Two types of adjustment models, namely the threshold autoregressive (TAR) and momentum threshold autoregressive (M-TAR) models were used to investigate asymmetry in farm-retail market prices, whereas the exponential generalised autoregressive conditional heteroskedasticity (EGARCH) model was used to measure the price volatility and the volatility spillover effect between retail and farm prices and between these prices and poultry feed ingredients (yellow maize, soybean and sunflower oilseed).

The result obtained with the M-TAR model shows that the relationship between farm and retail prices is asymmetric. The retail price was found to respond asymmetrically to both positive and negative shocks arising from changes in producer prices, but the response is greater when the shocks are negative, i.e. when the producer price rises to lower marketing margins in the value chain. The sizes of the adjustment parameters in the farm-retail combination reveal that retail prices do not respond to shocks completely and instantaneously, but respond within a distributed time lag. The results indicate that within one month, the retail prices adjust so as to eliminate approximate 2.8 % of a unit-negative change in the deviation from the equilibrium relationship caused by changes in producer prices. This implies that the retailers must increase their marketing margin by 2.8% in order to respond completely to a unit-negative change in farm prices. The results show that farm price granger cause retail price, implying that retailers depend on what happens at the farm level in order to form their market expectations.

The results obtained with the M-TAR error correction model were to a great extent consistent with the results obtained with the EGARCH model. For instance, results from the volatility model show that the magnitude of volatility in the retail and farm prices for the periods 2000M1 to 2008M8 is 1.8% and 2.8%, respectively. The volatility in the farm price was found to approximate the volatility implied by the adjustment shocks in the farm-retail price relationship investigated with the M-TAR error correction model. The results of the asymmetric volatility measurement show that there is significant asymmetric volatility spillover from the farm to the retail market implying that the response to rising prices differs from the response to a price decline. This relationship was also observed with the asymmetric price transmission model. An investigation into the impact of the prices of the major broiler feed materials, namely yellow maize, sunflower and soybean, shows that there is a volatility spillover from the yellow maize price to farm and retail prices. This implies that any change in the price of yellow maize will have a significant impact on the retail and farm prices. Market influence also flows from the sunflower oilcake price to the retail market price.

The presence of an asymmetric relationship between farm and retail prices signifies the existence of concentration and market power. In a situation like this, tighter anti-competition laws will discourage anti-competitive behaviours. It will be worthwhile to increase access to agricultural information systems amongst the role players in order to reduce information bottlenecks in the vertical market system.

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LIST OF ACRONYMS

ADF	Augmented Dickey-Fuller
AFMA	Animal Feed Manufacturing Association
AGARCH	Absolute generalized autoregressive conditional heteroskedasticity
AIC	Akaike's information criterion
APT	Asymmetric price transmission
AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARIMA	Autoregressive integrated moving average
BIC	Schwarz' Bayesian information criterion
CAPM	Conditional capital asset pricing model
CBOT	Chicago Board of Trade
CIA	Cumulative impact asymmetry
CONIA	Contemporary impact asymmetry
CPI	Consumer price index
DAFF	Department of Agriculture, Forestry and Fishery
DF	Dickey-Fuller
DGP	Data generating process
DLEA	Distributed lag effect asymmetry
DMAZ	Domestic yellow maize
DSUNF	Domestic sunflower
DSOYB	Domestic soybean
EAPA	Equilibrium adjustment path asymmetry
ECT	Error correction term
EGARCH	Exponential generalized autoregressive conditional heteroskedasticity
FIFO	First-in-first-out

FP	Farm price
FPMC	Food Price Monitoring Committee
GARCH	Generalized autoregressive conditional heteroskedasticity
GED	Generalised error distribution
IGARCH	Integrated generalized autoregressive conditional heteroskedasticity
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LIFO	Last-in-first-out
LM	Lagrange multiplier
LSM	Living standard measure
MAR	Missing at random
MCAR	Missing completely at random
MEAPA	Momentum equilibrium path adjustment asymmetry
MNAR	Missing not at random
M-TAR	Momentum threshold autoregression
NAMC	National agricultural marketing council
NDA	National Department of Agricuture
OLS	Ordinary least square
OECD	Organization for Economic Co-operation and Development
PACF	Partial autocorrelation function
PSE	Producer support estimate
REA	Regime effect asymmetry
REAPA	Regime equilibrium adjustment path asymmetry
RP	Retail price
RSS	Residual sum of squares
RTA	Reaction time asymmetry
SAFEX	South African futures exchange
SAPA	South African Poultry Association

SMME	Small, medium and micro enterprises
TAR	Threshold autoregression
TVEC	Threshold vector error correction
VAR	Vector autoregression

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Experience has shown that market price volatility, especially the unforeseen price variations in response to adverse and spontaneous exogenous or endogenous shocks has important consequences for the welfare of consumers and producers of agricultural products (Gardner & Gardner, 1977). At the producer level it creates uncertainty and volatility in profit margins and reduces the incentive to invest. At the consumer level, it translates to large price fluctuations that reduce their purchasing power (Gardner & Gardner, 1977). In most cases, the government becomes concerned about the effect on fiscal policy.

In a volatile commodity price regime, there are periods of high volatility and periods of tranquillity (Enders, 2004). This means that the volatility in commodity prices can change over a certain period of time. It will be prudent to determine whether there is a need to suspect that the South African agricultural commodity market has become more volatile over the last decade. It should, however, be noted in this regard that price changes in the last decade are a major cause for concern, because during the latter part of the year 2001 and early 2002, food prices rose to a record high. The inflation rate escalated and impacted on food security and the stability of the economy. The food price inflationary trend became less volatile between 2003 and 2005, but increased again to about 13 % in December 2007, contributing 3.4 % or 2.4 percentage points to the consumer price index (CPI) of 7.2 % in 2007 (NAMC, 2007). This price change generated concern as to the cause of the crises in food prices. Evidence from financial studies has shown that arbitrage from stock prices across markets resulted in volatility transmission from one market to another (Reyes, 2001; Tse, 1999). This phenomenon is referred to as volatility spillover between markets. Likewise, in agricultural commodity markets, arbitrage of physical commodity between one market channel and another may lead to volatility transmission as well. The question arises as to whether there is enough evidence to suggest that there have been volatility spill overs from one commodity market channel – say farm to retail level or vice versa – in South Africa. The answer to this question has policy implications. It is possible for government to intervene with policy if volatility is transmitted (spills over) from one market channel to another by effecting changes in the input side of a market, which primarily is the source of most price volatility in agricultural markets. This study investigates the transmission of volatility (volatility spillover) within the South African vertical poultry (broiler) supply chain.

Poultry was chosen for this study firstly because there is an increasing demand for poultry meat in South Africa, culminating in increased per capita consumption compared to other meat categories such as red meat (beef, lamb and pork). It is estimated that the per capita consumption of broiler increased by approximately 34 %, from 16.7 kg per person per annum to 22.41 kg, during the period 1994-2005 (NDA, NAMC & Commark Trust, 2007). Estimates from South African Poultry Association (SAPA) shows that this figure increased to 30.71 kg in November 2009. Secondly, the sector is one of largest and fastest growing agricultural sectors in the country. It contributes significantly to the total gross production value of agriculture. The estimated producer value during 2006/7 was R15.22 billion (DAFF, 2010). This represents a 12.88% increase from the 2005/6 production year. The poultry industry made the largest contribution to the gross value of agricultural production in 2007/8 and 2008/9, contributing 14.55 % and 17.18%, respectively. Apart from its role in the domestic market, the poultry industry plays a role in world broiler meat production. In 2007 its share in world poultry production amounted to 1.3 % (SAPA, 2008). Thirdly, it is easier and cheaper to establish a poultry project at a small scale compared to other livestock enterprises. This is because; a small backyard plot of land can support a poultry project that can make a significant contribution to the rural economy whereas other livestock enterprises require larger operating spaces. Hence poultry enterprise can be used as a quick outreach for food security intervention programmes in many countries of the world.

An important aspect in the transmission of volatility is the possibility of unequal (asymmetric) price transmission from one market channel to another, e.g. from upstream (producer) to downstream (retailers) or vice versa. Economic theory suggests that farm product prices depend on the current and expected levels of factors that affect the demand and supply of farm produce. On the other hand, in a competitive market, consumer demand is found to influence retail price at a given market supply. In other words, the farm-retail price spread will reflect the volatility inherent in the realisations of the prices of the two market channels. Given the vertical linkages and transmission of prices between the market channels, it will be reasonable to hypothesise that volatility would be transmitted between them (Haigh & Bryant, 2001). This hypothesis strongly depends on the price relationship between the two market channels. It is commonly perceived that the price relationship between vertical markets in a non-competitive market is asymmetric. As a result, there is concern that upstream markets pass on their cost increases to downstream market channels and to consumers more rapidly than they adjust prices during cost decreases. This asymmetric nature of price movement results in a longer time of adjustment by retailers to upstream market cost decreases, and therefore the response to price increases differs from the response to price decreases (Bakucs & Ferto, 2006; Ward, 1982). Therefore a secondary aspect of this study is to examine asymmetry in the volatility transmission between the markets. This implies examining whether the perception about price transmission at the farm-retail level is correct – that is, whether the upstream market channel of agricultural commodities has the power to asymmetrically influence prices at the retail level.

Knowledge of asymmetric price transmission between market channels is essential, because analysing the degree of asymmetry will give an indication of how markets are linked. It will aid in the process of measuring the flow of information by determining how price expectations are formed – an indication of causality. Causality implies that market channels, i.e. from the producer to the retailer, use information from one another when forming their price expectation. Also important issue is the direction of causality, which indicates whether the flow of information is uni- or bi-directional.

Concerns about the possible cause of this skewed asymmetric relationship in the price transmission mechanism of basic food commodities such as meat have received much attention in recent times. Asymmetry is caused by many factors, prominent amongst which is the adjustment cost considerations of firms. Due to adjustment cost considerations, retailers react more rapidly to price changes that squeeze their profit margin than to price changes that stretch the margin, and this may result in income redistribution and net welfare losses for the consumer (Meyer & Von Cramon-Taubadel, 2004).

The manner in which consumers are affected by this type of asymmetric pricing relationship depends on (a) the speed of adjustment to economic shocks, (b) the sign of the shock (positive or negative), and (c) the magnitude of the shock. The measurement of these factors is fundamental in understanding the nature of price volatility in the poultry industry. Therefore, with these factors in mind, this study analyses the magnitude and speed of adjustment within one market channel when facing economic shocks at a different market level within the same market supply chain. It is the explicit recognition of the impact of this asymmetric relationship and the fact that price volatility creates a certain level of risk and uncertainty in the commodity market that motivates this study.

1.2 PROBLEM STATEMENT

It should be noted that volatility in the price level of one agricultural commodity may influence the evolution of the prices of complementary products. For example, maize and oilseed price volatility has been observed to have spillover effects on several food prices in the food value chain, whereby increases in the price of maize and/or oilseed trigger price increases in other commodities. This relationship has also been found to exist between the input markets (feed) and the output markets (wholesale catfish) in the United States of America (Buguk, Hudson and Hanson, 2003). Similarly, a significant volatility feedback transmission among four meat categories namely, lamb, beef, pork and poultry have been found in the meat market in Greece (Rezitis, 2003). In light of this, it is expected in this study that volatile price changes in one poultry meat market level may spillover and trigger changes and volatility in others. The effect of such spillover is that price uncertainty on one level may influence price uncertainty in another market segment. Therefore it is necessary to determine (a) whether there is volatility in the farm-retail price relationship, and (b) the degree by which price uncertainty in one market influences another market. The volatility spillover effects have not as yet been investigated in any meat supply chain in South Africa. Given the importance of this food chain as explained earlier this study will provide valuable insight and an understanding of the forces that affect price in the poultry value chain.

It is estimated that poultry feed accounts for over 60 % of the total input cost in the broiler industry (FPMC, 2003:289). A major factor that influences feed cost is the cost of the individual items used in the poultry feed formulation, namely yellow maize, sunflower oilcake, and soybean oilcake. The inclusion rate of maize in the total production of feed rations is above 50 %, while oilcake makes up 20-35 % of the volume (FPMC, 2003:289). Since maize and oilseeds make up more than 70 % of the animal feed composition, intuitively, changes in the prices of these commodities should affect the price of animal feeds. It is therefore pertinent to investigate in this study whether there is a volatility spillover from these feed components to the poultry (broiler) farm and retail market channel.

After the food price crisis in 2002 there was a levelling off in prices in the latter part of 2002 and in 2003, with decreases in the prices of some commodities like meat products. The prices of these products, however, recently hit a record high. The Food Price Monitoring Committee report (FPMC, 2003:335) showed that exchange rate volatility influences the price volatility of the South African food basket including poultry meat prices. According to the report, poultry meat prices might be volatile, but it is not known whether the current level of volatility in this sector is persistent or time invariant. Due to the fact that volatility is a measure of risk and uncertainty, it is important to measure the level of volatility in order to measure the risk and uncertainty associated with changes in the prices of poultry meat. This is important for informed policy decisions and for the fact that price volatility affects the overall variability in the farmer's profit margin. It is therefore essential to quantify price volatility in the poultry meat sector to understand the price formation process.

To further understand the evolution of the price process, it is important to understand the price transmission mechanism by determining whether the price changes in the poultry meat market channels are asymmetric. If price changes are symmetric, prices are transmitted at the same rate. This implies that a shock to producer prices of a given magnitude would elicit the same response in retail prices regardless of whether the shocks reflected a price increase or a price decrease. Alternatively, if price transmission is asymmetric, the nature of price movements from upstream (producer) to downstream (retail) markets differs in terms of size and timing. In markets with highly asymmetric relationships, welfare distribution is skewed – thus efficiency is compromised (Meyer & Von Cramon-Taubadel, 2004). In this study, efficiency in the price transmission mechanism is measured by investigating the type of interrelationship between farm-retail prices in the poultry meat sector.

The approach used to measure price-dynamic interrelationships in the literature is extensive. Recently, emphasis has been put on lack of consistency in the various empirical tests (Boetel & Liu, 2008; Meyer & Von Cramon-Taubadel, 2004). The reason is that some important statistical protocols and analytical procedures are ignored, for example (a) the possibility of a structural shift in estimating interrelationships between economic variables, (b) the assumption of continuous adjustment to shocks, and (c) the bias in the assumptions of constant variance in volatile market prices.

Many studies of asymmetric price relationships simply test for the presence or absence of asymmetric price relationships without accounting for the possibility of a structural shift in the trend function of the data-generating process. For instance, the FPMC (2003:336) report investigating price adjustment processes in the meat sector used a procedure that is not capable of detecting the true price behaviour if there is a structural break in the underlying price process. This is because the test ignored the parameter stability test, which is crucial in empirical statistical inference. This study addresses these problems by incorporating structural change analysis into the unit root protocol. The assumption of structural change with an unknown change point is investigated while considering the possibility of multiple breaks in the break test.

The cointegration test proposed by Engle and Granger (1987) has been widely applied to test for long-run adjustments among economic variables in an error correction framework. However, the Engle and Granger (1987) procedure assumes that the adjustment mechanism of the error correction term is symmetric, which implies that the adjustment coefficients are similar regardless of whether the equilibrium error is positive or negative. Abdulai (2002), Enders and Granger (1998) and Enders and Siklos (2001) suggested that if the adjustment is asymmetric, the Engle and Granger (1987) procedure will be misspecified. Enders and Granger (1998) and Enders and Siklos (2001) therefore suggested a threshold type of adjustment model. The intuition behind this new procedure is the notion suggested by Balke and Fomby (1997) that adjustment towards equilibrium is not constant but depends on adjustment cost considerations whereby economic agents do not adjust continuously. Therefore this study measures price asymmetry by estimating threshold-type adjustments to shocks in error correction models. The threshold models allow for asymmetry in adjustment speed and, because economic agents do not adjust continuously, the non-linear threshold effect is used to explain price changes in alternate regimes defined by a threshold value.

Conventional econometric linear models assume that the variance of the disturbance error term is constant with mean zero and serially uncorrelated. This assumption has been criticised by Enders (2004) and Engle (1982) who proposed that the variance of the disturbance term may be heteroskedastic. Engle (1982) proposed estimating the conditional mean of the linear model together with the conditional variance to take care of heteroskedasticity in the error variance. To avoid the bias in the assumptions of constant variance in volatile market prices, this study estimates an exponential generalised autoregressive conditional heteroskedasticity (EGARCH) time-series model to account for a piecewise conditional mean, as well as an EGARCH description of the changing conditional variance in the asymmetric non-linear combination of farm-retail prices.

In summary, the study explores the hypothesis that the South African poultry meat market price is volatile, that price transmission is asymmetric and threshold-driven, and that market participants respond to price changes beyond a certain threshold. The threshold price change that triggers these responses is estimated using best-fit price adjustment models (the threshold autoregressive (TAR) and momentum threshold autoregressive (M-TAR) models). The EGARCH approach is used to investigate volatility and the volatility spillover effects. The EGARCH model accounts for both conditional mean and conditional variance of the farm-retail price relationship.

1.3 OBJECTIVES OF THE STUDY

The primary objective of the study is to measure the nature of price transmission and price volatility spillovers in the South African poultry meat supply chain. Firstly, price transmission is estimated with different adjustment mechanisms and secondly volatility in primary and retail prices is quantified. In order to achieve the primary objective, the following secondary objectives were set:

- Identify short- and long-run dynamics of the farm-retail price relationship.
- Identify the direction of flow of information (causality) between farmers and retailers.
- Examine the degree of asymmetric price transmission across the farm-retail market chain.
- Investigate volatility and volatility spillover effects across farm and retail prices.
- Investigate volatility spillover from feed materials to farm and retail market prices.
- Investigate whether critical price changes have influenced the price dynamics in a non-linear pattern.
- Estimate the price threshold that delineates non-linearity above which the price-adjustment-to-equilibrium relationship is triggered.

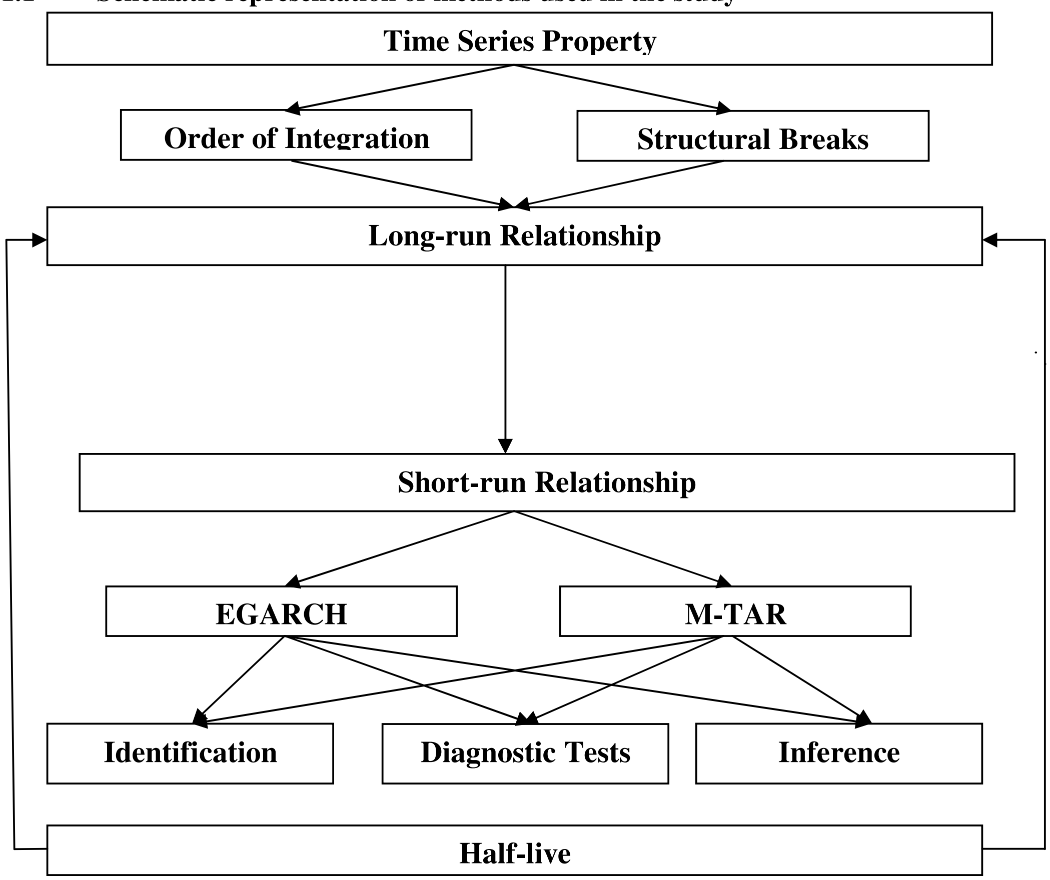
1.4 DATA AND METHODOLOGY

The data used was based on time-series monthly observations of farm and retail prices dated January 2000 to August 2008. The monthly retail prices are weighted prices of whole chicken in rand per kilogram, while the farm price represents the average carcass price in cents/kg slaughter weights. The farm price was obtained from the National Department of Agriculture, Land Reform and Rural development (DAFF), while the retail price was obtained from Statistics South Africa. Only nominal prices were used in the analysis. The monthly grain and oilseed price data was obtained from the historical database of the South African Futures Exchange (SAFEX) market.

The following methods were used: Firstly, the time-series properties of the price data were determined. This involved investigating the characteristics of the data-generating process (DGP) by employing the unit root procedure with appropriate consideration of the possibility of an exogenous shift in the trend function of the series. Secondly, the short- and long-run interrelationship between the price data was examined.

The short-run dynamics of the long-run equilibrium relationship between the farm-retail market prices were examined using the M-TAR model in an error correction specification. The EGARCH model was used to measure volatility and the volatility spillover effects in the farm-retail market channel. For the latter, threshold effects in the asymmetric price adjustment process were captured by means of the M-TAR model. A summary of the methodology is shown in Figure 1.1.

Figure 1.1 Schematic representation of methods used in the study



1.5 RESEARCH OUTLINE

This thesis consists of an introductory section (Chapter 1) and five subsequent chapters. A review of the literature on volatility spillover and the price transmission mechanism is conducted in Chapter 2. Theories, assumptions and approaches used to measure volatility and asymmetric price transmission are also reviewed in this chapter. In Chapter 3, the poultry industry supply chain is examined and a measure of the farm-retail price spread of the selected meat category is graphically illustrated. In Chapter 4, the methodology and the model specifications are presented, along with a description of plausible alternative econometrics methods and models used in the measurement of the asymmetric price relationships and the level of price volatility. A comparison of model approaches is also presented. Chapter 5 introduces the data, application and the parameter estimates from the adopted models. Chapter 6 provides the summary, conclusions and recommendations for further research.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, theories, assumptions and the approaches used by economists and agricultural economists to study the asymmetric price and volatility transmission mechanism is reviewed. Firstly, the theories about firms, production and the market of agricultural products are discussed. This is followed by the discussion of the nature, types and interrelationship among firms in a vertical market. A review of the methodological improvements and the empirical approaches adopted in the study is also described.

2.2 THEORY OF PRICE TRANSMISSION

2.2.1 Concept of market and price relationship

This section describes the relationship between price and the economic systems of production, consumption and marketing. Pricing signals regulate production, consumption and marketing decisions (Kohls & Uhl, 1998). In economic theory, the allocation of factors of production between different uses is determined by the price mechanism (Coase, 1937). The decision to allocate resources in the production of a fixed unit of output is often guided by the economic returns from the planned operation, which is a function of least cost input and output mixes. If input prices change, producers adjust their productive activities and produce where marginal cost equals marginal revenue. Therefore producers are driven by the relative input and output prices.

Output prices influence the demand for agricultural commodities. Consumers wish to maximise their welfare and the utility they derive from the consumption of a unit of agricultural product subject to their budget constraint. Since they are price-takers, they often adjust their demand as the prices of basic commodities change. When the prices of commodities increase, consumers tend to adjust their consumption expenditure, because high prices diminish their purchasing power.

In addition to driving production and consumption decisions, price signals also drive commodity markets. Market agents need to know the prevailing market price information in order to make appropriate market decisions. For price information to be transmitted perfectly and completely, markets need to be integrated and efficient. An important question is whether agricultural commodity markets in transition economies are efficient and integrated. If they are, the level of efficiency and integration should reflect the way in which prices are transmitted across markets. In the presence of market failure, price transmission will reflect the inefficiency and welfare losses in the economic system. Market categories and the conditions for efficiency are discussed in the next section.

2.2.2 Market integration

Employing the equilibrium price theory, Barrett (1996) categorised market relationships into spatial, inter-temporal and vertical. Inter-temporal relationship refers to markets linked by efficient arbitrage inter-temporarily across periods. The concept of a spatial market relationship relies largely on arbitrage[1]. It is used in spatial market studies to signify exploitation of profit opportunities created by market inefficiency.

Spatial price relationships relate to the price linkage across spatially distinct markets where arbitrage depends on whether the price difference is less than, equal to or greater than the transaction cost. If the price difference in the spatial market is less than or equal to the transaction cost, there will be little incentive to engage in trade – i.e. no arbitrage. If the price difference exceeds the transaction cost, an arbitrage opportunity will be created and arbitrageurs will compete for the opportunity of buying low and selling high until equilibrium price is restored. The length of time it takes for the market to return to equilibrium conditions underlies efficiency in the spatial market (see Goodwin & Piggott, 2001; Goodwin & Schroeder, 1991; Uchezuba, 2006).

Spatial market relationship is beyond the scope of this study. However, the concept of vertical market relationship, which is the main focus of the study, will be discussed further.

2.2.3 Vertical market relationship

The vertical market relationship involves the integration of stages in the production, processing and marketing channels. The traditional vertical market channel in the agricultural and food marketing system consists of a set of economic stages that starts with the farm and goes to the processor (manufacturer), then to the wholesaler and finally to the retailers. Various stakeholders are involved in the value-adding process by transforming and distributing agro-food products in form, space and time until products reach the final consumer (Kilmer, 1986; Kohls & Uhl, 1998). This act of transferring resources between economic stages is referred to as vertical co-ordination (Veselska, 2005).

Vertical market integration can be defined according to the type of co-ordination in the marketing chain. A vertically integrated market can be categorised according to whether the

[1] Arbitrage is a widely used concept in market analysis. It is defined as the attempt to profit by exploiting price differences of identical or similar commodity, on different markets or in different forms.

marketing, processing and distribution or the production and marketing processes are linked by ownership or through market exchange (Tomek & Robinson, 1990). According to Kilmer (1986), a vertically integrated firm is linked by ownership if it owns the production of a previously purchased input used in the manufacturing of an output or the production unit that previously purchased the output from a particular firm.

The implication of this type of market linkage, firstly, is that market exchange between market stages is controlled by internalising the exchange process. Secondly, the firms at one stage of production will exert more control over the quality of output at other stages of production. In that case, the decision made by the firm at an early stage might be transferred to a downstream firm in the supply chain. This will amount to transfer of control. For example, a processor can integrate backwards to produce farm commodities or forwards into retailing and final distribution to consumers. The food retailers often integrate backwards to the farm stage displacing wholesalers and processors (Kilmer, 1986; Royer, 1995).

In the absence of vertical linkages through ownership, market exchange will take place in the open market where market clearing equilibrium is determined by demand and supply. This is typical of vertical co-ordination that is linked through a competitive market process. In this type of vertical co-ordination, if food industries are perfectly competitive, the economic values are clearly reflected in the resources allocated to food production, in the variety and quality of food produced, and in the prices of the foods. This is because each firm in the perfectly competitive market would be a price-taker, and there will be free entry and exit. This concept is consistent with efficiency in the market system (Veselska, 2005).

Notably, the categorisation of the vertical market relationship given the above is based on the trade-off between simple open market transactions and internal organisation; that is, the decision to internalise market exchange or buy through the open market. The question is why would a firm prefer one marketing option to another or, put in another way, why would a firm choose to integrate vertically while others transact in the open market? Perhaps the decision to vertically integrate is a function of the relationship between the firm and the market (Coase, 1937). This relationship is explored in the theory of vertical integration in the next section.

2.2.4 Theory of vertical integration

The theory of vertical integration consists of a set of assumptions whose application may vary from sector to sector and from commodity to commodity. Motivated by the economic welfare distribution, economists attempt to explain the relationship between the firm and the market in lieu of the allocation of scarce economic resources, production and marketing efficiency in the economic system. A brief summary of the theory is explored below while examining the causes and consequences of vertical integration.

2.2.4.1 Factors that create incentive for vertical integration

Several factors motivate firms to integrate vertically. Economists suggest three main determinants of vertical integration, namely technological economies, transactional economies, and economies due to market imperfection (Garcia, Moreaux & Reynaud, 2004; Lawrence, Rhodes, Grimes & Hayenga, 1997).

If the production of a commodity involves different successive stages, a vertically integrated firm can produce complementary products more profitably than segmented firms. By vertically integrating, the firm may reduce total cost and allocation inefficiencies by internalising the production and the pricing decisions. The economies of scope or scale resulting from these physically interdependent production stages are referred to as "technological economies" (Garcia *et al.*, 2004; Lawrence *et al.*, 1997).

Transactional economies refer to the process of exchange. Coase (1937) reaffirms that economic theory suggests that price transmission mechanisms co-ordinate the production and marketing of goods and services. In practice, however, the vertical integration of firms, amongst other factors, may supersede the price mechanism. Thus the question is why would firms want to supersede the price mechanism? Coase (1937) relates it to some external network of relative prices and the cost of internal organisation and marketing. According to Coase (1937), the co-ordination of exchange by a price mechanism has some costs implications. Joskow (2006) stated that these transaction costs involve the cost of writing, monitoring and enforcing contracts, as well as *ex ante* investment and *ex post* performance inefficiencies arising from contractual hazards associated with market transactions and costs associated with internal organisation.

These costs in some cases may be high; consequently a firm may be able to reduce its transaction cost by vertically integrating. For example, in the case of a bilateral monopoly where there is one seller and one buyer, either firm may be able to eliminate the transaction cost through integration (Royer, 1995). The economies resulting from this type of integration are known as transactional economies.

Market imperfection refers to deviations from the neoclassical assumptions of the perfectly competitive market model. If markets are imperfect, market structures such as monopoly, oligopoly and monopsony resulting from the acquisition of market power will emerge. These market structures would strategically create or enhance market power in pricing. This results in an inefficient combination of inputs at the downstream stage (Garcia *et al.*, 2004). Successive monopoly, oligopoly and monopsony provide a profit incentive for upstream (downstream) vertical integration (Coase, 1937; Kilmer, 1986). Another incentive for this type of vertical integration is the market foreclosure of competitors' access to inputs or products whereby the integrated firms deny others access to essential goods or inputs in order to extend their monopoly powers from one market to another.

2.2.4.2 Consequences of vertical integration

The aim of this section is to highlight the cost-benefits of vertical co-ordination practices, whether mediated through the market (open market transaction), strategic alliance, non-standard vertical contracting, or vertical integration (co-ordinated by ownership). Opinions on whether a particular practice is beneficial or harmful vary. All of the practices may be beneficial in some instances and harmful in others (see Lawrence *et al*., 1997). The benefits and/or harm will depend on the impact on input and output prices and on the economic welfare of producers and consumers (Royer, 1995).

a) Harmful effects of vertical integration

- ***Vertical foreclosure***. Vertical integration results in the market foreclosure of the competitors' access to inputs and products. Foreclosure refers to the dominant (upstream) firms' denial of proper access to important goods or services to (downstream) firms in order to gain a competitive advantage or restrict entry or expansion of the downstream firms. This practice creates anticompetitive effects that arise when a monopoly firm has control over the supply of essential resources required by the downstream competing firms. Vertical foreclosure may enhance market power and create incentive for price fixing and collusion (Lawrence *et al*., 1997 & Joskow, 2006)

b) Benefits of vertical integration

- ***Mitigation of double marginalisation***. Vertical integration can mitigate the impact of inefficiency that arises when there is market power in both upstream producing and downstream retailing. Assuming an upstream monopoly has all bargaining power over prices charged for goods purchased by downstream firms, the upstream mark-up price will be transferred to the downstream firms and then subsequently to the consumers. This will result in double marginalisation (Joskow, 2006). Assuming the two firms integrate and charge one mark-up price, their aggregate profit will increase and the prices charged to the consumers will fall, resulting in increased welfare at both consumer and producer levels.
- ***Efficient utilisation of resources***. Vertical integration would restore efficiency in the utilisation of inputs used in the production of downstream goods and services and would increase aggregate profit for the firms, provided the downstream market is not perfectly competitive. In this instance, double marginalisation may not arise and the effect on consumer prices will be too ambiguous to imagine (Joskow, 2006).
- ***Economies of scope or scale***. Firms capture scope and scale economies through vertical integration. This will result in the reduction of total cost and allocation inefficiencies. Risk may also be reduced or diversified, and efficiency in market supplies is guaranteed through the synchronisation of inputs and product flows

(Lawrence *et al*., 1997). In principle, vertically integrated firms may reduce marketing costs, but in practice the integrated firms may not pass on such cost savings to downstream firms as lower retail and consumer prices unless they are compelled to do so by competition (Tomek & Robinson, 1990). This tendency may result in a non-linear asymmetric price relationship, as discussed in the next section.

2.3 SYMMETRIC-ASYMMETRIC PRICE TRANSMISSION

Although in general terms, vertical price transmission is the primary mechanism through which the different levels of vertical production and market stages are linked, in specific terms it is a process that reflects the relationship between vertical upstream and downstream prices. The upstream prices reflect the input prices at the farm-gate and processing (manufacturing) production stage or the prices offered at the higher wholesale market level, while the downstream prices are the output prices for the farm, processing (manufacturing) and production units or the prices offered at the lower retail market levels (see Frey & Manera, 2005; Meyer & Von Cramon-Taubadel, 2004).

For the vertical market to be integrated, price theory suggests that a long-run equilibrium relationship should exist between the upstream and downstream prices, implying that in the long-run, prices of goods engaged in the economic activity should reflect their scarce economic value (Veselska, 2005). In this instance, rational economic agents should be able to price their goods to maximise their utility, while in the process equitable distribution of economic welfare to consumers is ensured.

Given this equilibrium relationship, it is expected that any external shocks to the upstream prices should trigger short- and long-run adjustments towards the long-run equilibrium. For example, increases or decreases in upstream prices should simultaneously trigger appropriate changes in the downstream price both rapidly and completely. This type of equilibrium price relationship predicted by all canonical industry and market-pricing models (e.g. perfect competition, monopoly) is called symmetric price transmission.

In contrast to symmetric price behaviour, analysts have found evidence to suggest that in practice, the adjustment of prices to shocks may not be homogeneous but asymmetric (Abdulai, 2002; Kinnucan & Forker, 1987; Von Cramon-Taubadel, 1998; Ward, 1982). For example, retail prices may adjust more quickly to wholesale price increases than to decreases (Borenstein, Cameron & Gilbert, 1997). At the same time there is concern that retailers pass on high prices to consumers in response to price hikes at the upstream level but are reluctant to reduce their prices as upstream (wholesale) prices fall (Frey & Manera, 2005).

If this concern is true, asymmetric price transmission (APT) would imply a different distribution of welfare than would be the case under symmetry (Meyer & Von Cramon-Taubadel, 2004). This is because it alters the timing and size of welfare changes that are associated with price changes. In an imperfect non-competitive market where market power exists, APT may not only result in welfare redistribution but also welfare loss. This phenomenon has policy implications and has been the subject of many research works in the field of economics and agricultural economics in which analysts have attempted to classify and find possible explanations for the existence of asymmetry in price transmission.

2.3.1 Types of asymmetric price transmission

There are several classes of asymmetric price transmission in the literature. The two main classes of asymmetry are (a) asymmetry with respect to the magnitude and speed of price transmission and (b) positive and negative asymmetry.

2.3.1.1 Magnitude and speed of asymmetry

In a state of disequilibrium in the vertical market chain, the speed and magnitude of price transmission manifests in the behaviour of market participants. Both the magnitude and the speed of price transmission can be asymmetric (Von Cramon-Taubadel, 1998). In the former, short-run elasticities of vertical price transmission will differ according to the sign of the initial change, while in the latter long-run transmission elasticities also differ (Von Cramon-Taubadel, 1998). Meyer and Von Cramon-Taubadel (2004) used a graphical illustration to distinguish between asymmetry with respect to the magnitude and to the speed of price transmission. According to Meyer and Von Cramon-Taubadel (2004) the magnitude and the speed of the response of downstream prices to changes in upstream prices depend on the direction of the change and on the volume of transactions, assuming that downstream output demand is inelastic.

Asymmetry with respect to the speed of price transmission leads to temporary welfare redistribution from consumers to retailers, while asymmetry with respect to the magnitude of price transmission leads to a permanent transfer. These authors further explained that a combination of both types of asymmetries would lead to both temporary and permanent redistribution. The question is which of these two types of asymmetries is more harmful.

According to Meyer and Von Cramon-Taubadel (2004), it is difficult to determine *a priori* unless agents have monopoly pricing powers. In this instance, asymmetry with respect to the magnitude of price transmission will result in both welfare redistribution and welfare loss.

2.3.1.2 Positive and negative asymmetry

Von Cramon-Taubadel (1998) suggested that asymmetry may show the reaction of the price at one level of the market chain to a price change at another level depends on whether the initial change is positive or negative. In other words, price asymmetry reflects the intensity of output (downstream) price variation to positive or negative changes in the input (upstream) prices (Frey & Manera, 2005). If downstream (output) prices react more rapidly and completely to increases in upstream (input) prices than to decreases, this is termed positive asymmetry (Meyer & Von Cramon-Taubadel, 2004). On the other hand a negative asymmetry results if downstream (output) prices react more rapidly and completely to decreases in upstream (input) prices than to increases.

Considering the two asymmetries, positive asymmetry is harmful to the consumer while negative asymmetry is beneficial. Positive asymmetry implies that cost increases that squeeze margins are passed on to consumers more rapidly and completely than cost decreases that stretch margins. With negative asymmetry, on the other hand, cost decreases that stretch margins are passed on more rapidly and completely than cost increases that squeeze margins.

2.3.1.3 Other types of asymmetries

Frey and Manera (2005) extended the classifications of asymmetry given in sections 2.3.1.1 and 2.3.1.2 to include new categories of asymmetry that depend on the measurement of asymmetry based on these two prior classifications. The new categories of asymmetry are (i) contemporary impact asymmetry, (ii) distributed lag effect asymmetry, (iii) cumulative impact asymmetry, (iv) reaction time asymmetry, (v) equilibrium adjustment path asymmetry, (vi) momentum equilibrium path asymmetry, (vii) regime effect asymmetry, (viii) regime equilibrium adjustment path asymmetry, and (ix) spatial asymmetry

- **Contemporary impact asymmetry (CONIA)**. A widely held view is that shocks arising from changes in the upstream (input) prices are transmitted rapidly and completely to the downstream (output) prices. The impact of the positive and negative shocks on the downstream (output) prices and how the downstream (output) prices respond to these shocks define the contemporaneous relationship between the two market prices. The statistical test that shows whether this hypothesised relationship really exists has been the focus of many asymmetric price transmission studies for the past two decades. If this hypothesis is not supported by the statistical test, it implies that the contemporaneous relationship between the prices is symmetric.

- **Distributed lag effect asymmetry (DLEA)**. The response of downstream (output) prices to positive or negative changes in the upstream (input) prices may not be instantaneous but distributed over a time lag. The asymmetry resulting from this delayed response is known as distributed lag effect asymmetry (DLEA). Several reasons have been cited as to the cause of this delayed response. Menu cost (Heien, 1980), market imperfection (Ward, 1982), and the inertia involved in the storing, transporting and processing of food products have been cited as possible reasons for DLEA.

- **Cumulative impact asymmetry (CIA).** This type of asymmetry relates to whether there is a cumulative impact of contemporaneous and distributed lag effects on the upstream-downstream market price relationship. If the contemporaneous impact occurs at the same lag, the cumulative impact is symmetric, otherwise it is asymmetric. However, the joint existence of contemporaneous impact and distributed lag effect is a sufficient but not a necessary condition for cumulative impact asymmetry (Frey & Manera, 2005).

- **Reaction time asymmetry (RTA).** If there is a positive and/or negative shock to the upstream (input) price, the tendency is that the downstream (output) price will readjust to an equilibrium level depending on whether an equilibrium relationship exists between the prices. The readjustment to equilibrium level is not instantaneous but takes a time lag. The time taken for the downstream (output) price to readjust to an asymmetric upstream shock is termed reaction time asymmetry (RTA) and this can give an indication as to the nature of the upstream shock – that is, whether it is persistent or transitory.

- **Equilibrium adjustment path asymmetry (EAPA).** This is the type of asymmetry in response to adjustment towards equilibrium path. Adjustment toward equilibrium depends on the stationarity of the economic variables. Stationary stochastic series reverts back to equilibrium, while non-stationary series does not return to the equilibrium path. Engle and Granger (1987) developed an equilibrium term and proposed that a linear combination of non-stationary series has a long–run cointegrating equilibrium relationship depending on the level of the equilibrium term (also called error correction term). This implies that adjustment to equilibrium will depend on whether the equilibrium term is above or below the equilibrium level. If adjustment towards equilibrium is above or below equilibrium level, EAPA results. In contrast, if the adjustment remains at the same equilibrium level, this results in symmetric equilibrium adjustment path.

- **Momentum equilibrium path adjustment asymmetry (MEAPA**). It should be kept in mind that in the equilibrium adjustment path symmetric specification of Engle and Granger (1987), adjustment depends on the level of the equilibrium term. Enders and Granger (1998) proposed that adjustment could be allowed to depend on the previous period's change in the equilibrium term in such a way that an asymmetric adjustment will exhibit more momentum in one direction than the other. This type of adjustment is termed momentum equilibrium path adjustment asymmetry.

- **Regime effect asymmetry (REA).** In this case, asymmetric adjustment to equilibrium may be non-linear and threshold-driven. In other words, adjustment will exhibit threshold regime effect whereby the threshold variable is based on one of the explanatory variables. Regime effect asymmetry exists in the presence of more than one regime defined by the threshold variable.

- **Regime equilibrium adjustment path asymmetry (REAPA).** Unlike regime effect asymmetry, in a threshold regime shifting specification, if the threshold variable is defined by the equilibrium error correction term, the resulting asymmetry is called regime equilibrium adjustment path asymmetry.

- **Spatial asymmetry**. This is a type of asymmetric price relationship between spatially separated markets. For example, a rise in the export price of one commodity in one country may result in a proportionate rise in the export price of the same commodity in another country that is higher than a corresponding reduction in price of the same magnitude. According to Meyer and Von Cramon-Taubadel (2004), spatial asymmetry can be classified according to the speed and magnitude of price transmission and according to whether it is positive or negative.

The asymmetric price relationships described in this section have been found to exist in many input and output markets, for example in the agricultural, finance and energy sectors. The agricultural sector is of major interest in this study, because agro-food products constitute a significantly large proportion of consumer expenditure in developing countries. Due to this concern, many economists and agricultural economists have sought reasons to explain asymmetric price transmission. These reasons are discussed next.

2.3.2 Underlying causes of asymmetric price transmission

Analysts try to find explanations for the existence of asymmetric price transmission (APT) using different assumptions. Some of the assumptions are (a) adjustment cost, (b) inventory management, (c) perishable goods, (d) search cost, (e) market power, (f) tacit collusion, (g) government intervention, and (h) demand and supply shifts.

- **Adjustment cost.** Adjustment cost is the cost of adjusting the quantities and/or prices of inputs and/or outputs by firms. It is assumed that adjustment to increases or decreases in the quantities and/or prices of inputs and/or outputs by firms may be asymmetric. In other words, firms may adjust cost increases and pass these on more rapidly and completely to consumers than cost decreases. Firms may face different adjustment costs depending on whether the quantities and/or prices of inputs and/or outputs are rising or falling (Bailey & Brorsen, 1989). One example of adjustment cost in relation to responses to price changes is the menu cost. Menu cost includes the cost of changing nominal prices of goods, printing catalogues, dissemination of information about price changes, and cost of inflation. According to Kovenock and Widdows (1998), if input cost changes are perceived to be temporary, menu cost will firstly serve as an incentive not to adjust prices when input costs decrease. Blinder (1982) also showed that firms are more concerned with long-term sustained price movements that bring rapid changes to their inventories than with temporary price changes, simply because of menu cost. Secondly, firms would not want to signal to their consumers that the market conditions have changed, because rational buyers would then re-engage in search behaviour.

- **Inventory management**. Another important aspect in adjustment to input and output price changes is the type of accounting criteria firms use in evaluating their inventory. If a firm adopts historical criteria, i.e. first-in-first-out (FIFO), it does not adjust its output rapidly to cost changes, but waits until inventory is depleted. On the other hand, if the firm adopts last-in-first-out (LIFO) criteria, it would adjust prices rapidly in response to changes in input cost (Frey & Manera, 2005). The type of convention chosen will influence the speed of adjustment to shocks, because FIFO has a longer lag than LIFO.

- **Perishable goods.** Ward (1982) suggested that the perishability of commodities may create incentives for price asymmetry. According to Ward (1982), retailers with perishable goods may not raise prices as producer prices rises for fear of being left with spoilt goods due to sales reduction. With this type of asymmetry, Von Cramon-Taubadel (1998) suggested that the speed of price transmission may be asymmetric in the short-run but not in the long-run. This type of asymmetric price relationship (negative asymmetry) is beneficial to consumers (Meyer & Von Cramon-Taubadel, 2004). In contrast, Heien (1980) suggested that perishability would pose fewer problems compared to commodities with a long shelf-life. For commodities with a long shelf-life, price changing is costly in terms of both the time taken to put on new labels (menu cost) and in goodwill lost.

- **Search cost.** Another source of asymmetric price transmission is search cost. Search cost is the cost incurred in the process of obtaining market information. In a perfectly competitive market there are many firms (producers) and many consumers, and there is perfect and free transmission of market information. However, in an imperfect market, there is imperfect information and few firms (or retail market outlets) may enjoy market power because of lack of local rivalry and competition. In such instances, consumers can either accept the prices offered to them by these local merchants or search for alternative price in the neighbourhood. In practice, they may not have full knowledge of prices offered by other firms further away due to the search cost involved. Thus firms cash in on the situation and quickly raise prices when the upstream prices rise and slowly lower prices when upstream prices decline.

- **Market power**. The exercise of market power has been cited as one of the reasons for asymmetric price transmission (Bailey & Brorsen, 1989; Borenstein *et al.*, 1997; Boyd & Brorsen, 1988; Bakucs & Ferto, 2006; Meyer & Von Cramon-Taubadel, 2004; Von Cramon-Taubadel, 1998). In a non-competitive market structure with imperfect information, monopoly (upstream) markets pass on cost increases that squeeze their margins more rapidly and completely than cost decreases that stretch their margins, resulting in positive APT. Market power can also lead to negative APT if monopoly firms react less rapidly to price changes that squeeze their margin for fear of losing goodwill (Heien, 1980), or risk of having spoilt goods (Ward, 1982). Also, negative or positive APT may result if firms face a kinked demand curve depending on the price expectation of firms as input and output prices change (Bailey & Brorsen, 1989). According to Bailey and Brorsen (1989), if an individual oligopoly firm believes that other competing firms will match an increase in output prices as input prices increase, but not a reduction as input prices fall, a positive APT will result in a kinked convex demand function. On the other hand, if firms believe that competitors are less likely to match output price increases than cuts, the resulting negative APT will give rise to a concave demand curve. Market power can also give rise to short-run oligopoly collusive agreements if markets are highly concentrated with inelastic demand – although this agreement might break down in the long-run because one firm might have the incentive to surreptitiously cheat.

- **Tacit collusion.** Tacit collusion leads to asymmetric price transmission. To enhance market power, firms can tacitly collude. In that instance, if wholesale prices increase, each firm will rapidly increase its selling price. When wholesale prices fall, firms respond slowly in adjusting their prices to avoid running the risk of sending a signal that they are cutting their margins to gain a market share, hence breaking away from the agreement. According to Borenstein *et al.* (1997), firms in a collusive agreement can identify cheats by setting a trigger price. For example, a retail firm may be punished by others if it attempts to increase its market share by reducing prices below a certain trigger price set by the firms as a minimum.

- **Government intervention.** Asymmetry in farm-retail price transmission can occur because of policy intervention by government (Kinnukan & Forker, 1987). According to Kinnukan and Forker (1987), wholesalers or retailers face uncertainty in trying to determine the price of their goods based on cost changes. If cost changes are transitory, because of menu cost they would be reluctant to reprice their items in the short-run. However, the uncertainty associated with interpreting cost changes is greatly reduced if the government intervenes with price support programmes in the form of floor farm prices over an extended period. If that is the case, increased farm prices will be seen by retailers as permanent cost increases and will be transmitted rapidly and completely to the consumers, while a reduction results in slower and less complete pass-through.

- **Demand and supply shift.** Gardner (1975) made certain predictions about how shifts in the demand and supply of food will affect the farm-retail price spread and the farmer’s share of retail food expenditure. Under the assumption of long-run competitive equilibrium and constant return to scale, Gardner (1975) demonstrated that the farm-retail price transmission elasticity differs according to whether observed changes in the market margin are caused by retail-level demand shifts (demand-pull) for food or farm-level supply shifts (cost-push) for agricultural products. According to Gardner (1975), retail-level demand-pull has a stronger impact on the farm-retail price spread than farm-level cost-push. This differential impact could lead to APT (Kinnukan & Forker, 1987). Von Cramon-Taubadel (1998) pointed out that this will lead to APT only if the distribution of either demand or supply shift is predominantly positive or negative.

2.4 MODELLING ASYMMETRIC PRICE TRANSMISSION

2.4.1 Historical evolution of asymmetric price transmission models

Studies on price asymmetry differ and depend on the type of asymmetry being investigated, which is a function of the type of model used. Early studies on asymmetric price transmission focused on the irreversible behaviours of demand and supply functions. Emphasis has been on the short-run contemporaneous impact and the distributed lag effects of the variations in the input prices, while the long-run equilibrium relationship (cointegration) has been ignored. Due to the progress made in the modification of the statistical and analytical methods, studies that ignore the long-run relationship are assumed to give an inaccurate account of the asymmetric price relationship. Therefore the asymmetric price transmission literature is classified into studies with or without an equilibrium adjustment consideration.

2.4.2 Non-cointegration approach

The empirical application of asymmetric price transmission goes back to the early 1950s. Farrell (1952) investigated the irreversible behaviour of the demand function of some habitual goods such as tobacco, beer and spirits in the United Kingdom. Using variable splitting techniques, Farrell (1952) analysed the demand (y) for these goods in response to positive and negative changes in income (z) and price (x) with a model that can be logarithm transformed to give a functional form of the type

$$\Delta y_t = c + a^+ \Delta z_t^+ + a^- \Delta z_t^- + b^+ \Delta x_t^+ + b^- \Delta x_t^- + \mu_t \tag{2.1}$$

where Δy_t is the change in the quantity demanded in response to positive and negative changes in income (z) and price (x), c, a^+, a^-, b^+, b^- are parameter estimates, and μ_t is the disturbance term. Even though the results were inconclusive, Farrell (1952) suggested that irreversibility is an important factor in changes in taste or consumer preference. Farrell`s (1952) model framework has since been adopted in the modelling of asymmetric price transmission in various sectors. For example, in agriculture, Tweeten and Quance (1969) estimated an irreversible aggregate supply function of farm products in the United States of

America. The authors investigated the level of aggregate supply (y) and the ratio between input and output prices (x). Consider a linear price transmission equation of the form,

$$y_t = \alpha + \beta x_t + \mu_t \tag{2.2}$$

where x and y are two prices at different levels in the vertical market stages, and μ_t is the error term. To investigate the asymmetric relationship and the effect of x on y, Tweeten and Quance (1969) split the independent variable x into increasing and decreasing components. They used the equation of the form

$$y_t = \alpha + \beta^+ D_t x_t + \beta^- (1 - D_t) x_t + \mu_t \,, \tag{2.3}$$

where D_t takes the value of one if the first difference of x_t (i.e. $x - x_{t-1}$) is positive, otherwise zero. The dummy variable is used to split x_t into two, with one variable including only increasing input prices (price years) with adjustment coefficient β^+ and the other including only decreasing input prices (price years) with adjustment coefficient β^-. With this specification Tweeten and Quance (1969) evaluated asymmetry using the F-test. The null hypothesis of symmetric price transmission is rejected if β^+ and β^- are significantly different from each other. Using annual data from the period 1920-1966, the authors found asymmetry in the US supply structure but failed to reject symmetry for aggregate supply response to increasing and decreasing input prices.

The study by Tweeten and Quance (1969) provoked varying responses from researchers. Wolffram (1971) argued that the application of the splitting technique is correct only if the parameter estimates in the individual period are constant – that is, if the influence of the independent variable over the total period of investigation is constant (Wolffram, 1971:358).

As a solution, Wolffram (1971) modified the model of Tweeten and Quance (1969) by redefining the increasing and decreasing components of x_t as the summation up to a time period t of positive and negative changes in x_t (i.e. Δx_t) as

$$y_t = \alpha + \beta^+ \left(x_0 + \sum_{k-1}^{t} D_t \Delta x_k \right) + \beta^- \left(x_0 + \sum_{k=1}^{t} (1 - D_t) \Delta x_k \right) + \mu_t \tag{2.4}$$

where x_0 is the initial value of x_t at $t = 0$, and the value D is as defined in Tweeten and Quance (1969). In the Wolffram (1971) model (equation 2.4), the recursive sum of all the positive and negative changes is included as explanatory variables. Through the modification, the Wolffram (1971) model considers the effects of cumulative variation in the variable x_t compared to that of Tweeten and Quance (1969) where the direct impact of period-to-period variation in x_t is accounted for.

Houck (1977) pointed out that neither Tweeten and Quance (1969) nor Wolffram (1971) considered the starting point or initial observation of the dependent variable. He argued that since irreversibility is most commonly expressed in terms of asymmetrical change from a previous position in time, the identification of the initial observation is important even though this first observation has no independent powers, because the effects to be measured depend on the previous position not on its levels. Hence the dependent variable in Houck's (1977) specification y_t^* is defined as $y_t - y_0$, therefore,

$$y_t^* = \alpha + \beta^+ D_t \Delta x_t + \beta^- (1 - D_t) \Delta x_t + \mu_t \qquad (2.5)$$

This model directly considers the impact of positive and negative variations of x on y, cumulated from period to period. Houck (1977) also proposed using the first difference of the dependent variable such as

$$\Delta y_t = \alpha + \beta^+ D_t \Delta x_t + \beta^- (1 - D_t) \Delta x_t + \mu_t \qquad (2.6)$$

The studies on asymmetric price analysis so far discussed have centred on demand or supply irreversibility. Ward (1982) focused on asymmetric price transmission between prices in the vertical market system. Ward (1982) argued that the supply of most agricultural products to the markets is seasonal and a price change is distributed over a time lag. As a result he extended Houck's (1977) model by incorporating lag terms of the exogenous variables $D_t \Delta x_t$ and $(1 - D_t)\Delta x_t$ in the price transmission equation. According to Ward (1982), the lag lengths L can differ because they are the increasing and decreasing price changes and are not expected *a priori* to be the same.

Equations 2.6 and 2.7, in addition to measuring the contemporary impact of x on y, also measure the distributed lag effects of the cumulative variations of x on y. With the modified model, Ward (1982) investigated the impact of wholesale prices on the retail and shipping point prices of the USA fresh vegetable market. Using monthly data of various observation periods, Ward (1982) found asymmetry in the fresh vegetable market and also observed significant lag responses during periods of rising and falling prices.

$$y_t^* = \alpha + \sum_{K=1}^{L} \beta_K^+ D_{t-k+1} \Delta x_{t-k+1} + \sum_{K=1}^{L} \beta_K^- (1 - D_{t-k-1}) \Delta x_{t-k-1} + \mu_t \qquad (2.6)$$

$$\Delta y_t = \alpha + \sum_{K=1}^{L} \beta_K^+ D_{t-k+1} \Delta x_{t-k+1} + \sum_{K=1}^{L} \beta_K^- (1 - D_{t-k-1}) \Delta x_{t-k-1} + \mu_t \qquad (2.7)$$

The above models – referred to as pre-cointegration models by Meyer and Von Cramon-Taubadel (2004) – have widely been used to model asymmetric price relationships for more than two decades. Kinnukan and Forker (1987) used Ward's (1982) model to analyse the farm-retail price transmission of major dairy products in the USA. Using monthly data from 1971-1981 the authors found that retail dairy product prices adjust more rapidly and fully to

increases in the farm prices of milk than to decreases. Boyd and Brorsen (1988) studied the US pork market and found no evidence of asymmetric price transmission. According to their findings, wholesale prices respond similarly to farm price increases and decreases. The authors also found no significant difference between the retail price response to wholesale price increases and decreases.
In the USA, Peltzman (2000) used large samples of different products – 77 consumer and 165 producer goods – and found that output prices respond faster to input price increases than to decreases. This type of asymmetric relationship was found in more than two of every three markets examined by Peltzman (2000). Zhang, Fletcher & Carman (1995) found asymmetry in the short-run and symmetry in the long-run price transmission between peanut and peanut butter in the USA. A detailed report on the application of this type of methodological framework is documented in Meyer and Von Cramon-Taubadel (2004) and Frey and Manera (2005).

Notably, many of the studies described in this section exhibit the following common characteristics: Firstly, there is a common disregard of the time-series properties of the data used. Secondly, the majority of the studies reject symmetric price transmission while some have mixed results, and thirdly, their results are often characterised by first-order autocorrelation. Due to the disregard of the time-series properties of the data, Von Cramon-Taubadel (1998) and Meyer and Von Cramon-Taubadel (2004) argued that the potential for non-stationarity in the data will lead to results that are spuriously significant, hence suggesting the existence of a relationship that actually does not exist. For example, most of the results that are autocorrelated find asymmetry. Assuming the prices are non-stationary I(1) and the sum of the positive changes in input prices is also I(1), the result of a linear combination of the input and output prices will depend on whether the error term is stationary and the sum of the positive and negative price changes ($\beta^{+}-\beta^{-}$) differs from zero. If ($\beta^{+}-\beta^{-}$) $\neq 0$ and the error term is I(1), then the regression is spurious because the prices are not cointegrated. This implies that the estimated equation is misspecified and cannot be used for standard statistical inference. To avoid spurious regression involving economic time series, econometricians adopt approaches that incorporate stationarity tests that are consistent with plausible symmetric-asymmetric price transmission analysis.

2.4.3 Cointegration and error correction models

The shortcoming of the asymmetric price transmission models in section 2.4.2 is that they fail to account for the possibility of the presence of a long-run equilibrium cointegration relationship in the price data. Cointegration analysis is an alternative procedure for evaluating the presence of stochastic trends in the price series. It was developed and applied in earlier work by Engle and Granger (1987) and Engle and Yoo (1987). Cointegration analysis ensures that deviations from equilibrium conditions between two economic variables that are individually non-stationary in the short-run should be stationary in the long-run. Intuitively, the concept of cointegration implies that economic forces do not allow persistent long-run deviations from equilibrium (Goodwin & Schroeder, 1991; Negassa, Meyers & Gabre-Madhin, 2003). An important implication of this is that while individual economic variables such as price drift apart, certain pairs of such variables do not diverge from one another in the long-run (Goodwin & Schroeder, 1991).

2.4.3.1 Engle and Granger cointegration test

In the economic estimation of cointegration relationships, it is often important to integrate short-run economic behaviour with long-run equilibrium relationships. That is, if the short-run relationship is known, the long-run relationship can also be identified. However, economic theories do not provide much information about short-run relationships. Engle and Granger's (1987) cointegration theory addresses the issue of integrating short-run dynamics with long-run equilibrium. Assuming that the two price data x and y in equation (2.2) are non-stationary, Engle and Granger (1987) suggested that a linear combination of the two variables is stationary. This implies that their stochastic trends are linked, and even though they may meander in the short-run they do not drift apart in the long-run – hence they are cointegrated.

Granger's representation theorem states that if economic variables are cointegrated, then error correction models can be developed to study the cointegrating relationship. Based on Granger's representation theorem, Engle and Granger (1987) suggested a two-step approach to estimate cointegration in an error correction specification. Firstly, cointegration regression is estimated by simple ordinary least squares (OLS), obtaining the residual of the cointegrating relationship and applying a residual-based unit root test for cointegration. The null hypothesis of unit root (no cointegration) is investigated using the Dickey-Fuller (DF), the augmented Dickey Fuller (ADF), the Phillips-Perron and the Johansen multivariate test procedures. The error correction model (ECM) is then estimated.

Cointegration technique in an error correction model has been used in the study of asymmetric price transmission. Following the Engle and Granger (1987) representation theorem, if y and x are cointegrated, an error correction model is fitted as follows:

$$\Delta y_t = \alpha + \varphi \Delta x_t + \sum_{i=0}^{k} \beta_i \Delta x_{t-i} + \sum_{j}^{q} \gamma_j \Delta y_{t-j} + \lambda ECT_{t-1} + \mu_t \tag{2.8}$$

Considering the cointegrating relations given by equation (2.2), the error correction term ECT_{t-1} is given as $y_{t-1} - \alpha - \beta x_{t-1}$. Using this framework, Manning (1991) tested for asymmetry in the contemporary impact of price increases and decreases between crude oil, retail petrol prices and excise duty using the model:

$$\Delta \ln y_t = \alpha + \psi_t^{+} + \sum_{i=0}^{k} \beta_i \, \Delta \ln x_{t-i} + \sum_{j=0}^{q} \beta_j^{+} \Delta \ln x_{t-j} + \sum_{h=1}^{r} \gamma_h \Delta \ln y_{t-h}$$

$$+\sum_{n=1}^{p}\theta_n \Delta \ln tax_{t-n} + \lambda ECT_{t-1} + \mu_t \tag{2.9}$$

Where ECT_{t-1} is the lagged residual from the long-run regression involving the three prices, ψ^{+} is an intercept dummy which is equal to one if $\Delta \ln x_t > 0$. If the coefficients ψ_t^{+} and β_j^{+} are not statistically different from zero, the effect of the positive and negative impacts of crude oil price on retail price is symmetric. Using monthly data from 1973-1988, Manning (1991) found evidence to support an asymmetric relationship between petrol prices, excise duties and the spot crude oil price. Manning's (1991) results show that there is a short-run asymmetric pricing reaction in the petrol market. Granger and Lee (1989) modified equation (2.8) by splitting the error correction term into ECT^{+} and ECT^{-} segments to allow for the testing of asymmetric price transmission between cointegrated variables, as shown in (2.10). Von Cramon-Taubadel (1998) suggested splitting Δx_{t-1} into positive and negative components to test asymmetric contemporaneous adjustment to give equation (2.12).

$$\Delta y_t = \alpha + \varphi \Delta x_t + \sum_{i=0}^{k}\beta_i \Delta x_{t-i} + \sum_{j}^{q}\gamma_j \Delta y_{t-j} + \lambda^{+} ECT_{t-1}^{+} + \lambda^{-} ECT_{t-1}^{-} + \mu_t \tag{2.10}$$

$$\Delta y_t = \alpha + \sum_{i=0}^{k}\beta_i \Delta x_{t-i} + \lambda^{+} ECT_{t-1}^{+} + \lambda^{-} ECT_{t-1}^{-} + \mu_t \tag{2.11}$$

$$\Delta y_t = \alpha + \sum_{i=1}^{k}\beta_i D^{+} \Delta x_{t-i} + \sum_{i=1}^{M}\beta^{-} D^{-} \Delta x_{t-i} + \lambda^{+} ECT_{t-1}^{+} + \lambda^{-} ECT_{t-1}^{-} + \mu_t \tag{2.12}$$

The error correction term (ECT) in these models measures the deviations from the long-run equilibrium between sets of upstream (input) and downstream (output) prices as indicated by the variables x and y, respectively. ECT is an attractor that compels the downstream (output) prices to respond to changes in the upstream (input) prices. It also corrects any deviation (error) from equilibrium in the long-run relationship between the prices that occurred in previous periods. ECT^{+} stands for positive deviation while ECT^{-} is the negative deviation. Using an F-test, the null hypothesis of symmetry can be tested by checking whether the coefficients of the positive and negative errors are significantly different from each other (i.e. $\lambda^{+} = \lambda^{-}$).

Granger and Lee's (1989) modifications nest equation (2.8) into (2.10). Equations (2.11) and (2.12) are variants of equation (2.10) that can be estimated. Borenstein *et al.* (1997) used equation (2.12) without segmenting the error term. Von Cramon-Taubadel (1998) tested for asymmetric price adjustment to long-run equilibrium with equation (2.10).

2.4.3.2 Threshold autoregression (TAR)

The cointegration and the error correction representation discussed in sections 2.4.2 and 2.4.3, although accounting for the shortcomings in the earlier asymmetric studies, have certain limitations. The Engle and Granger (1987) representation theorem uses a standard time-series model to investigate cointegration. It should be kept in mind that standard time-series unit root (cointegration) models assume linearity and symmetric adjustment. In these models, adjustment to long-run equilibrium is assumed to be continuous, implying that the movement towards the equilibrium occurs in every period. Balke and Fomby (1997) and Enders and Granger (1998) suggested that the cost of adjustment may prevent economic agents from adjusting continuously. It is only when the deviation from equilibrium exceeds a critical threshold that the benefits of adjustment exceed the cost and hence economic agents act to move the system back to equilibrium.

Threshold cointegration is used to model the possibility that the short-run dynamic relationship behaves in different ways depending on the magnitude of deviation from the equilibrium. In a threshold model delineated by two regimes, the short-term dynamic relationship depends on whether or not the absolute value (magnitude) of the equilibrium error is within a range defined by a threshold (i.e. lies below or above a critical threshold). This relationship can be represented in a threshold autoregressive (TAR) model, as described below.

Consider the Engle and Granger (1987) linear model that defines the dynamic long-run equilibrium relationship between input and output prices given in equation (2.2). Firstly, Engle and Granger (1987) recommended ordinary least square estimation of equation (2.2), where (y,x) are non-stationary variables, α and β are parameter estimates and μ_t is the error term which may be serially correlated. The residual from the estimation of equation (2.2) is used to test for unit root (no cointegration) following the standard Dickey-Fuller test using the equation (2.13).

$$\Delta\mu_t = \rho\mu_{t-1} + \varepsilon_t \qquad (2.13)$$

where ε_t is a white noise process. If the null hypothesis of no cointegration (i.e. $\rho = 0$) is rejected, the alternative of ($-2 < \rho < 0$) is accepted, implying the long-run equation (2.2) is stationary (cointegrated). Enders and Granger (1998) proposed that the Engle and Granger (1987) unit root test will be misspecified if adjustments are asymmetric. Therefore, to test for the stationarity of the error terms and incorporate asymmetric adjustment into the model, Enders and Granger (1998) and Enders and Siklos (2001) proposed that an alternative specification is to fit a threshold model, for example the threshold autoregressive (TAR) model. An example of a TAR process is

$$\Delta\mu_t = \begin{cases} \rho_1\mu_{t-1} + \varepsilon_t & if\ \mu_{t-1} \geq r \\ \rho_2\mu_{t-1} + \varepsilon_t & if\ \mu_{t-1} < r \end{cases} \qquad (2.14)$$

where r is the threshold value and ρ_1 and ρ_2 are the speed of adjustment parameters to be estimated. The sufficient condition for the stationarity of $\{\mu_t\}$ is that $-2 < (\rho_1, \rho_2) < 0$.

Petruccelli and Woolford (1984) defined the necessary and sufficient condition for the $\{\mu_t\}$ sequence to be stationary as $\rho_1 < 0, \rho_2 < 0$ and $\rho_1\rho_2 < 1$ for any value of the threshold r. Enders and Siklos (2001) rewrote the conditions as $\rho_1 < 0, \rho_2 < 0$ and $(1+\rho_1)(1+\rho_2) < 1$.

Due to the asymmetry, the threshold process may be non-linear and would require estimating the threshold cointegration in a multivariate framework. Tong (1983) showed that the least square estimates of ρ_1 and ρ_2 have an asymptotic normal distribution. This is quantified in Enders and Granger (1998) and Enders and Siklos (2001) as

$$\Delta\mu_t = I_t\rho_1\mu_{t-1} + (1-I_t)\rho_2\mu_{t-1} + \varepsilon_t \tag{2.15}$$

where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 & if\ \mu_{t-1} \geq r \\ 0 & if\ \mu_{t-1} < r \end{cases} \tag{2.16}$$

According to Enders and Granger (1998), the convergence to equilibrium is the point where $\mu_t = 0$. If μ_{t-1} is above its long-run equilibrium value, the adjustment is equal to the value $\rho_1\mu_{t-1}$ and if μ_{t-1} is below its long-run equilibrium, the adjustment is $\rho_2\mu_{t-1}$. Note that adjustment is symmetric if $\rho_1 = \rho_2$. If $\rho_1 \neq \rho_2$, the adjustment process is asymmetric.

Note that the residual errors in equation (2.15) must be white noise. In that instance, equation (2.15) is not sufficient to capture the dynamic adjustment of $\Delta\mu_t$ towards its long-run equilibrium value. Enders and Granger (1998) and Enders and Siklos (2001) suggested estimating a higher order process if the residuals are serially correlated. The higher order process is achieved by augmenting the TAR processes with lagged changes in the $\{\mu_t\}$ sequence. For example, equation (2.15) can be augmented as such that it becomes the p th-order process.

$$\Delta\mu_t = I_t\rho_1\mu_{t-1} + (1-I_t)\rho_2\mu_{t-1} + \sum_{i=1}^{p}\beta_i\Delta\mu_{t-1} + \varepsilon_t \tag{2.17}$$

Estimating equation (2.17) will require a diagnostic check of the residuals to determine the appropriate lag length (Tong, 1983). The test can be carried out with any diagnostic test statistics like the autocorrelogram of the residual test, the Ljung-Box test and the model selection information criterion tests. If series are cointegrated, error correction representation can be estimated by fitting equation (2.18).

$$\Delta y_t = I_t\rho_1\mu_{t-1} + (1-I_t)\rho_2\mu_{t-1} + \sum_{j=1}^{k}\beta_j\Delta x_{t-j} + \ldots\ldots\sum_{j=1}^{k}\beta_{nj}\Delta x_{nt-j} + e_t\,, \tag{2.18}$$

2.4.3.3 Momentum threshold autoregression (M-TAR)

An alternative threshold specification is the momentum threshold autoregression (M-TAR) model proposed by Enders and Granger (1998) and Enders and Siklos (2001). Note that in the TAR model (2.16) the Heaviside indicator depends on whether the threshold variable is above or below the long-run equilibrium path. In other words, the autoregressive decay is allowed to depend on the level of μ_{t-1}. Enders and Granger (1998) suggested an alternative process that allows the decay to depend on the first difference of threshold variable, μ_{t-1}. To allow for this, the Heaviside indicator is specified as follows:

$$I_t = \begin{cases} 1 & if\ \Delta\mu_{t-1} \geq 0 \\ 0 & if\ \Delta\mu_{t-1} < 0 \end{cases} \tag{2.19}$$

Note that the threshold models defined by equations (2.15) and (2.16) are known as TAR models, and equations (2.15) and (2.19), known as M-TAR models, can be estimated for known and unknown threshold value r. For instance, the TAR and M-TAR models can be estimated by assuming the value of r is zero, and also when the value of r is unknown. If r is set to zero, the cointegrating vector will coincide with the attractor. In the case of an unknown value of r, the consistent threshold estimate may be preferred to the attractor (Abdulai 2002). According to Enders and Granger (1998) and Enders and Siklos (2001), it is better to estimate the consistent threshold with the best-fitting model selected by means of Akaike's information criterion (AIC) and/or Schwarz's Bayesian information criterion (BIC).

TAR and M-TAR cointegration tests have been used by several analysts to investigate asymmetric price transmission. Abdulai (2000) used TAR and M-TAR cointegration models to study the relationship between the central maize market in Techiman and local markets in Accra and Bolgatanga in the country of Ghana. The threshold cointegration and asymmetric error correction models revealed that wholesale maize prices in the local market respond more rapidly to increases than to decreases in the central price. Abdulai (2002) then went on to examine short-run adjustment in producer-retail price changes in Switzerland using TAR and M-TAR cointegration models. Asymmetry was found to exist between the producer-retail market price transmission. In both the 2000 and 2002 studies, Abdulai found the M-TAR model to be a better fit than the TAR model in modelling the asymmetric price relationship. Grasso and Manera (2005) applied the TAR and M-TAR method to confirm the asymmetric price relationship in the gasoline markets of France, Germany, Italy, Spain and the United Kingdom over the period 1985-2003. In this study, TAR and M-TAR models are used to investigate the asymmetric price relationship in the poultry (broiler) market in South Africa.

An important challenge in the analysis of TAR or M-TAR is the confirmation of the presence of the threshold effect, as well as the selection of optimum lags and the threshold value that delineate the adjustment regimes. These important issues are discussed in the next section.

2.4.3.4 Selecting the threshold lags

The procedure developed by Tsay (1989) was used to select the threshold lags (p, k, d). Firstly, the autoregressive order p, and other threshold lags were arbitrarily selected. The autoregressive (AR) order (p) was selected using a partial autocorrelation function (PACF), which measures correlations between time-series observations that are k time periods apart after controlling for correlation at intermediate lags (Enders, 2004). If the ADF test conducted on the residual of the OLS-level regression is lagged k times, the number of p can be determined from the number of AR coefficients that are significant from the t-ratio. The AR order may differ from regime to regime and from one linear combination to another. AIC can be used to select p (Tong & Lim, 1980). Tsay (1989) used PACF, because AIC best define linear models and could be misleading if the process is non-linear. PACF provides a good approximation for non-linear models, and it can also be refined if desired. The delay parameter d defines the number of lags appropriate to the error correction term in the threshold autoregression.

The equilibrium error determines the regimes. Because it could take more than one period for regime switch to occur, regime switch is allowed to occur according to the value of equilibrium error lagged d times where d = 1, 2, 3…. Tsay (1989) suggested that the choice of d is optional, although many researchers prefer d to be one. Other parameters can also be used to select the value of d. For instance, the value of d can be chosen by minimising the AIC or BIC, especially when the optimal value of p and the threshold depend on the value of d. Tong and Lim (1980) used AIC while Tsay (1989) proposed a procedure based on the performance of the F-statistics. If the AR order p is known, Tsay (1989) suggested selecting a d value that maximises the F-statistics. For purposes of this study, d was chosen based on PACF.

2.4.3.5 Non-linearity test

Many procedures have been developed to test for the presence of threshold effect in the cointegrating series. Most tests are based on a process of examining the residual of the linear combinations for the presence of residual autocorrelation. One of the most popular residual-based tests is Tsay's (1989) F-test, which is based on arranged autoregression and predictive residuals. Significant F-statistics of the resulting regression reject the null hypothesis of linearity and confirm the presence of non-linearity in the series. Non-linearity in the series indicates the presence of a threshold effect. Non-linearity is a necessary condition for TAR, without which the basis for the threshold cointegration analysis is not credible. If non-linearity is confirmed, the threshold values can then be estimated.

An important feature of the Tsay (1989) non-linearity test is that it performs well for both small and large samples. This study used the Tsay (1989) approach to test for non-linearity in the threshold cointegration analysis.

2.4.3.6 Estimating the threshold value

The aim with this is to locate the number and location of potential threshold value(s). Tsay (1989) suggested using internal estimate or point sample percentiles as point estimates to locate thresholds. Accordingly, thresholds may not be found at the extreme points on the percentile due to a lack of sufficient observations to provide efficient estimates. Excluding the lowest and the highest 10 % of the data is suggested (Enders, 2004; Tsay, 1989). Balke and Fomby (1997) suggested using the interior 80 % of the arranged sample, the reason being that the number of observations in the algorithm search is expected to be reasonable enough to increase the chances of locating a potential threshold. Thus, the threshold must lie between the maximum and minimum values of the data. A minimum of at least 20 observations is recommended for the search in each regime. Each data point within the chosen band is treated as a potential threshold. The search for thresholds is carried out on the residuals arranged in ascending order.

For the TAR model, arranged autoregression orders the data according to the value of the potential threshold variable rather than by time (Balke & Fomby, 1997; Tsay, 1989). Tsay (1989) pointed out that arranged autoregression provides a means whereby the data points are grouped so that all of the observations in one group follow the same linear AR model. However, arranged regression allows more power in discerning thresholds according to which data is concentrated in a particular regime at either end of the arranged series (Goodwin & Piggott, 2001). It does not change the dynamic relationship between the dependent variable and its lag, but if the data follows a threshold model, the threshold translates to structural breaks in the arranged series (Trenkler & Wolf, 2003).

A grid search algorithm is used to locate threshold values, and different grid search algorithms can be embarked upon. For example, Obstfeld and Taylor (1997) used a grid search to obtain thresholds that maximise a likelihood function, while Balke and Fomby (1997) used a grid search that minimises the sum of squared error criterion. Tsay (1998) used a grid search that minimises AIC. For each data point, the TAR model equations are estimated until all the observations within the band are exhausted. At the end of the algorithm search, the regression containing the smallest residual sum of squares contains the estimate of the threshold.

Tsay (1998) used a graphic device developed by Chan (1993) to find the consistent estimate of a threshold. The sum of squared residuals (SSR) from a grid search in an arranged autoregression is plotted in a graph. The idea is that the SSR will form local minima at a threshold. The closer to the true threshold, the smaller the SSR should be. Hence, the SSR should be minimised at the true value of the threshold. If there is a single threshold, there should be a single trough; if multiple thresholds exist, the SSR will have several local minima. A grid search that minimise SSR error criterion was used in this study.

2.4.4 Vector autoregression (VAR)

Asymmetric price transmission, which is often analysed with a single-equation specification of the autoregressive (AR) and threshold autoregressive (TAR) univariate models, can also be modelled with system equation multivariate methods or vector autoregressive models. Multivariate models differ from single-equation models in the manner in which the cointegration parameters are determined. For instance, in the case of the single-equation models of Engle and Granger (1987) as discussed in section 2.4.3, only one cointegrating parameter is estimable, but in a multivariate vector cointegrating relationship, one or more cointegrating vectors may be estimated. As with the univariate models, error correction models can be specified in the VAR framework provided there is a cointegration relationship. Similarly, threshold vector error correction (TVEC) models can be fitted.

VAR and TVEC models are used to account for non-linear and threshold-type adjustment in error correction models. These models are said to be suitable for asymmetric adjustments to deviations in response to price shocks when the standard linear AR or TAR models proposed by Engle and Granger (1987) become inadequate to measure cointegration because price adjustments are non-linear and asymmetric. However, Enders and Granger (1998) recommended an alternative to multivariate asymmetric price analysis. According to Enders and Granger (1998), the least square estimate of the coefficient of equilibrium adjustment has an asymptotic multivariate normal distribution, which can be easily generalised to a higher-order TAR process. Taking this into consideration, M-TAR approximates multivariate vector asymmetric price analysis. Therefore the VAR and TVEC models are not considered in this study. Instead, asymmetric price transmission is investigated using the TAR and M-TAR models.

2.4.5 Bias in the analysis of asymmetric price transmission

There has been a general lack of conformity in the empirical tests of asymmetric price transmission in the literature. This is as a result of the lack of consistency in the analytical approach and the econometric models used, which in some cases leads to empirical findings that are not reliable. For example, studies that ignore equilibrium relationships have been accused of bias in the inferential results. Recently, threshold cointegration and error correction models have been augmented with a first difference specification of the threshold variable to account for the momentum effect and avoid bias due to model misspecification (Enders & Granger, 1998). In addition, a number of other issues that might lead to bias in the results of asymmetric test have been identified as follows:

> **Size distortion and power property of unit root test.** The procedure, power property and size distortions of the unit root test can influence the results of long- and short-run asymmetric price analysis. The common procedures for the evaluation of unit root hypothesis are the Dickey-Fuller (DF), augmented Dickey-Fuller (ADF) and Phillips-Perron tests. These tests have been criticised for size distortions if the

underlying series have a moving average component, made worse if the moving average is large (Gujarati, 2003; Maddala & Kim, 1998). Gujarati (2003) suggested that the power property of the unit root test may depend on many factors. According to Gujarati (2003), for a given sample, the power of the test is greater when the series is larger. For example, if the series is non-stationary and the random walk component has arbitrarily small variance, the unit root test will have little power in small samples (Cochrane, 1991). Furthermore, if the parameter coefficient of the test is closer to unity, the test may fail to reject the null hypothesis due to lack of power. Normally, in the unit root test, the null hypothesis of I(1) is tested against the alternative of I(0). If the series being examined is integrated of the order I(2), the conventional unit root test will perform poorly. However, Gujarati (2003) suggested that no uniformly powerful test for unit root exists thus far in the literature. The ADF and Johansen multivariate test have been widely applied and were adopted in this study to evaluate the stationarity of the price data.

Null and alternative hypothesis underlying unit root test. The **c**onventional unit root test is based on the null hypothesis of unit root or the absence of cointegration (non-stationarity) against the alternative hypothesis of stationarity. Phillips and Ouliaris (1990) and Kwiatkowski, Phillips, Schmidt and Shin (1992) acknowledged that the power properties of many standard tests depend critically on the choice of the null and alternative hypothesis. The choice of unit root null hypothesis has been criticised based on the fact that most standard unit root tests suffer from size distortion and lack of power, which leads to under-rejection of the unit root null hypothesis (Kwiatkowski *et al.,* 1992). To solve this problem, the use of cointegration (stationarity) as the null hypothesis has been suggested (Kwiatkowski *et al.,* 1992). Kwiatkowski *et al.* (1992) tested for both level and trend stationarity using the null hypothesis of cointegration. According to those authors, the null hypothesis of trend stationarity corresponds to the modified version of the Lagrange multiplier hypothesis that the variance of the random walk equals zero. The random walk is assumed to be normal and errors are white noise. Kwiatkowski *et al.* (1992) suggested simultaneous testing of the null hypothesis of stationarity, as well as the unit root. However, the result under the null hypothesis of stationarity performs better than the null hypothesis of unit root (no cointegration) (Kwiatkowski *et al.,* 1992).

Structural stability of time series. Most economic policy reforms impact greatly on the structural stability of macro-economic time series. Hence, it is appropriate to account for structural shift when analysing economic variables, especially prices, because failure to detect and account for structural change will result in misspecification, poor performance and inferential bias. Structural instability affects the results of unit root tests. Unit root tests that ignore structural shift will be biased towards under-rejecting the hypothesis of I(1) when the series has a deterministic time trend with a structural shift (Boetel & Liu, 2008:3). Perron (1989) tested for unit root considering structural breaks as an exogenous event. This implies that economic shocks to the series occur exogenously. Since the work of Perron (1989), many studies have adopted a different approach by assuming that shocks to economic series do not occur exogenously, but are aberrant events that occur endogenously (Banerjee, Lumsdaine & Stock, 1992; Christiano, 1992; Perron & Vogelsang, 1992; Zivot & Andrews, 1992). Bai and Perron (1998; 2003) tested for structural breaks in a linear model by considering multiple breaks with unknown timing. This procedure selects the break date by minimising the sum of squares residual allowing for the case in which some parameters of the model can change. This test is more flexible than Perron's (1989) and its modified versions. Bai and Perron (2003) showed that the break fraction identified under this procedure is consistent and converges to the true fraction at a faster rate of T, allowing one to obtain the standard root-T consistency and asymptotic normality for the estimated parameters (Boetel & Liu, 2008:3). Bai and Perron (2003) used dynamic programming to implement the procedures described by Bai and Perron (1998). This study used the dynamic programming of Bai and Perron (2003) to test for structural change while considering multiple breaks.

Direction of causality. In asymmetric price transmission modelling, it is commonly assumed that upstream (output) prices cause downstream (output) prices. Therefore many studies model output prices' response to changes in input prices, implying that causality runs from input to output price. If causality flows in the opposite direction, the relationship between input and output prices will be misspecified. This can be avoided by testing the direction of causality statistically.

Multicollinearity. Houck (1977) pointed out that the problem of multicollinearity may arise in asymmetric price transmission tests if variables are segmented into positive and negative components. This problem is common in models that include the recursive sum of positive and negative price changes as regressors. Examples are the models discussed in section 2.4.2. According to Meyer and Von Cramon-Taubadel (2004), these models, compared to cointegration and error correction models, are unlikely to reject symmetry, but spuriously some of them find significant asymmetric price relationships.

Data frequency and aggregation. Von Cramon-Taubadel and Loy (1996) pointed out that tests for asymmetric price transmission require data with a frequency that exceeds the frequency of the adjustment process. If price adjustments occur faster than usual, say within weeks or days, it is inappropriate to examine asymmetric price relationships with lower-frequency data like monthly, quarterly or yearly. While monthly data has been widely used to study asymmetry, Meyer and Von Cramon-Taubadel (2004) suggested that the use of quarterly data has no basis for the testing of asymmetry. This is because as data frequency becomes lower, the speed of adjustment coefficient (a measure of long-run equilibrium adjustment) approaches unity. This implies that instead of being quick and dynamic, adjustments takes too long to occur (Von Cramon-Taubadel, 1998).

Data aggregation has also been cited as a possible source of bias in asymmetric tests. Von Cramon-Taubadel and Loy (2006) compared data at a disaggregated level (individual retail stores) and the corresponding national aggregates and found systematic differences between the results of estimation using the two data sets. According to their findings, disaggregated data performs better. Due to limited time and lack of adequate research fund to collect disaggregated data, the study at hand encompassed data aggregated at national level.

Missing data. Missing data consists of observations in the time series or survey samples that are missing. A data set containing missing observation(s) is incomplete. If not handled appropriately, missing observations introduce ambiguity and bias into statistical analysis. It does not matter if data is missing in either the response or explanatory variables or both, the properties of the estimators will be affected – for example, the means, percentages, percentiles, variances, ratios, and regression parameter estimates. To ensure that statistical analysis produces consistent estimators and that the statistical inferences are valid under the null hypothesis, researchers have adopted various measures to deal with missing data. However, the way in which missing data is handled depends on the level of the researcher's statistical expertise.

The most common, naïve and ad hoc approaches to handling missing data are: (a) list-wise deletion approach; (b) simple mean imputation approach; (c) regression mean imputation approach; (d) adding extra category approach; and (e) carrying last observation forward. With the list-wise deletion approach, cases with missing data are omitted and analysis is carried out on the remaining data set. Some computer software (for example E-views) ignores the omitted values and computes estimators based on the observed data. This approach is inefficient, especially when too many data points are missing. It is problematic when covariate values are missing and models with several sets of explanatory variables need to be compared (Carpenter & Kenward, 2005).

With the simple mean imputation approach, the arithmetic mean of the observed data is computed and the computed mean is substituted for the missing data. This approach is inappropriate, because it will lead to improper estimation of measures of association and will underestimate standard errors. Moreover, it increases sample size without adding any new information to the data as any of the missing data sets would. The regression mean imputation approach is used in some instances to predict the value of the missing data based on the values of the observed data. This is carried out by regressing the incomplete data with a set of random draws or instrumental variables and substituting the predicted mean for each missing data point. This method is more efficient than the simple mean imputation approach, but has certain limitations. The variability of the imputation is too small and therefore the estimated precision of the regression coefficient will be incorrect, resulting in misleading inferences. Some approaches involve carrying the last observation forward to replace the missing value. In some instances where categorical variables have missing data, it is common practice to add an extra missing value category.

None of these ad hoc approaches are still in use, because more robust and modern approaches exist to appropriately impute the missing data. These approaches are based on the assumption that the missing observations are (i) missing completely at random (MCAR), (ii) missing at random (MAR), and (iii) missing not at random (MNAR). These assumptions are important, because the nature of the missing data – that is, the missingness mechanism – is not known and cannot be determined from the observed data. Under these assumptions, the distribution of the missing data is estimated given the observed data.

Several methods are used to impute missing data. For example, the linear mixed model-based approaches perform some form of integration or averaging over the missing data. Other approaches include the weighted method, the simple stochastic imputation method, and the multiple imputation method. The weighting method and the simple approach (Rao & Shao, 1992) are much less precise than the multiple imputation approach (Rubin, 1996). The multiple imputation approach is preferred, because it produces more statistically valid estimates (Rubin, 1996). The multiple imputation approach, unlike the simple method, creates variability by imputing several (at least five) plausible sets of missing values in the incomplete data based on the observed data, thus resulting in several completed data sets. The completed data sets are then analysed separately using a standard regression software package by fitting a particular regression model (Raghunathan, Lepkowski, Van Hoewyk & Solenberger, 2001). The estimates of the regression are then combined using Rubin's rule[2].

Multiple imputations can be achieved through the classical or Bayesian framework. Use of the Bayesian approach is common, because it is straightforward. According to Raghunathan *et al.* (2001), the Bayesian framework simply specifies a model for the missing data based on the observed data and also sets *a priori* distribution for the unknown parameters and a model for the missing data mechanism. The model then generates a posterior predictive distribution of the missing values based on the observed values. This method was used to impute missing observations in the retail meat price series for purposes of this study.

[2] For Rubin's rule, see Meng and Rubin (1992), Raghunathan *et al.* (2001) and Rubin (1996). Note that the original 1987 reference book for Rubin's rule could not be accessed by the researcher.

2.5 COMMODITY PRICE VOLATILITY

In the previous sections, it was demonstrated that a vertical market relationship may lead to oligopolistic competition resulting in price movement that is asymmetric. In this section, the asymmetric volatility and volatility spillovers in the price process is discussed. Many analysts, for example Tomek and Robinson (1990), have found that most agricultural commodities are volatile in relation to non-agricultural commodities. The volatility in this sector can be attributed to several factors, including the lag and seasonality in the production and marketing of agricultural products, the inelastic supply constraint of agricultural commodities, and the effect of macro-economic instability – resulting chiefly from exposure to exchange rate volatility, which has an impact on the terms of trade. Commodity price volatility is a major concern for most economies, because it affects the decisions taken by producers and consumers and plays a crucial role in commodity-related investments where returns are expected. Economic projects often fail due to volatility in economic prices, putting pressure on project appraisals and strategic planning. Due to the impact of commodity price volatility on general economic activity, an important concern for producers, policymakers and strategic analysts in the business circle is to measure the level of volatility and forecast the impact of current and future changes in prices on investment returns.

However, a problem arises in attempting to predict future prices, because the predictable and unpredictable component of the price process depends on the information sets that may or may not be available to the agents. The major concern in this study lies in determining how this affects the price expectation in the agricultural sector. This concern is based on the notion that producers and market agents are rational in the sense that their expectations of price levels and volatility reflect some form of adaptive expectation; that at any time their expectation of the distribution of future prices is a function of past realisations (Moledina, Roe & Shane, 2003). Intuitively, they are deemed to have the ability to detect regular features in the price process, from which they may generate a probabilistic assessment about the predictable and the unpredictable components of the process from one period to another. The predictable component constitutes the price variability that the agents can anticipate from one period to another, while volatility is the unpredictable component of the future price process. The question is how an accurate measure of volatility can be determined given its unpredictability. This question is explored in the next section.

2.5.1 Measuring volatility

Since the unpredictable component of volatility is not observable, Dehn (2000) and Moledina *et al.* (2003) suggested modelling the predictable elements using an approach that is capable of distinguishing between unpredictable and predictable components. The approaches used thus far to measure volatility include the unconditional standard deviation or coefficient of variation method (see Negassa *et al* 2003), the Black-Scholes-Merton method (NAMC, 2003), the autoregressive models, such as the autoregressive integrated moving average (ARIMA) model (Moledina *et al.,* 2003) and some family of econometric volatility models such as the autoregressive conditional heteroskedasticity (ARCH) method, the generalised ARCH (Rezitis, 2003) and the exponential GARCH methods (Buguk *et al.,* 2003).

The unconditional standard deviation method adopts the standard deviation as a measure of volatility. The approach is said to be inappropriate to measure volatility for the following reasons: (a) The approach treats all price movement as unpredictable (Dehn, 2000), implying that past realisations of price and volatility have no influence on the current and future realisations (Moledina *et al.,* 2003); (b) It does not control for the predictable component of the price evolution process, hence it does not distinguish between unpredictable and predictable components of the price process; and (c) If the price process is trended, this method will overstate the degree of volatility (Dehn, 2000).

The time-series ARIMA model is used to distinguish between the predictable and the unpredictable components of the price process. To obtain the predictable elements of the price process, Dehn (2000) suggested removing the predictable components of the price process (e.g. seasons, time trends, inflation, etc.) in an ARIMA model and using the standard error of the regression as a measure of volatility that accounts for the unpredictable components of the price process.

The approach treats as predictable the past values and trends of the series, including seasonal components that are captured as accumulated knowledge by the agents (Moledina *et al.,* 2003). It should be borne in mind that apart from measuring the level of volatility in commodity markets, it is important to determine whether volatility (if any) across periods persists. Volatility persistence is an indication of the level of efficiency in the market economy, because an efficient market system restores equilibrium rapidly, and in that instance the effect of shocks is transitory. However, whether the effect of price shocks is transitory or permanent depends on the process that generated the shocks. Another important aspect is asymmetric price volatility and the tendency for volatility to spill over from one market to another. These aspects are relevant in the time-series volatility literature and cannot be wholly determined using the ARIMA model.

The ARIMA model has a particular limitation in that volatility is time invariant and cannot account for periods of changing volatility. One approach that distinguishes between unpredictable and predictable components of the price process and at the same time allows for variance of the unpredictable element is the family of autoregressive conditional heteroskedasticity (ARCH) models, namely the generalised autoregressive conditional heteroskedasticity (GARCH) models, the integrated GARCH (IGARCH), the absolute GARCH (AGARCH)[3], the exponential GARCH (EGARCH), etc.

[3] The IGARCH and AGARCH models are outside the scope of this study and will not be discussed further. For more details on these models, readers are referred to any standard econometrics textbook.

2.5.2 ARCH and GARCH models

Conventional econometric models like the ones described in section 2.4 assume that the variance of the disturbance error term is constant. Such assumptions have been criticised as being inappropriate, because according to Enders (2004) and Engle (1982) the error variances in most linear time-series models are heteroskedastic. The autoregressive conditional heteroskedastic (ARCH) time-series model proposed by Engle (1982) is used to address the problem of heteroskedasticity. The ARCH models are mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but with constant unconditional variances.

In an ARCH model, the conditional error variance of the time series is represented by an autoregressive (AR) process, with conditional variance equal to a linear function of past squared errors[4]. Consider an AR(1) process,

$$y_t = \alpha + \beta y_{t-1} + \varepsilon_t \qquad (2.21)$$

In the absence of conditional heteroskedasticity, the $\{\varepsilon_t\}$ sequence has a mean of zero and a constant variance, and all autocorrelations between ε_t and ε_{t-i} are zero. Assuming that the conditional normally distributed errors sequence $\{\varepsilon_t\}$ has zero mean and conditional variance of h_t, the ARCH (p) representation is:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 \qquad (2.22)$$

where p is the order of the ARCH process and α_i is a vector of unknown parameters. The model is stationary if $\alpha_0 > 0; 0 < \alpha_i < 1$. This model is used to analyse periods of volatility and tranquillity within the univariate framework.

Bollerslev (1986) generalised the ARCH model by allowing the conditional variance of the error process to be an autoregressive integrated moving average (ARIMA) process. The resulting model is known as the generalised autoregressive conditional heteroskedasticity (GARCH) model. In the case of a GARCH model, the conditional variance depends not only on the past values of the time series, but also on a moving average of the past conditional variance. According to Bollerslev (1986), this allows for a more parsimonious representation of the data. To specify the GARCH (1,1) model, consider the error sequence of equation (2.21):

[4] A more general specification of the ARCH model may contain exogenous and lagged endogenous variables (Nelson, 1991).

$$\varepsilon_t = v_t(\alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-q})^{0.5} \tag{2.23}$$

Where v_t is a multiplicative disturbance (Engle, 1982) the $\{v_t\}$ sequence is $i.i.d \sim N(0,1)$ (Enders, 2004; Lundbergh & Terasvirta, 2002), $\varepsilon_t = v_t(h_t)^{0.5}$, hence the relationship between h_t and ε_t^2 is $\varepsilon_t^2 = v_t^2 h_t$, since $Ev_t^2 = E_{t-1} = 1$, $E_{t-1}\varepsilon_t^2 = h_t$. Equation (2.21) models the mean of the $\{y_t\}$ sequence while equation (2.23) models its variance, and the (p,q) are the orders of the GARCH model. The GARCH (p,q) model is defined as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{2.24}$$

Where $\sum_{i=1}^{p} \alpha_i \varepsilon_{t-1t-j}^2$ and $\sum_{j=1}^{q} \beta_j h_{t-j}$ are the moving average (MA) and the autoregressive (AR) components of the GARCH (1,1) model respectively (Peseran & Pesaran, 1997). To ensure covariance stationarity and non-negativity of the conditional variance, the following conditions must be fulfilled: $\alpha_0 > 0$; $\alpha_i, \beta_j \geq 0$ and $\sum \alpha_i + \sum \beta_j < 1$. According to Peseran and Peseran (1997), a well-defined GARCH has $\alpha_0 > 0$; $|\beta_j| < 1$, and $1 - a_i - \beta_j > 0$. This restriction ensures that the unconditional variance of ε_t given by $\sigma^2(\varepsilon_t) = a_0 / (1 - a_i - \beta_j)$ is positive.

The GARCH model is suitable for the modelling of conditional volatility in time series. It has been widely applied to model volatility in financial markets, such as in risk management, portfolio analysis and derivative asset pricing (Chu & Freund, 1996; Roh, 2007). Bollerslev, Engle and Wooldridge (1988) used multivariate GARCH (1,1) to test a conditional capital asset pricing model (CAPM) with time-varying covariances of asset returns. This has been applied to model exchange rate volatility (Ghebrechristos, 2004; Vilasuso, 2002) and volatility in agricultural commodity markets (Dehn, 2000; Moledina *et al.*, 2003). The National Agricultural Marketing Council (NAMC, 2003) used the GARCH model to measure volatility in beef prices. The presence of discrete spikes and secular increases in the conditional standard deviation of the beef price indicates the volatility prevalent in the beef price during the sample period (May 1994 to July 2003). Rezitis (2003) investigated volatility and volatility spillover effects between producer and consumer prices in the lamb, beef, pork and poultry markets in Greece using the GARCH approach. According to Rezitis (2003), there is relative uncertainty in the producer-retail price movement and the degree by which price uncertainty at one market level influences price uncertainty in another market.

2.5.3 Exponential GARCH model

Although the GARCH model has been widely used to model changing conditional variance in asset returns in financial markets and the conditional volatility in agricultural commodity markets, it has some limitations that weaken its theoretical appeal and empirical success. Nelson (1991) pointed out that the GARCH model has some drawbacks: (i) the GARCH model posits positive autocorrelation in the conditional variance (i.e. large (small) changes in the conditional variance are followed by large (small) changes in either sign) and ignores the fact that the conditional variance may be negatively correlated with future changes in prices or stock volatility, which implies that volatility is measured only by the magnitude and not the sign of the conditional variance; (ii) the GARCH model imposes non-negativity constraints on the parameters of the model to avoid the conditional variance being negative. The implication of this assumption is that the one-period-ahead-forecast conditional error variance will always increase if the squared standardised residual increases. This assumption does not allow for a situation where, due to random oscillatory movements, the conditional error variance could be negative.

According to Nelson (1991) the GARCH model lacks simplicity because its implicit restrictive assumptions make it difficult to explicitly achieve the desired result; hence the restrictions are often violated by the estimated coefficients. In addition, it requires much skill to fit the GARCH model, since in most instances the researcher restricts the coefficients to ensure convergence and non-negativity (see Dehn, 2000). To increase computational simplicity and empirical success in modelling conditional variance, Nelson (1991) proposed a model called the exponential GARCH (EGARCH) model, which possesses features that are more attractive than those of the GARCH models. Fundamentally, it is required that the conditional variance of the error sequence is non-negative with a probability of one; however, the practical approach to this concept between different volatility models such as GARCH and EGARCH differs. To ensure non-negativity in the variance, the GARCH model makes the conditional variance a linear combination of the positive random variables using a positive weight. This ensures that the coefficient from the model is non-negative.

Unlike the GARCH model, the EGARCH model does not impose non-negativity restrictions on the estimated coefficient. Instead, to ensure that the conditional variance remains non-negative, it uses the log linear form of the conditional variance (at a given set of time) and the lagged standardised residuals, i.e. the log of the variance is conditional on its own past values, as well as a function of the standardised residual. A typical EGARCH model is shown as follows:

$$\log(\sigma_t^2) = \exp\left[\psi + \sum_{i=1}^{q} a_i g(z_{i-1}) + \sum_{k=1}^{p} b_k \log\left(\sigma_t^2\right) + \right] \tag{2.25}$$

where $\{\psi_t\}_{t=-\infty,\infty}$ and $(a_t)_{t=1,\infty}$ are real (positive or negative) and non-stochastic (stationary) scalar sequences and z is the standardised residual (Nelson, 1991). To accommodate asymmetrical relationships between prices and volatility changes, the model considers both the magnitude and sign of the standardised residuals. The coefficients are therefore allowed to be negative or positive, which implies that the response to price changes could be asymmetrically positive or negative, thus measuring the asymmetric impact of shocks as follows:

$$g(z_t) \equiv \theta z_t + \gamma[| z_t | - E | z_t |] \qquad (2.26)$$

The term $[| z_t \} - E | z_t |]$ captures the ARCH or GARCH effect. The parameter θ allows the ARCH or GARCH effect to be asymmetric. In an EGARCH model, the persistence of shocks is interpreted differently from that of GARCH models. Practically, the coefficient of GARCH or integrated GARCH (IGARCH)[5] models could be explosive or approximate unity even under strict stationarity and ergodic conditions (Nelson, 1991). In the EGARCH model, this is different. The regularity condition of the EGARCH model requires that the coefficient associated with persistence be less than unity. The persistence of volatility is measured by the absolute value of the parameter $\sum_{k=1}^{p} b_k < 1$ in equation (2.25). The smaller the value of b, the less persistent volatility is after a shock.

2.5.3.1 Volatility spillover

Agricultural commodity prices often change within and across seasons. Changes in consumer demand and supply constraints like seasonal fluctuations, climate and production lags are some of the factors that cause prices to fluctuate. Price expectations also play a major role in that prices tend to fluctuate across growing seasons as new information regarding expected production and demand reaches the market. Goodwin and Schnepf (2000) found that futures market activities, the ratio of stock use and the growing conditions influence the volatility of corn and wheat in the United States of America (USA). Other studies have found that price volatility influences market expectations. For example, Buguk, Hudson and Hanson (2003) showed that volatility in one market channel influences price expectations in the alternate market and that the relationship is often asymmetric. Buguk *et al.,* (2003) investigated the extent to which volatility in the primary input markets for soybeans and corn spills over into prices at the catfish feed, farm and wholesale levels. A strong spillover effect was found to flow from corn, soybean and menhaden to farm and wholesale catfish prices. The study found the spillover effects to be unidirectional, implying a one-way flow of market influence.

[5] This is a member of the ARCH family in which shocks are usually persistent because the coefficient of the model always approximates unity. Nelson (1991) referred to this type of model as a natural model of persistence.

The risk and uncertainty caused by price volatility has also been investigated. Haigh and Bryant (2001) investigated the extent to which transportation price risk affects price dynamics in international grain markets. They found that volatility in transport cost has an impact on both the prices and marketing margins of the grain industry in the USA. In the same vein, this study investigated the extent to which volatility in the primary input markets – sunflower oilseed, soybeans and yellow maize – spills over into farm and retail prices. The EGARCH model is best suited for this exercise and was used for this purpose.

2.6 SUMMARY

This chapter reviewed the theories, assumptions and approaches used by economists and agricultural economists to study asymmetric price and volatility transmission in the vertical market.

Market relationships can be categorised as spatial, inter-temporal or vertical (Barrett, 1996). Inter-temporal markets are linked inter-temporarily. Spatial price relationship relates to price linkages across spatially distinct markets where market arbitrage depends on whether the price difference is above or below the transaction cost. The vertical market relationship consists of a set of economic stages that are involved in the transformation and distribution of commodities. The vertical market relationship is categorised according to whether market exchange is based on open market operations or internal organisation by the firms involved. Theories have been propounded to explain why a firm would prefer one market structure to another. Economists suggest three main determinants of vertical integration that occur through the internal organisation of market exchange, namely technological economies, transactional economies, and economies due to market imperfection (Garcia *et al.*, 2004; Lawrence *et al.*, 1997). Technological economies are the economies of scope or scale that result from reduced total cost due to increased production efficiency. Transactional economies refer to cost of exchange, while market imperfection refers to incentives for vertical integration that are created by market failure.

Economic theory states in principle that the allocation of scarce economic resources should reflect their economic value, thus maximising producer and consumer welfare. In practice, however, welfare distribution is skewed because of inefficiency in the economic system of production, distribution and marketing. The structure, conduct and performance of the different economic units have roles to play in the equitable distribution of welfare. For example, in the market economy, an asymmetric price relationship in a vertical market has been found in some cases to result in welfare redistribution from one market to another or in total welfare loss (Meyer & Von Cramon-Taubadel, 2004). This is because upstream market participants pass on increases in market costs more rapidly to downstream markets than cost decreases. Also, responses towards price changes in the upstream market by downstream participants are relatively slow.

This asymmetric price relationship has been a matter of concern for economists and agricultural economists for more than two decades. Many assumptions have been put forward to explain the cause of this phenomenon. It is assumed that due to adjustment cost considerations, menu cost, search cost, market power, tacit collusion and government interventions, firms may pass on cost increases to consumers more rapidly and completely than cost decreases, resulting in a harmful asymmetric price relationship. In some instances, asymmetric price transmission can benefit consumers. For example, Ward (1982) demonstrated that retailers selling perishable goods may not raise their prices as producer prices increase for fear of being left with spoilt goods. In this case, consumers will benefit from lower prices in the midst of increased producer costs, and in doing so consumers tend to react more rapidly to cost decreases than to cost increases.

Approaches to the empirical measurement of asymmetric price transmission vary. Earlier studies on asymmetric price transmission ignored the long-run cointegration relationship (Farrell, 1952; Houck, 1977; Peltzman, 2000; Tweeten & Quance, 1969; Ward, 1982; Wolffram, 1971; Zhang *et al.*, 1995). Due to the progress made in the modification of statistical and analytical methods, these studies are assumed to give an inaccurate account of the asymmetric price relationship. The cointegration and error correction approaches have opened up a new era in the estimation of asymmetric price transmission. In this new era, short-run economic behaviour is integrated with the long-run equilibrium price relationship. In the cointegration and error correction specifications, cointegration ensures the presence of long-run equilibrium while the error term measures deviation from the equilibrium relationship. This is consistent with the Granger representation theorem of Engle and Granger (1987).

The potential for asymmetric non-linearity and threshold-type adjustments in error correction models has recently been recognised (Goodwin & Holt, 1999; Von Cramon-Taubadel, 1998). Regime-switching models have recently been used to account for non-linearity and the discontinuous adjustment to equilibrium relationship, which is not accounted for by the cointegration and error correction approach. This discontinuity is captured in the threshold autoregressive (TAR) and momentum threshold autoregressive (M-TAR) models. With the TAR model, the autoregressive decay depends on the state of the variable of interest, while the M-TAR model allows the degree of autoregressive decay to depend on the first difference of the variable. These models have been used by analysts to give consistent estimates of asymmetric price relationships (Abdulai, 2000; 2002).

Further diversification in the methodology has been considered in the modelling of asymmetric price transmission. Enders (2004) and Engle (1982) suggested that economic time series may be heteroskedastic in contrast to the conventional assumption of constant error variance. Autoregressive conditional heteroskedasticity (ARCH), the generalised autoregressive conditional heteroskedasticity (GARCH) and the exponential autoregressive conditional heteroskedasticity (EGARCH) models have been used to address this problem. In the ARCH model, the conditional error variance is represented by an AR or ARIMA process, with conditional variance equal to a linear function of past squared errors. In the GARCH model, the conditional variance depends not only on the past values of the time series, but also on the moving average of the past conditional variance. In the EGARCH model, the log of the variance is conditional on its own past values, as well as a function of the standardised residual. The EGARCH model was used in this study to measure the level of volatility in poultry meat prices and the volatility spillover effect between producer and retail prices.

CHAPTER 3

OVERVIEW OF THE SOUTH AFRICAN POULTRY INDUSTRY

3.1 INTRODUCTION

This chapter provides an overview of the South African poultry industry. The main focus is a review of the South African economic features that influence the micro and macro environment in the poultry industry. A review of the South African agricultural sector is given with an emphasis on the poultry meat sector and the factors that contribute to price instability in the sector. The chapter concludes with a chapter summary.

3.2 SOUTH AFRICAN AGRICULTURE IN PERSPECTIVE

Agriculture is an important sector in South Africa for a number of reasons. Firstly, it is a major source of employment for the rural poor. It is estimated that about 16 million South Africans are poor, while 72 % of the poor live in the rural areas where the majority depend on agriculture for sustainable livelihoods (NDA, 1998). Nonetheless, formal agriculture, forestry and fishery provided employment to 13.844 million people out of an estimated total population of 49.321 millions in South Africa in 2009. This represents about 28 % of the populace (DAFF, 2010). Agriculture has strong forward and backward linkages with other sectors, providing raw materials and intermediate products to the manufacturing sector while utilising inputs from the industries. It is estimated that 68 % of the agricultural output is used as intermediate products in the sector (NDA, 2008). International trade in agricultural commodities earns foreign exchange. For instance, the total agricultural export in 2008 was R46.93 million (DAFF, 2010). Therefore, the sector is important for the growth and development of the entire economy.

Despite its potential, the agricultural sector faces many challenges. It is dualistic with a well-established commercial sector and resource-poor subsistence and emerging farming sectors. This dualism in terms of sectors has been attributed to the pre-democratisation policy measures that seriously distorted agricultural development. Policy changes to correct these inequalities have been in place since 1998. Amongst the policies are the introduction of the land reform programme and the restructuring and deregulation of the financial and agricultural markets, including the replacement of quantitative import controls with tariffs, the fiscal treatment of agriculture – including the removal of tax concessions – as well as a reduction in budgetary allocation, and land and institutional reforms. Subsequently, as a result of these changes, there has been a shift from strict and rigid control measures to a more market-oriented agricultural economy.

With the repeal of the 1968 Marketing Act and the adoption of the Marketing of Agricultural Products Act (Act no. 47 of 1996), the price-setting, quality standards, sale and supply of agricultural products are now market driven. As a result of the deregulation and liberalisation process, the economy has become integrated with the global market and therefore the commodity market has become sensitive to global competition.

3.3 SOUTH AFRICAN POULTRY VALUE CHAIN

This study of the South African poultry value chain involves the analysis of the extended network of organisations that are involved in the adding of time, form and space value to poultry products from the farm gate (production unit) through agro-processing, distribution and marketing until these products reach the final consumers. It also includes participants in logistics, finance, information technology, industry-governing bodies, regulatory agents and national representative organisations that interact with one another on different levels within the framework of the organised poultry product value chain in South Africa. The South African poultry value chain is schematically shown in Appendix A.1.

3.3.1 Market share in the poultry industry

3.3.1.1 Concentration

The poultry sector is grouped into the egg, broiler, and day-old-chick industries. This study focuses on the poultry meat value chain, and therefore only the broiler industry is considered in the investigation. There is a high level of concentration in the broiler industry. The two largest producers, namely Rainbow and Astral, dominate the industry, together accounting for 54 % of the market share in the broiler industry (Table 3.1). The standing production capacity of these two firms amounts to 4.1 million and 3.4 million birds per week, respectively. Country Bird produces more than 1.2 million birds (9%) while other medium-sized firms, namely Tydstroom, Daybreak, Chubby Chick, and Rocklands, account for 15 % of the market share, with each producing more than 400 000 birds per week. Argyle owns 2% of the market with more than 300 000 broilers per week. The informal and subsistence producers and small, medium and micro enterprises (SMMEs) account for the remaining 20 %. According to a report by the NDA, NAMC and Commark Trust (2007) there are approximately 1 745 informal, subsistence and SMME poultry producers in the country. Of these, about 49 producers (DAFF, 2009) account for more than 90 % of production, while the remaining producers account for the balance (NDA, NAMC & Commark Trust, 2007). This implies that there is also a high level of concentration among the small and emerging producers.

3.3.1.2 Vertical integration

Firms in the production stages of the broiler industry show a high level of vertical integration, because most of the broiler firms either have links with feed mills or are part of or a subsidiary of other broiler production firms. For example, the Astral Foods Group has links with Meadow Feeds, while Rainbow has links with Epol. In addition, Tydstroom has links with Pioneer Foods, while Country Bird has links with Senwesco Voere (NDA, NAMC & Commark Trust, 2007). Daybreak is a subsidiary of AFGRI, while Rocklands is a subsidiary of Sovereign Food Investments.

Table 3.1 Role players in the poultry industry

Name of firm	Standing production capacity (Broilers per week)	Market share (%)
Rainbow	4.1 million	29
Astral	3.4 million	25
Country Bird	1.2 million	9
Tydstroom	>400 000	4
Daybreak	>400 000	4
Chubby Chick	>400 000	4
Rocklands	>400 000	4
Argyle	>300 000	2
SMMEs	500 000	20
Other	>200 000	

Sources: DAFF (2009); NDA, NAMC and Commark Trust (2007)

Country Bird is a subsidiary of Astral Foods (DAFF, 2009), while Astral has a 50 % share in Early Bird. Only eight producers account for 80 % of the broilers entering the poultry meat value chain, while the SMMEs and small emerging farmers account for 20 %. It should also be noted that the poultry value chain includes feed companies, breeders and contract growers. There are about 27 feed companies, 37 breeders and about 207 contract growers in South Africa. Meadow, Epol and Agfri make up a 75 % share of the feed industry (Appendix A.1). Cobb Birds, Ross and Hybro Birds are the three primary breeders, with Cobb Birds and Ross being the main suppliers of day-old chicks in the country. These firms have linkages with major contract growers like Early Bird, Country Bird and Rainbow. Hybro Birds is a franchise of Tydstroom and as such is contracted to supply day-old chicks to Tydstroom only.

3.3.2 Trends in poultry meat production

It is estimated that in South Africa there are 296 poultry abattoirs, 42 of which are high-throughput, about 187 are low-throughput, 12 rural and 55 other abattoirs (SAPA, 2008). Poultry abattoirs supply the carcasses of slaughtered birds to the market through processors or packers that process poultry meat into meat products or through the retailers for sale as processed and/or fresh meat to consumers.

The poultry industry is estimated to be the largest agricultural sector, contributing significantly to total agricultural production. The sector contributed approximately an average of 16.78 % of total agricultural production between the 2005/6 and 2006/7 production years (Figure 3.1). The percentage contribution increased during 2008/09. During this period, the total gross value of agricultural production in South Africa was R130.7 billion; poultry industry had the largest contribution of R22.5 billion, representing 17.18 % of the total value of agricultural production (DAFF, 2010).

According to the National Department of Agriculture (NDA, 2007) about 599 million broilers were slaughtered during 2004, representing a 0.6 % increase from the number slaughtered in 2003. This number rose to 608 million in 2005, about 1.6 % higher than in 2004. The annual slaughter for 2006/07 is estimated at 778 million broilers at 1.91 kg live weight and 1.32 kg carcass weight (DAFF, 2009). There was a 39.7% overall increase in the number of broilers slaughtered from 2000 to 2009. The number of birds slaughtered in 2000 was 666.6 millions, this increased to 931.4 million in 2009 (SAPA, 2010). The producer value of broilers slaughtered, including offal, during 2009 was about R18 200 million. The average weighted price received by producers of broilers increased by 16.4 %, from R14.95/kg in 2008 to R17.88/kg in the first half of 2009.

The industry also plays a role in global broiler meat production. For instance, of the 202 countries listed as producing 73.6 million tons of world broiler meat in 2007, South Africa occupied 15th position with a market share of 1.3 %. The USA, China, Brazil and Mexico topped the world chart in poultry meat production in that year. These four countries controlled 50 % of the world's broiler production in 2007, led by the USA with a 21.7 % market share, followed by China (13.9 %), Brazil (11.8 %) and Mexico (3.4 %) (SAPA, 2008).

3.3.3 Trends in poultry meat consumption

Economic theory suggests that people's consumption patterns change as their incomes increase. In addition, people (especially in less-developed countries) consume less traditional carbohydrate staples but more meat products as development and civilization improve. Since the democratisation of South Africa in 1994, the average disposable income of households has increased following a period of steady economic growth. The average disposable income per capita of households measured at 2005 constant price increased from R18 286 in 1998 to R22 529 in 2009 (South African Reserve Bank, 2009). In light of the changes in disposable income and economic activities, the overall consumption pattern of the population has changed, with meat and meat products claiming a greater share of the consumer rand than other food items in the average South African's food basket. It is estimated that meat and meat products comprise 32 % of the consumer rand, which is by far the largest share (NDA, 2006). In terms of the nation level grocery expenditure on meat classified by the living standard measure (LMS 1-10)[6], the middle class (LSM 4 to 6) spend a larger share of their grocery food budget on meat compared to the upper (LSM 7 to 10) and lower (LSM 1 to 3) classes (Meyer, Vermeulen, Taljaard and Jooste, 2008). According to report by Meyer *et al.* (2008), the middle class dominates the grocery spending on beef and poultry, the upper class

[6] The living standard measure (LSM) is a marketing tool developed by the South African Advertising Research Foundation (SAARF) which is used to categorize consumers based on their socio-economic status. Consumers of least socio-economic status form the segment LSM 1 and those of the highest status, LSM 10.

dominate the spending on mutton/lamb and pork, whereas lower class spend most of their income on poultry, followed by beef, mutton/lamb and then pork. The report also shows that poultry has the highest percentage contribution to the national aggregate meat expenditure, contributing a 16.7% share of the meat and meat product basket.

Since 1991/92 white meat (broiler meat) which makes up the largest proportion of poultry meat sold has surpassed beef as the principal meat type in the food basket (NDA, 2006). This can be attributed to the following factors: (a) The average consumer (retail) price of broilers is relatively lower than the price of red meat; (b) There is a marked technological advancement in the production of poultry meat in terms of improvements in quality, taste and hygiene; (c) Several domestic and global outbreaks of disease epidemics have reduced consumer confidence in red meat; (d) The volume of production of white meat makes it more easily available than red meat, which also contributes to the lower price and gives white meat an advantage over red meat; (e) It is more convenient to rear, slaughter, process and consume broilers than any of the animals in the red-meat category; (f) Consumers are more health conscious now than ever before and they therefore prefer foods that pose less of a health hazard, for example foods with a lower fat content. The per capita consumption of the different meat categories is shown in Figure 3.2.

It is estimated that the per capita consumption of broiler meat increased by about 34 % from 16.7 kg to 22.41 kg during the period 1994-2005 (NDA, NAMC & Commark Trust, 2007). According to SAPA (2008), the per capita consumption of broiler meat increased by 1.2 % between 2007 and 2008, going from 29.6 kg meat per person per annum to 30.5 kg per person per annum. The NDA, NAMC and Commark Trust (2007) suggest that the increase is partly driven by imports, domestic expansion and a more value-added chicken supply. SAPA (2008) attributes this increase to a proper response to consumer demand by the poultry industry in terms of meeting consumer expectations through quality, brand-names and convenience and not by merely meeting supply needs. Per capita consumption increased from the 2008 estimate of 30.5 to 30.71 in 2009 (SAPA, 2010). It is expected that the per capita consumption of broiler meat in particular and poultry meat in general will continue to rise if the South African economy continues to grow.

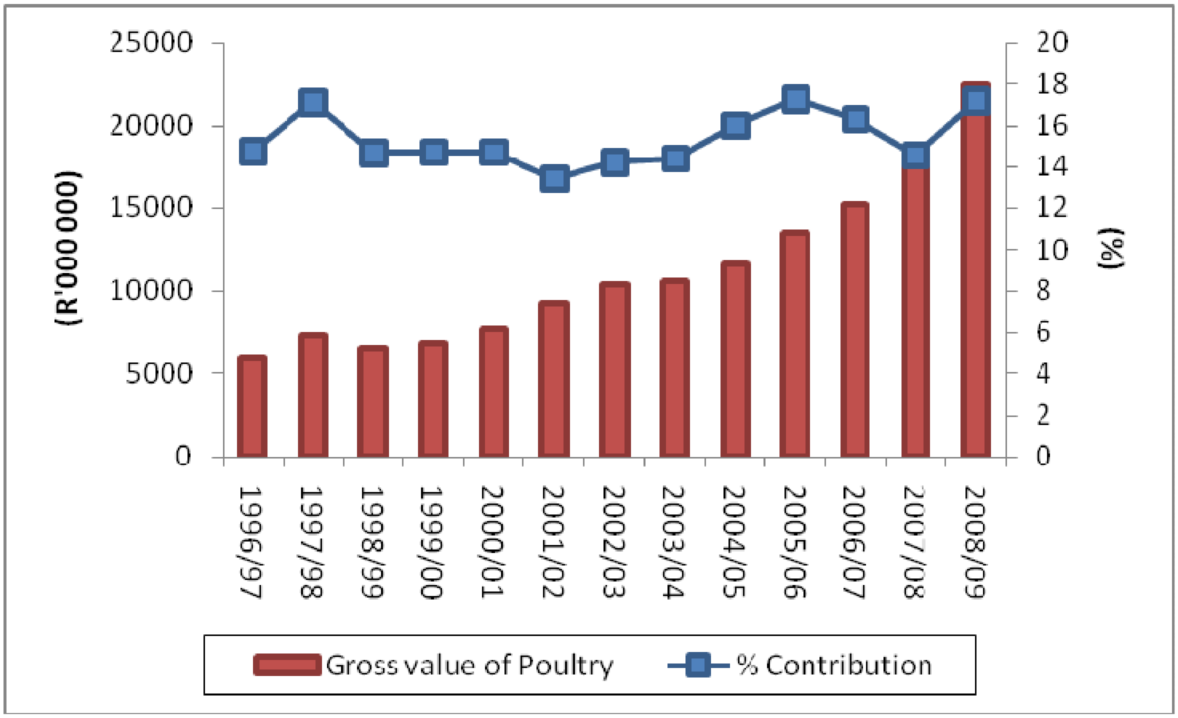


Figure 3.1 Gross production values of poultry
Source: DAFF (2010)

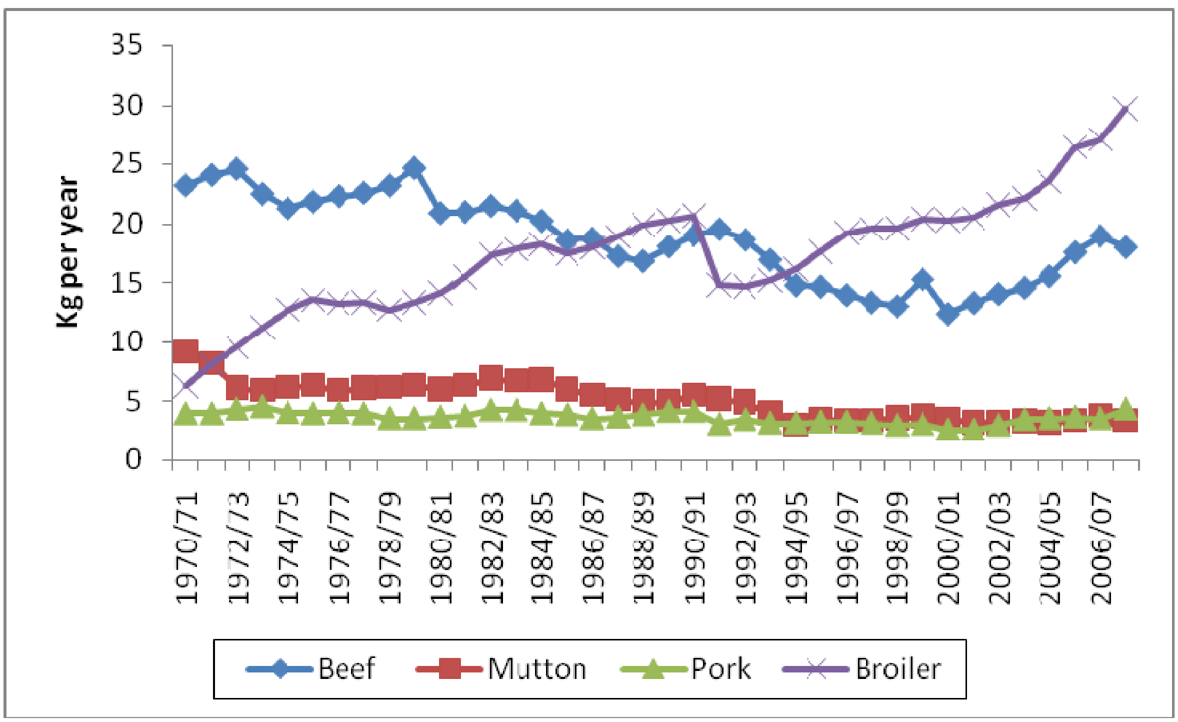


Figure 3.2 Per capita consumption of broiler meat and red meat
Source: DAFF (2009)

The average production and consumption of broiler meat over the past decade is shown in Figure 3.3. It can be seen from Figure 3.3 that the average consumption of broiler meat increased steadily from 1998 to 2008. The consumption of pork and mutton are relatively lower than the average consumption of beef and broiler meat as average household disposable income increases (Figure 3.4).

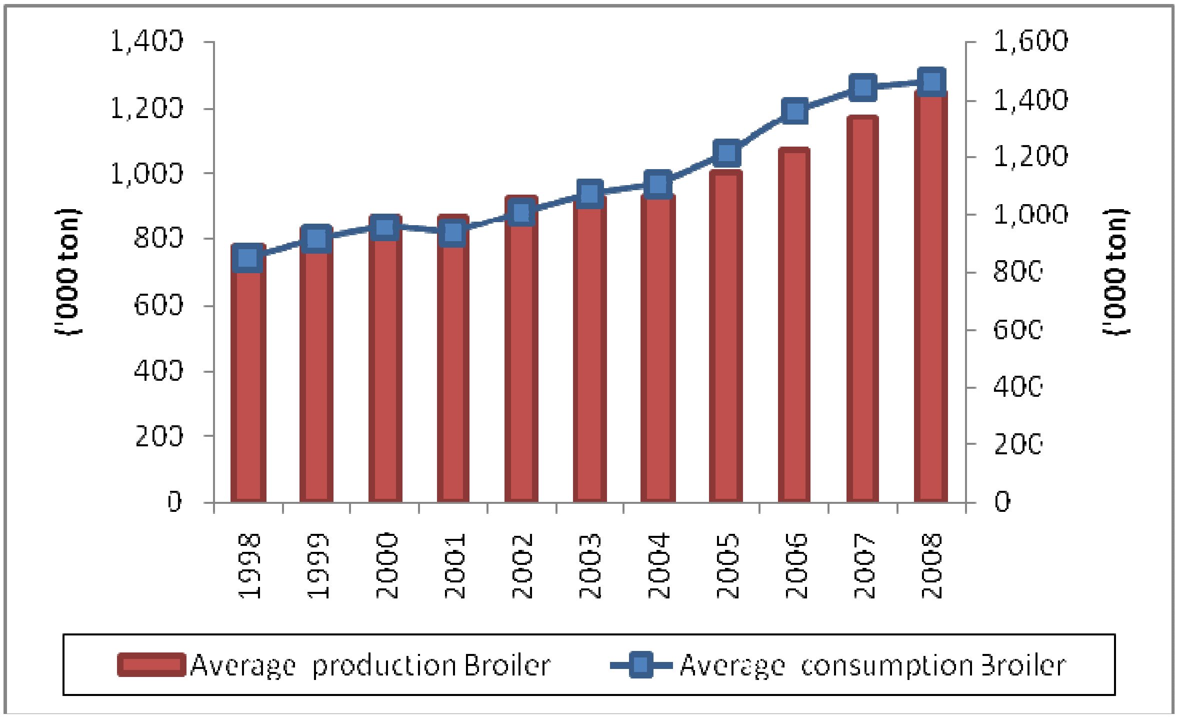


Figure 3.3 Average production and consumption of broiler meat
Source: DAFF (2009)

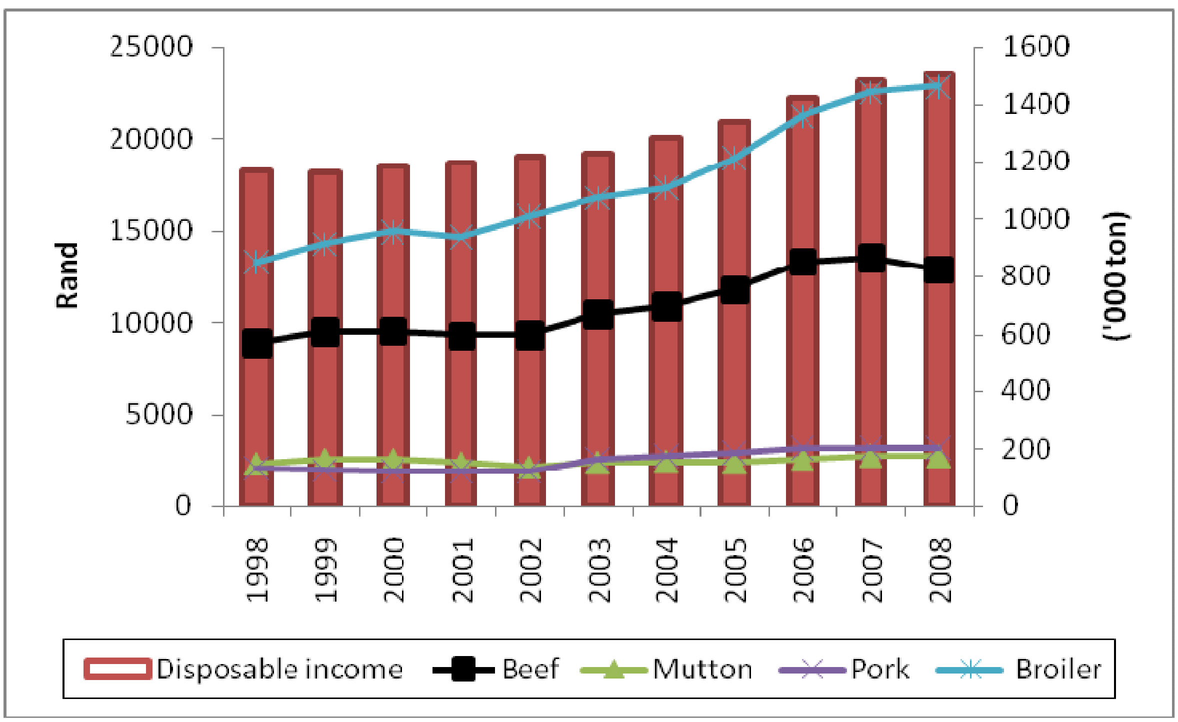


Figure 3.4 Disposable income and meat consumption
Source: DAFF (2009); South African Reserve Bank (2009)

3.4 FARM-RETAIL PRICE SPREAD

Price transmission has been described in Chapter 2 as playing a major role in a market economy. In this section, the farm-retail price spread for broilers is described.

The price of meat and meat products reflects the following: (a) The payment to the farmer for the raw materials utilised in the production of the animal units; (b) The remuneration of the farmer for his entrepreneurship; and (c) The activities that occur from the time the product leaves the farm gate – such as processing, distribution (transportation) and marketing (wholesaling and retailing) – until the time the product reaches the consumer. In other words, meat prices comprise both farm prices paid to the producer and the cost of value-adding activities that take place before the meat reaches the final consumer. As a result of the value-adding process and the mark-ups in the marketing chain, the farm and retail prices are often not equal. The retail price (the price that consumers pay for meat) is invariably higher than what farmers receive. This is as a result of mark-ups as the product travels along the distribution and marketing chain. The gap between the two prices is a reflection of the nature of price movement and the degree of efficiency in the food marketing system. The level of efficiency is captured by measuring the relationship between the farm and the retail prices – a concept also known as the farm-retail price spread.

A narrow gap between the retail and farm prices implies that there is price stickiness at the retail level, which is beneficial to the consumers. This can also mean lower transaction cost along the value chain, low cost of value adding or no value adding at all. In such an instance price parity between market channels will be lowered. On the other hand, in an inflationary regime marked by market failure, the economic process of value-adding widens the gap, reduces the farmer's profit margin due to high marketing or transaction costs, and reduces the farmer's share in the consumer's rand.

The farm-retail price spread is statistically measured by fitting an appropriate empirical mark-up pricing model (Heien, 1980; Kinnucan & Forker, 1987). The mark-up pricing model is built on the assumption that the retail price is a function of farm price and some exogenous vector of market inputs with underlying assumptions of Leontief production technology, constant return to scale and competitive markets

Due to lack of availability of time-series data on the variables of interest, the farm-retail price spread could not be fit using an empirical pricing model in this study. Instead, a graphical representation of the relationship is used to relate the farm value to its retail-level equivalent. The farm-retail price spread for the broiler meat market is shown in Figure 3.5. It can be seen that from January 2000 to August 2008 the real retail price for the broiler sector increased slightly by 5.83 %, while the real producer price declined by 14.46 %.

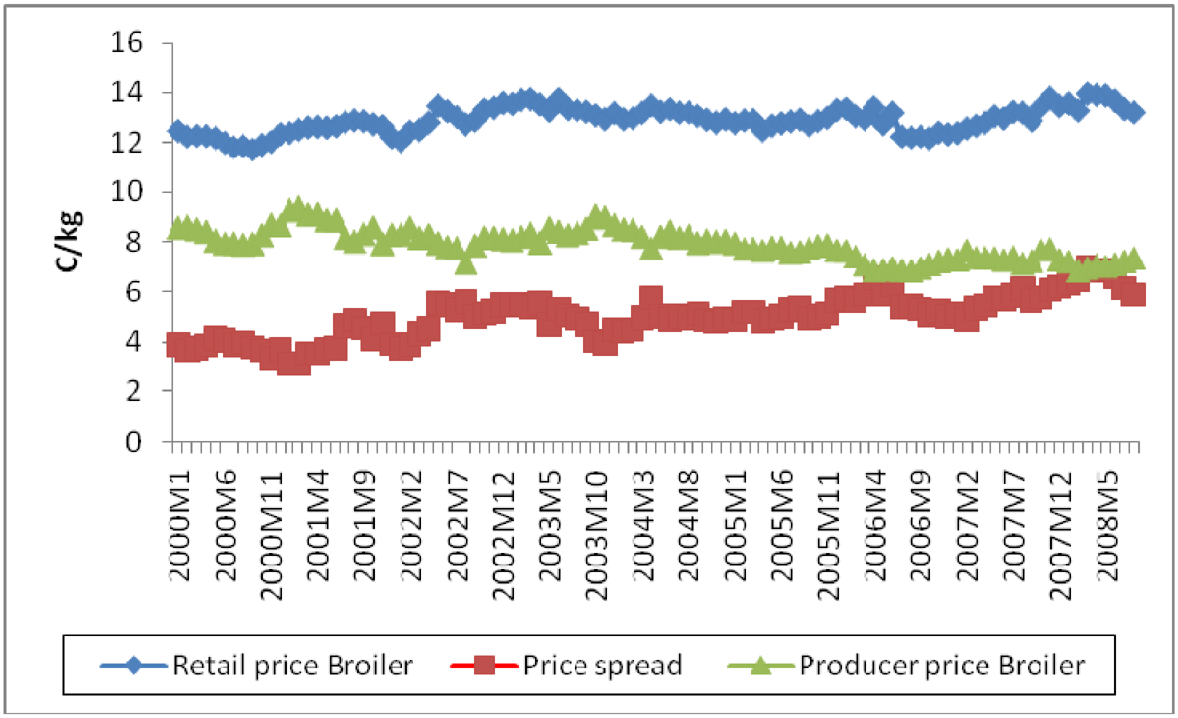


Figure 3.5 Real farm-retail price spread for broiler meat
Source: Author's compilation

3.5 OTHER CHALLENGES FACING THE POULTRY INDUSTRY

Challenges in the poultry sector include climatic, environmental and structural or institutional changes that affect competitiveness, productivity and efficiency in this sub-sector.

3.5.1 Access to productive resources

One of the major challenges facing the poultry industry is lack of an adequate productive base, support services, and market infrastructure. Land, capital and labour are important factors in production and should not have a limiting effect. Land ownership is a critical issue in South Africa. Under the land reform programme, the government is committed to transferring 30 % of all white-owned agricultural land to previously disadvantaged individuals by 2015. Practically, the land-transfer process has been slow and marred by criticisms. Land is being transferred to large numbers of beneficiaries who lack the potential to optimally utilise the land. The government has so far maintained that land reform is aimed at ensuring equitable access to land and increasing the capacity of the majority of the people for broader agricultural productivity.

The lack of equitable access to productive resources such as land and financial support is a major constraint to both emerging and commercial livestock production. Poultry farmers cannot access credit from banks if they do not have collateral security such as land or enough livestock to stand as an equity base. The cost of production inputs makes matters worse, as farmers face a cost price squeeze. Input prices are constantly increasing at or above the inflation rate while producer prices increase marginally or remain stagnant for extended periods of time. This situation impacts on the long-term growth and sustainability of the existing poultry enterprise and reduces incentives for potential entrants into the industry.

Competitiveness and productive efficiency in the poultry sector can also be linked to infrastructural development. Access to market infrastructure such as adequate market information and accessible transportation networks is essential.

3.5.2 Producer support services

On the international front, the playing-field is not level because there are differences in the tariff regimes and the level of support in agriculture for most of South Africa's trade partners. For example, producers from developed countries receive subsidies and export rebates while in South African there are relatively low and declining levels of support to producers. The Organization for Economic Co-operation and Development (OECD, 2006) estimated that the aggregate percentage of the producer support estimate (PSE) for South Africa between 2000 and 2003 was 5 % of gross farm receipts. Figure 3.6 shows the PSE by country, European Union (EU) and OECD average. A comparison of producer support in South Africa with the principal world agricultural players shows that the percentage PSE in South Africa is roughly at the level of such non-OECD economies as Brazil, China and Russia, as well as such OECD countries as Australia, while it is somewhat above that of New Zealand (Figure 3.6). The support level in South Africa is well below that in the United States (US) and far below that in the EU (OECD, 2006).

The OECD (2006) reported that at commodity level, there is an uneven distribution of support across commodity groups. The PSE by commodity range for South Africa is shown in Figure 3.7. The OECD (2006) gave the average percentage PSE as 5 %. It can be seen from the chart that mutton is the only livestock product that has above-average support, which is predominantly in the form of border protection. The beef sub-sector receives below-average support – about 0.8 % - while poultry (broilers) has a negative PSE, implying that this sub-sector receives no meaningful agricultural support from the government.

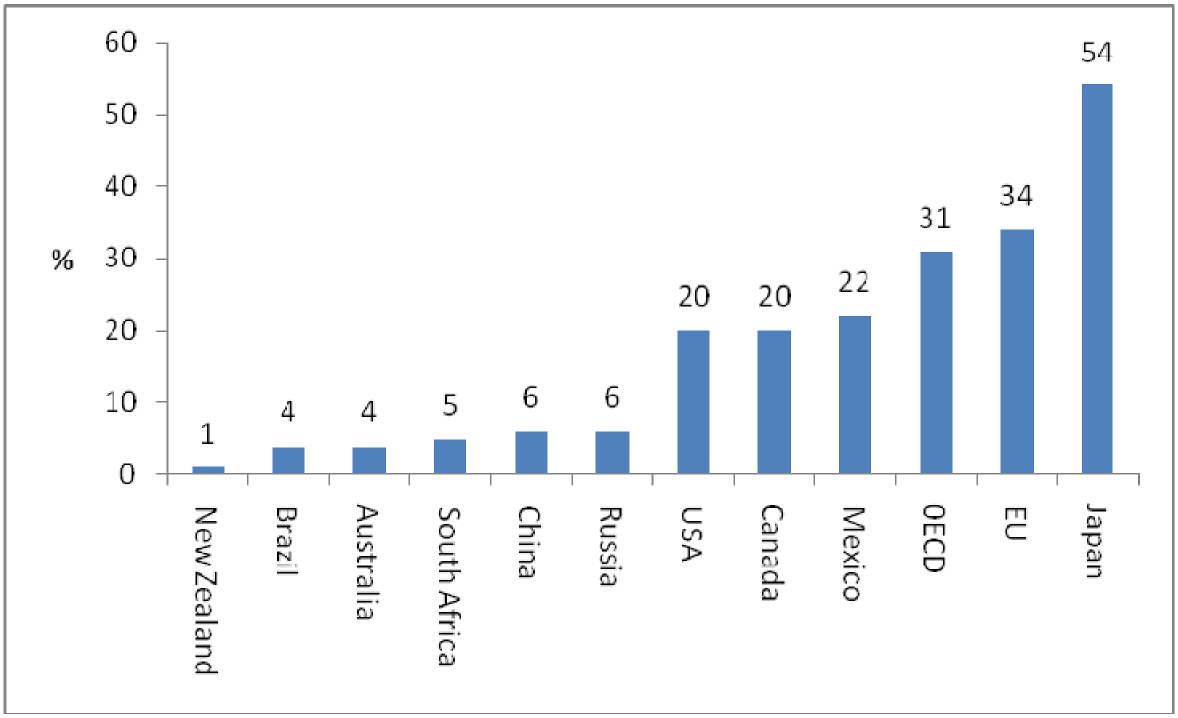


Figure 3.6 Producer support estimate for global agriculture
Source: OECD (2006)

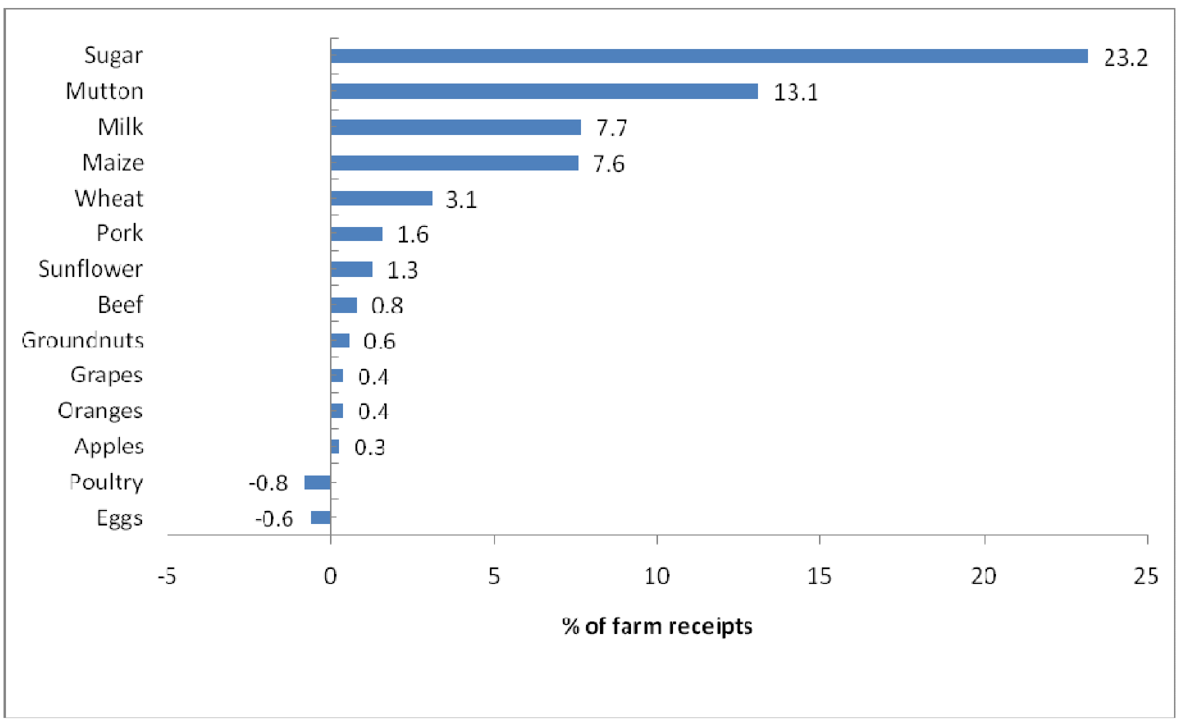


Figure 3.7 South African producer support estimate by commodity
Source: OECD (2006)

3.5.3 Disease prevalence

Disease poses a major threat to poultry farmers. The disease factor has major economic implications in terms of both the private and public cost of any disease outbreaks and the cost of the measures taken at individual, national and international level in order to prevent or control infection and disease outbreaks. At individual and national level, there is a potential major loss of revenue when infected animals have to be destroyed, along with the variability of animal supply and price fluctuations. Moreover, there are trade-related losses due to import and export embargos to and from the affected area or region.

Some of the most important invasive poultry diseases are Newcastle disease and avian influenza. The most recent outbreak of Newcastle disease in the country occurred between January 2006 and April 2007. Diseases constrain the supply of animals and animal products, reduce consumer confidence, and destroy international trade relations.

3.5.4 Changes in input costs

Input costs are the operational costs incurred at the different economic stages of production, processing, distribution and marketing. Input costs consist of feed prices, veterinary services (including the cost of medicines), packaging costs, transport costs, labour, and other miscellaneous costs such as stationery, utilities and transactions such as taxes, levies and commissions paid to market agents. Such costs play a significant role in determining the market margins and the percentage mark-ups of the different role players in the value chain. At the producer level, feed costs constitute a major portion of the total input costs in the poultry sector. In the poultry industry, the cost of feed is a major challenge, since it is estimated to constitute over 60 % of total input costs in the broiler and layer industries (FPMC, 2003). Apart from the need to achieve maximum output at the lowest cost, quality is also built into the feed ration combination, hence the need for optimal production.

A major factor influencing the cost of feed is the cost of the individual items used in the poultry feed formulation. The major components of these ingredients are yellow maize, sunflower oilcake and soybean oilcake, although their inclusion rates in feeds differ. About two million tons of yellow maize is used annually by the Animal Feed Manufacturing Association (AFMA) to produce animal feed. This represents about 30 % of the average maize harvest. In addition, 534 000 tons of soybean and 212 000 tons of sunflower oilcake are used (NDA, NAMC & Commark Trust, 2007).

The inclusion rate of maize in the total production of feed rations is above 50 %, while oilcake makes up 20-35% of the volume (FPMC, 2003). This implies that the maize price has a major influence on the evolution of poultry prices. Since maize and oilseeds make up more than 70 % of animal feed composition, intuitively, changes in the price of these commodities should affect the price of animal feeds.

The price of maize and other feed components is influenced by several factors, including the prevailing exchange rate, the size of local crop harvests, and import parity. The exchange rate affects the commodity price through its impact on the cost of imported inputs. For instance, South Africa is a net importer of soybean cake for livestock feeds and maize is imported to augment domestic production during shortages. The prices of these inputs are also determined by the domestic supply. If there is a supply shock, demand pressure domestically puts upward pressure on prices. The price of maize is chiefly influenced by the difference between the domestic price and the price that local producers will pay to import the maize (import parity), which is a function of Chicago Board of Trade (CBOT) prices.

The impact of other factors such as packaging, transport, labour and miscellaneous costs on the poultry value chain cannot be overlooked. Processors, meat-packers, wholesalers and retailers incur costs through the amount spent in purchasing packaging materials such as plastic containers, paper wrapping and so on. Transport costs, labour costs and others miscellaneous costs like levies and commissions are also inhibitive.

3.6 TRENDS IN BROILER IMPORTS

The poultry industry is the fastest growing meat industry in South Africa due to increasing demand. It is also for this reason that poultry must be imported to augment domestic supply. The majority (75.8 %) of imports into South Africa originate from Brazil (Figure 3.8). Broiler meat accounts for 86.1 % of all poultry imports, with the balance being largely made up by turkey products (SAPA, 2008). About 16.2 % of broiler consumption in 2007 originated from imports, while this percentage dropped to 13 % in 2008. According to the DAFF (2009), the import value of broiler meat increased by 28.62 % in 2007 compared to 2006, while the quantity of imports decreased by 4.14 % during the same year.

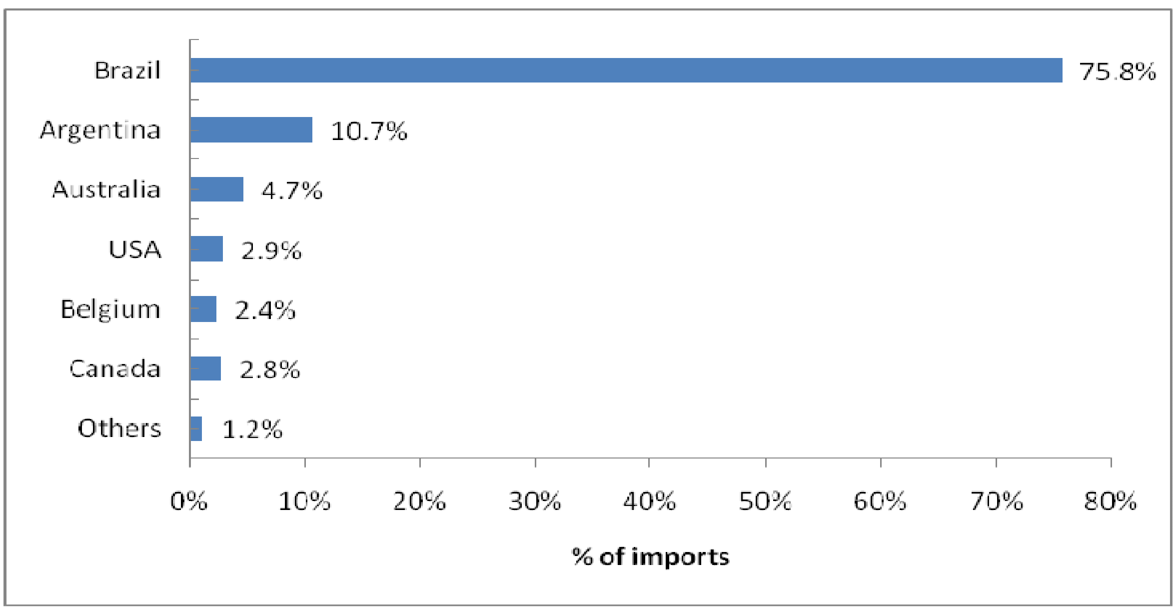


Figure 3.8 Poultry imports
Source: SAPA (2008)

The quantity imported further declined from 281 429 tons in 2007 to 222 886 tons in 2008, representing a 21 % decrease from the 2007 estimate (SAPA, 2008). This decline in imports is attributed purely to exchange-rate dynamics (weaker rand) and the world financial crisis. Broiler meat imports from 1998 to 2007 are represented in Figure 3.9.

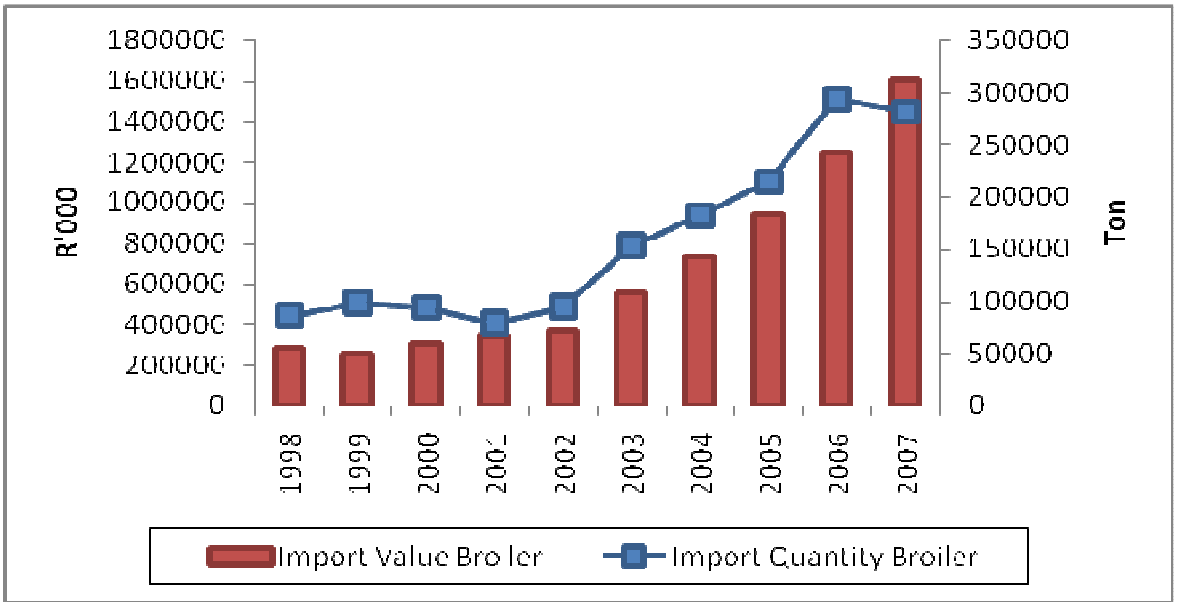


Figure 3.9 Import value and quantity of broiler meat
Source: DAFF (2009)

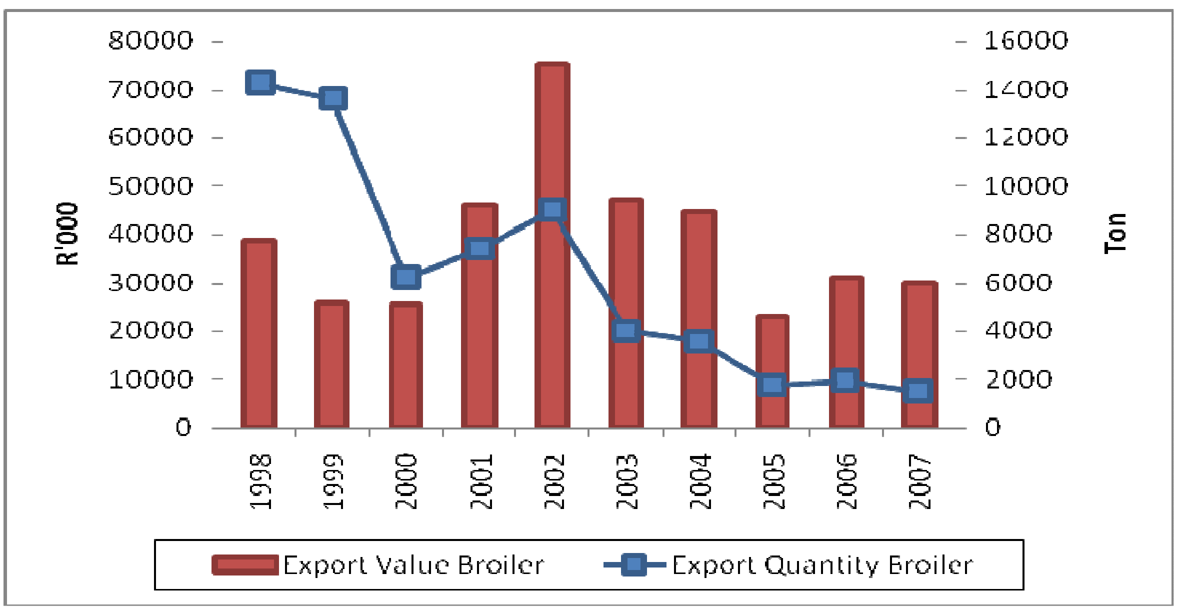


Figure 3.10 Export value and quantity of broiler meat
Source: DAFF (2009)

3.7 TRENDS IN BROILER EXPORTS

There was a major drop of about 54.19 % in the quantity of broiler meat exported between 1999 and 2000. Overall broiler exports show a decline over the depicted period (Figure 3.10).

3.8 SUMMARY

The South African livestock sector contributes significantly to food security and sustainable macro-economic growth. For instance, livestock products accounted for 47.5 % of the total agricultural output value in 2008 (NDA, 2008).

The livestock sector has undergone some major changes since liberalisation in 1995 and deregulation of agriculture in 1997. It is now exposed to demand and supply shocks and also to competition from both local and international markets. In spite of these, the livestock sector has remained strong, contributing significantly to the gross value of agricultural production. The increased performance in this sector can be attributed to many factors amongst which are, increased demand for meat due to increased household disposable income and the fact that some meat categories are cheap. For example, evidence has shown that there is an increase in the number of consumers in the lower LSM group that can now afford protein (Meyer *et al.,* 2008). Amongst the meat categories, poultry is the cheapest source and hence the increase in its consumption. On the other hand, the fast food sector also plays a role in the increase in overall and per capita demand of meat and meat products especially poultry. Major challenges facing the poultry industry are lack of adequate productive base, support services, and market infrastructure. Other challenges include climatic, environmental and structural or institutional changes that affect competitiveness, productivity and efficiency in the sub-sector.

Over the past decade, production in the poultry sector has fluctuated while the average price of meat and meat products has steadily increased. The real farm-retail price spread for broiler meat shows an increasing trend, although with some fluctuations since 2000. From January 2000 to August 2008, the real farm-retail price spread for broilers increased by about 51 %. The disparity in the real farm and retail prices and the fluctuations in the farm-retail price spread are major cause for concern because they may influence the price transmission mechanism, which is empirically investigated in the next chapter.

CHAPTER 4

METHODOLOGY

4.1 INTRODUCTION

The main objective of this chapter is to highlight the approaches and models used to quantify volatility, volatility spillover and price transmission in the South African poultry industry.

Cointegration and error correction specifications are used to capture the essence of the non-linear equilibrium adjustment process that occurs in the farm to retail prices in the poultry value chain. These adjustments are characterised in terms of threshold cointegration, which defines regimes within which cointegration does or does not occur. Identification of the threshold and the regimes delineated by the threshold underlies the threshold adjustment process. It is argued that the plausibility of the results depends on the type of adjustment model used to quantify the process. Two types of adjustment models have been suggested: With the Engle and Granger (1987) approach, namely the TAR model, adjustment is symmetric, while the approach taken by Enders and Granger (1998), namely the M-TAR model, assumes asymmetric adjustment such that adjustment in one direction has more momentum than the other. In this chapter, the TAR and M-TAR threshold cointegration and error correction models are adopted and the econometric method used in their estimation is discussed.

After establishing the level of price transmission using the TAR and M-TAR models, the method that accounts for price volatility and the volatility spillover effect between retail and farm prices, and between these prices and sets of poultry feed ingredients (yellow maize, soybean and sunflower oilseed), is discussed. This method is called the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model and has been commonly used in financial studies. Recently, this method has been applied in agricultural economics to analyse price dynamics behaviour.

The rest of the chapter is organised as follows: Section 4.2 contains a discussion of missing data and Rubin's rule, which is a rule used to combine estimates of the regression involving imputed missing data. This is followed by section 4.3, which contains an examination of the statistical properties of the data. In this section, the data-generating process (DGP) is determined through unit root and structural change protocols, while the procedure for the least square estimate of the cointegration relationship is also discussed. Threshold cointegration is discussed in section 4.4, while section 4.5 explains the specifications of the volatility models.

4.2 IMPUTATION OF MISSING DATA

The missing values in the retail meat price are imputed using the sequential regression multiple-imputation method discussed in Lacerda (2006) and Raghunathan *et al.* (2001). This procedure imputes five missing values per data point. The procedure can be explained as follows: Assuming that k complete data sets are imputed and each of the sets is analysed giving the k estimate, which represents the original estimate of interest, say Q. Let us say that Q takes the value $Q1,......Qk$. Each Q represents a coefficient from five sets of regression with the imputed values whereby estimates of Qk, say $\sigma^2 k$, are obtained. Thus $\sigma^2 k$ represents the variance estimates from the model. These estimates and their covariance are combined using Rubin's rule, made popular by Donald Rubin in 1987.

4.2.1 Rubin's rule

A simplified version of the original rule suggested by Rubin can be described as follows: The multiple imputation (MI) estimate is given as the average over the distribution of the series with missing data (Y_M) based on the series with observed data (Y_O) of Q. This is the same as saying that $Q_{MI} = E_{YM/YO} E[Q(Y_{O,} Y_M)$. Notably, the variance of the imputed values should reflect two things, i.e. the variance of each Q estimate plus the variances of all Q estimates above their mean. These are known respectively as the between-imputation variance and the within-imputation variance. This can be expressed mathematically as

$$V[Q_{MI}] = E_{YM/YO} V[Q(Y_O, Y_M)] + V_{YM/YO} E[Q(Y_{O,} Y_M)] \tag{4.1}$$

4.2.2 Combining the estimates

The estimates are combined as follows. Let the MI estimates of Q be Q_{MI} from equation (4.1)

$$Q_{MI} = \frac{1}{K}\sum_{K=1}^{K} Q_k \tag{4.2}$$

Therefore the within-imputation variance and the between-imputation variance are defined as

$$\sigma_\omega^2 = \frac{1}{K}\sum_{i=1}^{K} \sigma_k^2, \text{ and } \sigma_b^2 = \frac{1}{K-1}\sum_{K=1}^{K} \left(Q_k - Q_{MI}\right)^2 \tag{4.3}$$

where $\hat{\sigma}_k^2 = V[Q_k]$. Then the variance of Q_{MI} is

$$\sigma_{MI}^2 = \left(1 + \frac{1}{K}\right)\sigma_b^2 + \sigma_\omega^2 \tag{4.4}$$

4.3 STATISTICAL PROPERTIES OF THE DATA

The statistical properties of the data are examined in order to determine the process whereby the data was generated. The data may either be generated by a stochastic trend process or is characterised by a deterministic time trend. Data generated by a stochastic trend process is non-stationary, meaning it has no constant mean and varies with time. It requires first difference of the series to render it stationary; hence, it is a difference stationary process. Data characterised by a deterministic time trend has a constant mean and is time invariant. A linear detrending of the trend-stationary process makes it stationary; hence it is a trend-stationary process.

There are some distinguishing features when it comes to the stochastic and trend-stationary processes: (a) In a trend-stationary process, the effects of economic shocks are transitory, while in a stochastic process shocks are permanent and persist to the next period; (b) A trend-stationary variable is trend-reverting, i.e. it reverts to its long-term mean, but there is no trend reversion in a stochastic process; (c) A shock does not alter the long-term forecast horizon of a trend-stationary series, but economic shocks alter the long-term forecast of a stochastic series; (d) The forecast error variance of a trend-stationary process is bounded, while that of a stochastic process is unbounded.

The formal statistical test to distinguish between these two properties is known as the stationarity test.

4.3.1 Stationarity test

Usually, the null hypothesis of difference stationary (unit root) against the alternative of trend stationary dominates stationarity tests in the time-series literature. Due to the lack of power and the size distortion of unit root tests, an alternative procedure was suggested by Kwiatkowski *et al.*, (1992). This involves the use of trend-stationary null hypothesis instead of unit root. The two procedures are used simultaneously for the stationarity test in this study.

4.3.1.1 Difference-stationary null hypothesis

Dickey and Fuller (1979; 1981) suggested the use of equation (4.5) for unit root test.

$$y_t = \alpha + \beta t + \rho y_{t-1} + \varepsilon_t \tag{4.5}$$

where y_t is a linear function of time, and ε_t is independently and identically normally distributed with a mean of zero and a variance of one ($i.i.d$, $\varepsilon_t \sim$ N$(0, \sigma^2)$). The assumption under the null hypothesis is that the series is an integrated difference-stationary process with a unit root, that is $\rho = 1$ against the alternative of $\rho < 1$. The model has been widely applied to test for the statistical properties of time series (see Nelson & Plosser, 1982). However, because of size distortion and low power, this model may not be able to distinguish a process with unit root from a trend-stationary process. In addition, the results are often unreliable because of possible autocorrelation in the residuals. Said and Dickey (1984) augmented this model by adding an extra lag structure to deal with the problem of autocorrelation in the first difference of the variable as follows:

$$\Delta y_t = \alpha + \beta t + \phi y_{t-1} + \sum_{i=1}^{k} \theta_i \Delta y_{t-1} + \varepsilon_{t,} \tag{4.6}$$

This is the augmented Dickey-Fuller regression equation (Dickey & Fuller, 1981) widely used in unit root tests, where $\phi = (1-\rho)$ and ρ is a parameter estimate of a first-order or autoregressive (AR) (1) process. Under the null hypothesis of $\phi = 0$, and the alternative of $\phi < 0$, the first-difference series follows an autoregressive integrated moving average (ARIMA) (p, q) process. This regression model is valid if the number of lag structure k of the first difference used as an extra regressor increases at a controlled rate with the sample size (Perron, 1988; Said & Dickey, 1984). An appropriate lag structure eliminates any serial correlation problem in the model and also ensures that the limiting distribution of the t-statistics on the coefficient of the lagged dependent variable y_{t-1} has the same non-central distribution with independently and identically distributed ($i.i.d$) errors (Perron, 1988).

4.3.1.2 Trend-stationary null hypothesis

With the trend-stationary assumption, the null hypothesis of level and trend stationarity is tested, as in Kwiatkowski *et al.* (1992), using equation (4.7)

$$y_t = \xi t + r_t + \varepsilon_t \tag{4.7}$$

$$r_t = r_{t-1} + \mu_t, \tag{4.8}$$

where t is the deterministic time trend, r is a random walk and μ_t is $i.i.d \sim N(0, \sigma_\mu^2)$. The null hypothesis of stationarity follows the assumption that the variance of random walk is $\sigma_\mu^2 = 0$, ε_t is stationary and y_t is a trend-stationary process. Also, in terms of the null hypothesis of stationarity y_t is stationary around a level if ξ is set to zero, implying that there is no trend.

The test statistic is a one-sided Lagrange multiplier (LM) test. It is defined as the partial sum process of the residuals as follows:

$$S_t = \sum_{i=1}^{t} e_t, \qquad t = 1,2,3 \ldots\ldots\ldots\ldots T. \tag{4.9}$$

where e_t is the residual from the regression of y_t on an intercept and a time trend for the null hypothesis of trend stationarity and the regression of y_t on an intercept for the null hypothesis of level stationarity. Let $\hat{\sigma}_{\varepsilon}^{2}$ be the estimate of the error variance from the regression (i.e. the sum of squared residuals divided by T). The LM statistics[7] can be given as

$$LM = \sum_{i=1}^{T} s_t^2 / \hat{\sigma}_{\varepsilon}^{2} \tag{4.10}$$

4.3.1.3 Determining the lag length

Perron (1997) suggested that it is better to determine the appropriate lag order when performing a stationarity test rather than choosing it arbitrarily. The aim of determining the truncation lag order is to remove the autocorrelation in the series so that the error term becomes white noise. However, a problem arises in determining the size of the lag order. According to Stewart (2005) using too few lags introduces size distortion in the Dickey-Fuller test statistics (Dickey & Fuller, 1981) so that the actual size may differ from the nominal size. On the other hand, too many lags weaken the power of the test so that it has a low probability of rejecting the null hypothesis of unit root when it is appropriate to do so.

Several methods can be used to choose the optimal lag length. Said and Dickey (1984) tested the joint significance of additional lag using an F-test on the estimated coefficients. The lag structure can also be determined based on model selection information criteria such as Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (BIC). Perron (1997) criticised the use of information criteria, since this involves the selection of parsimonious models and results in tests with serious size distortion and power loss. Ng and Perron (1995) demonstrated how using an information criterion leads to the selection of a lag structure, say k, that increases to infinity as the number of observation T increases.

Ng and Perron (1995), Perron (1997) and Perron and Vogelsang (1992) suggested using a data-dependent general-to-specific approach to test for truncation lag. This approach produces test statistics that have a stable size and higher power. This procedure selects the value of k, say k^*, such that the coefficient on the last lag in an autoregression of the order k^* is significant and the last coefficient in an autoregression of the order greater than k^* is insignificant up to k maximum. In using this approach, the question arises as to the maximum lag length to begin with. The maximum lag length is selected using equation (4.11) as stated in Stewart (2005).

$$k_{\max} = \mathrm{int}\left(12(n/100)^{0.25}\right) \tag{4.11}$$

4.3.2 Test for structural breaks

The procedure developed by Bai and Perron (1998; 2003) was used to test for structural change in the linear farm-retail price relationship. The Bai and Perron (2003) dynamic-

[7] The critical value for the test is tabulated in Kwiatkowski *et al.* (1992:166).

programming algorithm was used to implement the procedure described in Bai and Perron (1998). A GAUSS program written by Bai and Perron (1998) was used for this purpose. The assumptions about the break date and whether serial correlation and heteroskedasticity are allowed is accommodated in the model and therefore structural change is tested under very generous conditions on the data and errors (Bai & Perron, 2003). The procedure selects the break date by globally minimising the sum of squares residual, allowing for cases in which some parameters of the model can change and cases where the parameters cannot change. In the partial structural change model, the parameters of the model are not subject to shift and therefore the model is estimated with the entire sample. The pure structural change model allows all coefficients to change. This study investigated structural change while allowing for no shift in the parameters of the model.

4.3.3 Test for long-run cointegration relationship

The order of integration of cointegrating variables precedes the cointegration test. The order of integration is first determined in a unit root test using the techniques described in section 4.3.1.1. This is then followed by a process of determining the long-run cointegration relationship.

4.3.3.1 Test for cointegration

Consider two price variables, y and x, which are integrated of the same order. The long-run equilibrium relationship between y and x is estimated in the form

$$y_t = \alpha + \beta x_t + \mu_t \tag{4.12}$$

where y and x are the retail and farm price respectively and μ is the disturbance term. The least square residuals of (4.12) are measures of the equilibrium error, $y_t - \alpha - \beta x_t$. The Dickey-Fuller test (Dickey & Fuller, 1981) was performed on the residuals to determine the presence of a long-run equilibrium relationship between the variables – that is, whether the linear combination of the variables is cointegrated. The least square autoregression of the residuals can be estimated from the equation

$$\Delta\mu_t = \rho\mu_{t-1} + e_t \tag{4.13}$$

$$\Delta\mu_t = \rho\mu_{t-1} + \sum\nolimits_{i=1}^{n} \lambda_i \Delta\mu_{t-1} + e_t \tag{4.14}$$

If the null hypothesis of $\rho = 0$ is rejected, the residual series does not contain a unit root, hence, the $\{y_t\}$ and $\{x_t\}$ sequences are cointegrated. If the residuals are not white noise, equation (4.13) is augmented with extra lag, and equation (4.14) is estimated (Enders, 2004).

4.3.3.2 Multivariate test for cointegration

The cointegration test discussed in section 4.3.3.1 is known as the Engle and Granger (1987) two-step residual test. In this test, an arbitrary choice of normalisation is adopted by choosing the residual as the dependent variable in equation 4.13 whereby the cointegrating vector depends on it. Enders (2004) pointed out that the error from the first regression will be transferred to the second and bias the result. Stewart (2005) noted that the practice will generate a different residual series that may yield an entirely different unit root test result.

To solve this problem, this study made use of the multivariate test for cointegration developed by Johansen (1988), as well as other cointegration methods as discussed in section 4.4. The Johansen test utilises two test statistics, namely eigenvalues and trace statistics. This is a maximum likelihood ratio test involving a reduced rank regression between two variables, say I(1) or I(0), providing n eigenvalues $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$ and corresponding eigenvectors $\hat{V} = (\hat{v}_1, \ldots, \hat{v}_n)$, where the r elements of $\hat{V}$ are the cointegration vectors. The magnitude of λ_i is a measure of the strength of correlation between the cointegrating relations for $i = 1 \ldots\ldots\ldots r$. The trace statistic tests the null hypothesis of r cointegrating vectors against the alternative of $r+1$. The maximum eigenvalue statistic tests the null hypothesis of $r = 0$ against the alternative of $r = 1$. The null hypothesis that there are r cointegrating vectors can be stated as:

$$H_0 : \lambda_i = 0 \quad i = r+1 \ldots\ldots, n \tag{4.15}$$

The maximum eigenvalue ($\lambda - \max$) statistic is given by:

$$\lambda_{\max} = -T \log\left(1 - \hat{\lambda}_{r+1}\right) \qquad r = 0, 1, 2, \ldots\ldots, n-1 \tag{4.16}$$

where T is the sample size and $\left(1 - \hat{\lambda}_{r+1}\right)$ is the max-eigenvalue estimate.
The trace statistic is computed as

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \log\left(1 - \hat{\lambda}_i\right) \qquad r = 0, 1, 2, \ldots, n-1. \tag{4.17}$$

4.4 THRESHOLD MODELS

In this section, the procedures used to estimate the threshold cointegration and error correction models are discussed.

Two threshold cointegration models, namely the TAR model and the M-TAR model, are used to measure the threshold cointegration and equilibrium adjustment processes. The TAR model captures asymmetrically ‘deep’ movements in the series, while the M-TAR model captures asymmetrically sharp or 'steep' movements. Model selection information criteria such as BIC are used to select the best adjustment mechanism.

4.4.1 Threshold autoregressive (TAR) model

Following equation (4.13), the TAR cointegration and adjustment process is specified as

$$\Delta\mu_t = \begin{cases} \rho_1\mu_{t-1} + \varepsilon_t & \text{if } \mu_{t-1} \geq r \\ \rho_2\mu_{t-1} + \varepsilon_t & \text{if } \mu_{t-1} < r \end{cases} \tag{4.18}$$

where (r) represents a critical threshold. The sufficient condition for the stationarity of $\{\mu_t\}$ is $-2 < (\rho_1, \rho_2) < 0$. Enders and Granger (1998) quantified this adjustment as follows:

$$\Delta\mu_t = I_t\rho_1(\mu_{t-1} - r) + (1 - I_t)\rho_2(\mu_{t-1} - r) + \varepsilon_t \tag{4.19}$$

where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 & \text{if } \mu_{t-1} \geq r \\ 0 & \text{if } \mu_{t-1} < r \end{cases} \tag{4.20}$$

Using the TAR model (4.19) and (4.20), the null hypothesis of unit root (no cointegration) is tested against the alternate of threshold cointegration.

According to Enders and Granger (1998), the convergence to equilibrium is the point where $\Delta\mu_t = 0$. When $\mu_{t-1} = r$, $\Delta\mu_t = 0$. However, if μ_{t-1} is above its long-run equilibrium attractor (r), the adjustment $\Delta\mu_t = \rho_1(\mu_{t-1} - r)$, and if μ_{t-1} is below its long-run equilibrium attractor (r), the adjustment $\Delta\mu_t = \rho_2(\mu_{t-1} - r)$. The value ($r$) is the attractor since the expected value of $\Delta\mu_t$ is zero when $\mu_{t-1} = r$. The test for symmetric adjustment is conducted with this type of model specification. Note that adjustment is symmetric if $\rho_1 = \rho_2$.

Enders (2004) demonstrated that a high order of the error sequence $\{\mu_t\}$ can be estimated if the residuals are correlated. In that instance, equations (4.20) and (4.21) are estimated instead of equations (4.19) and (4.20).

$$\Delta\mu_t = I_t\rho_1(\mu_{t-1} - r) + (1 - I_t)\rho_2(\mu_{t-1} - r) + \sum_{i=1}^{p}\beta_i\Delta\mu_{t-1} + \varepsilon_t \tag{4.21}$$

Estimating equation (4.21) requires a diagnostic check on the residuals to determine the appropriate lag length (Tong, 1983). The test is performed using the diagnostic test statistics, for instance by examining the autocorrelogram of the residual, or by using the Ljung-Box test or the model selection information criterion test.

After confirming the presence of an equilibrium attractor (cointegration), an error correction model is fitted as follows:

$$\Delta y_t = I_t \rho_1 (\mu_{t-1} - r) + (1 - I_t)\rho_2 (\mu_{t-1} - r) + \sum_{i=0}^{k} \beta_i \Delta x_{t-i} + \sum_{i=1}^{k} \xi_i \Delta y_{t-i} + \ldots\ldots\ldots\ldots\ldots \sum_{=1i}^{k} \phi_{ni} \Delta x_{n,t-i} + \varepsilon_t , \tag{4.22}$$

where ρ_1 and ρ_2 are the adjustment coefficients for positive and negative disturbances respectively. The lag length k is determined by the general-to-specific method.

4.4.2 Momentum threshold autoregressive (M-TAR) model

An alternative to the TAR model is the M-TAR model. The M-TAR model is introduced where the exact nature of the non-linearity is not known. It then becomes possible to alloy the autoregressive decay to depend on the change in μ_{t-1} (i.e. $\Delta\mu_{t-1}$) rather than the level of μ_{t-1} as depicted in the TAR model discussed in section 4.4.1. In that instance, the M-TAR model is given as

$$\Delta \mu_t = I_t \rho_1 (\mu_{t-1} - r) + (1 - I_t)\rho_2 (\mu_{t-1} - r) + \varepsilon_t \tag{4.23}$$

where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 & if\ \Delta\mu_{t-1} \geq r \\ 0 & if\ \Delta\mu_{t-1} < r \end{cases} \tag{4.24}$$

This model is used to capture the asymmetrically sharp or 'steep' movements in the autoregressive series.

4.4.3 TAR and M-TAR model estimation

The procedure developed by Tsay (1989) is used to (a) select the threshold lags (p, k, d); (b) test for the presence of threshold; and (c) locate threshold values.

4.4.3.1 Selecting autoregressive (AR) order (p)

The AR order is selected using the partial autocorrelation function (PACF) of μ_t by estimating equation (4.25)

$$\mu_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-1} + v_t \tag{4.25}$$

whereby p is selected for an increasing order of q, and choosing the order of q for which the coefficient α_q of the t-ratio from the ordinary least squares (OLS) regression is significant. This is the q[th] partial autocorrelation coefficient, $\alpha_{qq.}$. The AR (p) is chosen such that

$$[\alpha_{qq} \neq 0 \quad for \quad q = p, \text{ and } \alpha_{qq} = 0 \quad for \quad q > p] \tag{4.26}$$

The α_{qq} are approximately normally distributed with a mean of zero and a variance of 1/N for $q > p$, where N is the sample size. It is appropriate for the significant test of α_{qq}.

4.4.3.2 Test for threshold non-linearity[8]

The Tsay test is used to confirm that there is significant threshold behaviour in the cointegrating relationship of the variables. If there is no significant threshold behaviour, the relationship between the variables is linear and adjustment is assumed to be symmetric.

The test for threshold non-linearity is based on arranged autoregression and predictive residuals. The residuals are arranged according to the threshold variable μ_{t-d}. For the given threshold model, (k, p, d) is determined, where, k is the number of regimes separated by $k-1$ non-trivial thresholds (r). In a two-regime threshold as specified in equations (4.20) and (4.24) the value of k is 2, p is the AR order selected through the process described in section 4.4.3.1, and the delay parameter (d) is chosen to be one.

For fixed p and d, the effective number of observations in arranged autoregression is $n-d-h+1$, where $h = \max\{1, p+1-d\}$. and assuming that the autoregression starts with b number of observations so that there are $\{ n-d-b-h+1 \}$ standardised residuals available. Tsay (1989) suggested regressing the standardised residual on the arranged autoregression using OLS estimates for the first m cases as follows:

$$\hat{e}_{\pi_i+d} = \omega_0 + \sum_{v=1}^{p} \omega_v z_{\pi_i+d-v} + \mu_{\pi_i+d}, \tag{4.27}$$

For $i = b+1, ..., n-d-h+1$, the significance of the test is determined from F-statistics

[8] The test procedures are adopted from Tsay (1989), and more details on the test can be found in this publication.

$$\hat{F}(p,d) = \frac{\left(\sum \hat{e}_t^2 - \sum \hat{e}_t^2\right)/(p+1)}{\sum \hat{e}_t^2 /(n-d-b-p-h)}, \tag{4.28}$$

This is summed over all observations in equation (4.27), where $\hat{e}_t$ is the least square residual. The test depends on the value of (p,d). Tsay (1989) suggested selecting d that maximises the F-statistics. If the F-statistics exceed the critical value of the F distribution with { $p+1$ } and { $N-d-m-p-h$ } degrees of freedom, the null hypothesis of linearity is rejected and a threshold model is estimated.

4.5 MEASURING VOLATILITY

Dehn (2000) regards the methods that do not distinguish between unpredictable and predictable components of price process as naïve. For purposes of comparison, both the naïve and the orthodox methods of measuring volatility are considered.

4.5.1 Unconditional volatility

A measure of volatility is computed using the coefficient of variability computed from the sample unconditional standard deviation. The coefficient of variation represents the ratio of the standard deviation to the mean, and it is a useful statistic for comparing the degree of variation from one data series to another, even if the means are drastically different from each other. The standard deviation is computed as shown in equation (4.29):

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}{(n-1)}} \tag{4.29}$$

where σ is the standard deviation of the distribution, n is the total number of observations in the sample, X_i is the sample data, and $\overline{X}_i$ is the mean of the sample. The coefficient of variation is calculated by dividing the standard deviation by the mean.

4.5.2 Measuring conditional volatility

The more orthodox methods used to measure volatility are the time-series models such as the ARIMA model and the EGARCH model. These models measure conditional volatility based on past information in the series. First, the models are estimated and then the variance of the residual error is used as a measure of volatility. The Box-Jenkins procedure (Box & Jenkins, 1976) is used in the identification of the ARIMA and EGARCH models. The flowchart of the Box-Jenkins methodology is shown in Figure 4.1.

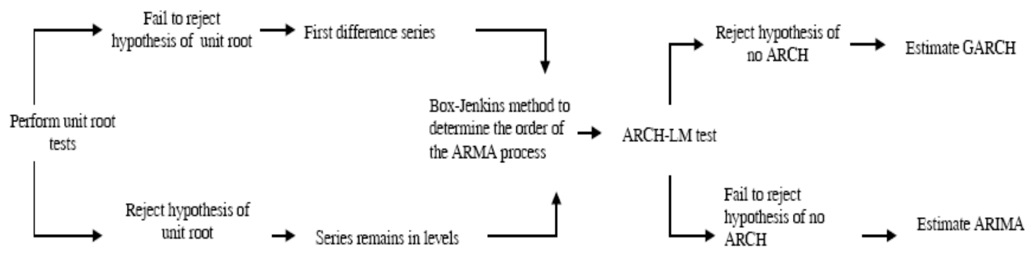


Figure 4.1 Flowchart showing the Box-Jenkins procedure for computing conditional volatility

Source: Moledina *et al.,* 2003

The Box-Jenkins approach (Box & Jenkins, 1976) is summarised as follows:

- A stationarity test is performed using the procedure described in section 4.3.1.
- The price series is differenced if the data is non-stationary, otherwise it remains on levels.
- The Box-Jenkins method with BIC is applied to select the orders of the ARIMA (p,d,q) and GARCH (1,1) models.
- The hypothesis of no EGARCH effect is tested using the procedures described in section 4.5.5.
- The ARIMA model is estimated if the hypothesis of no GARCH effect is not rejected, otherwise, an EGARCH model is fitted.

The ARIMA (p,d,q) model is given by

$$y_t = \alpha_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j}^{q} \varpi_j \varepsilon_{t-j} + \sum_{k}^{n} \eta_k D_t + e_t, \tag{4.30}$$

where (p,q) are the orders of the ARIMA (p,d,q) model. The model is selected using BIC. According to Hannan (1980), the BIC provide consistent order-estimation in the linear ARIMA models and are therefore preferred. The MA part of the model is represented by ε_{t-j} while y_{t-i} is the AR component. D_t represents seasonal dummies while the coefficients α, ϕ, ϖ and η are parameters to be estimated. After controlling for the predictable components, the standard deviation of the remaining unpredictable element over the sample period as captured in the error term e_t is taken as a measure of conditional volatility. However, in the ARIMA model, the variance of the unpredictable element is time-invariant and therefore it cannot be applied to measure volatility changes.

The EGARCH approach is used to measure the time-varying conditional volatility of the price process. In addition to distinguishing between predictable and unpredictable components, it allows for the variance of the unpredictable element. A univariate EGARCH model is given by the equations

$$\log(\sigma_t^2) = \exp\left[\psi + \sum_{i=1}^{q} ag(z_{i-1}) + \sum_{k=1}^{p} b_k \log(\sigma_{t-1}^2)\right] \tag{4.31}$$

$$g(z_t) \equiv \theta z_t + \gamma[\mid z_t \mid - E \mid z_t \mid] \tag{4.32}$$

where σ_t^2 is the variance of the residuals from the mean equation, as such that the ARIMA model (4.30) is conditional upon information at period t. The fitted values of σ_t^2 are the conditional variances whose square root is the measure of conditional volatility.

4.5.3 Seasonality in volatility

Seasonality in the production and marketing of agricultural commodities plays an important role in their price volatility. For example, poultry meat prices increase during festive periods because of strong demand for meat. Also, the winter and summer seasons play a role in the availability, demand and supply of grain and livestock products, including livestock feeds, which constitute a large portion of the production costs of the livestock sector. Therefore, following Goodwin and Schnepf (2000), the seasonal component of price volatility is taken into account by incorporating a deterministic seasonal component into the volatility model, as shown in equation (4.33):

$$s_t = \sum_{i=1}^{k} [\phi_i \cos(2\pi d_t / 12) + \phi_i \sin(2\pi d_t / 12)] \tag{4.33}$$

where s_t represents the seasonal component for the selected prices at the period d_t where d is the month of the year for observation t. The model captures the seasonal pattern within a period of twelve months. Four seasons are considered, but three seasons are included in the model with the fourth serving as a base. Therefore the value of k is taken to be three[9].

4.5.4 Measuring volatility spillover

Measuring volatility spillover with the univariate EGARCH model using ARIMA representation requires two steps. In the first step, the ARIMA model of the prices is fit, while in the second step, the residuals from the regression are used in the variance equation of the EGARCH model. Another approach is to estimate the EGARCH model simultaneously. In this type of specification, the mean and the variance equation will contain lagged endogenous and exogenous explanatory variables. In this study, the bivariate EGARCH spillover model is fit assuming an AR(P) specification as follows: Let $rp_{1,t}$ be the monthly nominal retail price and let $fp_{2,t}$ denote the monthly nominal farm price. The

[9] The reason for this type of specification is to avoid dummy trap.

volatility spillover between the two market channels is measured from the AR(p)-EGARCH(1,1) model – see equations (4.34) to (4.42).

Mean equation

$$rp_{1,t} = \delta_{1,0} + \sum_{i=1}^{k} \delta_{1,1i} rp_{1,t-1} + \sum_{i=1}^{k} \delta_{1,2i} fp_{2,t-1} + \xi_{1,t} \tag{4.34}$$

$$fp_{2,t} = \delta_{2,0} + \sum_{j=1}^{r} \delta_{2,1j} rp_{1,t-1} + \sum_{j=1}^{r} \delta_{2,2j} fp_{2,t-1} + \xi_{2,t} \tag{4.35}$$

$$\xi_{1,t} / \Omega_{t-1} \approx N(0, \sigma_{1,t}^2)$$
$$\xi_{2,t} / \Omega_{t-1} \approx N(0, \sigma_{2,t}^2)$$

Variance equation

$$\log(\sigma_{1,t}^2) = \exp\left[\psi_{1,0} + a_{1,1} g(z_{1,t-1}) + a_{1,2} g(z_{2,t-1}) + \sum_{k=1}^{p} b_{1,k} \log(\sigma_{1,t-1}^2)\right] \tag{4.36}$$

$$\log(\sigma_{2,t}^2) = \exp\left[\psi_{2,0} + a_{2,1} g(z_{1,t-1}) + a_{2,2} g(z_{2,t-1}) + \sum_{k=1}^{p} b_{2,k} \log(\sigma_{2,t-1}^2)\right] \tag{4.37}$$

$$g(z_{1,t}) = | z_{1,t-1} | - E(| z_{1,t-1} |) + \gamma_1 z_{1,t-1} \tag{4.38}$$

$$g(z_{2,t}) = | z_{2,t-1} | - E(| z_{2,t-1} |) + \gamma_2 z_{2,t-1} \tag{4.39}$$

$$z_{1,t} = \xi_{1,t} / \sigma_{1,t} \tag{4.40}$$

$$z_{2,t} = \xi_{2,t} / \sigma_{2,t} \tag{4.41}$$

$$\sigma_{1,2,t} = \rho_{1,2} \sigma_{1,t} \sigma_{2,t} \tag{4.42}$$

where ξ_t is the innovation term, σ_t^2 is the conditional variance, and $\sigma_{1,2t}$ denotes the conditional covariance between retail and farm prices. Equations (4.34) and (4.35) are AR(p) mean equations describing the monthly retail price as a function of its own lag and the lag of the monthly farm price. The bivariate model is used to measure spillovers between retail (farm) and poultry feed components (maize, soybean and sunflower). Equation (4.36) specifies the conditional variance from the mean equation (4.34) as a function of its own lagged standardised residual ($z_{i1,t}$) and the standardised residual from equation (4.34), ($z_{2,t}$), while the same applies to equation (4.37). A significant $a_{1,2}$ suggests a volatility spillover from farm to retail market whereas a significant $a_{2,1}$ indicates a volatility spillover from retail to farm-level market prices. The coefficient γ_t indicates whether the spillover effect measured by the coefficients ($a_{1,2}$ and $a_{2,1}$) is symmetric or asymmetric. If the coefficient γ_t is insignificant, the spillover effect is symmetric, i.e. the positive and negative shocks have the same effect on volatility, otherwise it is asymmetric – that is, the response to rising prices (positive shock) at any production and marketing stage (farm or retail) differs from the response to price drops (negative shock). If $\gamma < 0$ (negative), a negative shock increases volatility, whereas a positive shock decreases volatility (Nelson, 1991).

Volatility persistence is measured by the coefficients (b_1) and (b_2) in equations (4.36) and (4.37). The regularity conditions in the EGARCH model require that $0 < b_k < 1$. If the unconditional variance is finite, the absolute value of $b_k < 1$. If the coefficients are significant, there is a significant evidence of persistence of shock. The smaller the absolute value of b_k the less persistent volatility will be after a shock. If the value of b_k approximates unity, the shock will persist into the future. This implies the presence of long memory and indicates that the fluctuations in the market will remain for a long period of time (permanent).

Since shocks can be transitory or permanent, it is intuitively appealing to assess persistence in terms of how long it takes for one half of the shocks to be eliminated. This is termed the half-life, which is calculated as $\ln(0.5)/\ln(b)$.

4.5.5 EGARCH[10] model identification

Identifying EGARCH orders (p,q):

The process involves estimating the $\{y\}$ sequence as an ARIMA process using an appropriate lag structure. The ACF and PACF of the squared residuals are then used to identify the order of the EGARCH from the correlogram of the squared residuals plot.

Testing for EGARCH effects (Lagrange multiplier (LM) method:

An OLS regression of the best-fitting ARIMA process is used for the LM test. The squared residual from this regression is used to test the presence of EGARCH errors by regressing the squared residual on its q lagged values as follows:

$$\hat{\varepsilon}_t^2 = a_0 + a_1\hat{\varepsilon}_{t-1}^2 + a_2\hat{\varepsilon}_{t-2}^2 + \ldots\ldots\ldots\ldots + a_q\hat{\varepsilon}_{t-q}^2 \quad (4.43)$$

The test statistics are constructed from TR^2, where T is the sample of residuals and R^2 is the coefficient of determination. TR^2 has a chi-square distribution with q degrees of freedom. The null hypothesis is that the coefficients $a_1, a_2 .... a_q = 0$. Rejection of the null hypothesis is equivalent to rejection of the null of no EGARCH effect. Note that if there is no EGARCH effect, the estimate from a_1 to a_q is zero, and the R^2 value is relatively low. However, Enders (2004) suggested an alternative test for small sample size on the basis of an F-test being superior to an χ^2 test. An F-test is used for the null hypothesis that $a_1, a_2 .... a_q = 0$. The

[10] Note that the conventional test for model identification is based on the ARCH and GARCH models; this is applicable to the EGARCH model.

sample value F from the regression is compared to the value of the F-distribution table with q degrees of freedom in the numerator and $T-q$ in the denominator (Enders, 2004).

4.5.6 **Diagnostic test**

The aim of this test is to check whether the estimated EGARCH model fits the data. It should be noted that in a standard EGARCH model, (a) the estimated parameters should be stationary (constant), (b) the estimated residuals should be orthogonal, and (c) there should not be any remaining conditional volatility in the residual errors. To verify these conditions, the following tests can be performed:

Test for stationarity of the model: According to Nelson (1991), for the EGARCH model to be strictly stationary and ergodic, the following conditions must be fulfilled:

i) $\sum_{k}^{\infty} b_k < \infty$

ii) If log (σ_t^2) follows an AR(1) process, with coefficient Δ, then $|\Delta| < 1$

iii) If generalised error distribution (GED) is assumed, z_t is not too fat-tailed and (σ_t^2) and (ξ_t) have finite unconditional moments of arbitrary order; hence, when the parameter of GED is ≥ 2, z_t has a thinner tail than normal.

Test for residual serial correlation: This test is performed on the standardised residual of the EGARCH model. The residuals are standardised by using the conditional standard deviation as follows:

$$\hat{s}_t = \hat{\varepsilon}_t / \hat{h}_t^{0.5}, \tag{4.44}$$

where $\hat{\varepsilon}_t$ is the residual error and $\hat{h}_t^{0.5}$ is the conditional standard deviation of the residual error. The $\{\hat{s}\}$ sequence has a mean of zero and a variance of one. The autocorrelation function of the sequence is examined to determine whether there is any serial correlation. The Ljung-Box Q-statistics for the $\{\hat{s}\}$ sequence are calculated as shown in equation (4.45).

$$Q = T(T+2)\sum_{i=1}^{N} \rho_i / (T-i) \tag{4.45}$$

The Q-statistics have an asymptotic chi-square distribution with n degrees of freedom. The null hypothesis of the test is that the joint Q-statistics are equal to zero. Rejecting the null hypothesis implies that the $\{\hat{s}\}$ sequence is serially correlated and that the model of the mean is not correctly specified. In that instance, a higher EGARCH order or a different type of volatility model may be appropriate.

Test for remaining EGARCH effect: The remaining EGARCH effect is also tested with the $\{\hat{s}\}$ sequence derived in equation (4.44) by estimating a regression of the form

$$s_t^2 = a_0 + a_1 s_{t-1}^2 + ... + a_n s_{t-n}^2 \tag{4.46}$$

The Ljung-Box Q-statistics for the $\{\hat{s}\}$ sequence are used to test the joint significance of the parameters $a_1 = a_2 .... a_n = 0$. Rejecting the null hypothesis implies that the standardised residuals are serially correlated, which is equivalent to rejecting the null hypothesis of no remaining GARCH effect.

An alternative to this test is the F-test. The significance of the parameter estimates is determined from the sample value of the F-test.

4.6 SUMMARY

This chapter discussed the analytical procedure used to examine the farm-retail price relationship. The statistical properties of the series were examined first to determine their data-generating properties. In addition to the widely used difference-stationary (unit root) null hypothesis, the procedure developed by Kwiatkowski *et al.* (1992) for the trend-stationary null hypothesis was discussed. This procedure is also applicable to the long-run cointegration test, which constitutes an important part of the study.

The two threshold cointegration processes, namely the TAR model and the M-TAR model, which were used to capture the two different adjustment processes, were also discussed in this chapter. The chapter also contained a discussion of the methods used to verify the volatility of the farm-retail price change and to determine whether that volatility persisted over the period under review. A volatility model, namely the EGARCH model, was used for this purpose. The Box-Jenkins time-series modelling method was used for the identification, parameter estimation and diagnostic checking of the ARIMA and EGARCH models.

CHAPTER 5

EMPIRICAL RESULTS

5.1 INTRODUCTION

This chapter reports the results of the asymmetric price and volatility spillover models. In the first part, price transmission is estimated with different adjustment mechanisms and the results are compared. In the second part, volatility in prices at the producer and retail levels is quantified. Volatility spillover and adjustment to shocks are then compared to the results obtained in the first part of the analysis.

5.2 DATA

The data used for this study include farm and retail poultry prices, as well as the daily near-market monthly spot prices for yellow maize, sunflower seed and soybeans. The spot prices (measured in rand per ton) were obtained from South African Futures Exchange (SAFEX) historical database. Since the futures exchange on grain and oilseed crops did not take place simultaneously in some years, the frequency of the data sets varies. The yellow maize prices span from January 2000 to August 2008, while the sunflower prices range from April 2001 to August 2008 and the soybean prices from April 2002 to August 2008.

The farm and retail prices were obtained from a number of different sources. The farm data was obtained from the National Department of Agriculture (Directorate: Statistics) in Pretoria. The data set consists of monthly producer prices representing average carcass prices of whole chickens, measured in c/kg, ranging from January 2000 to August 2008. The retail prices used are the average prices of chicken measured in c/kg that were obtained from the Statistics South Africa database. The analyses commence by first investigating the price transmission mechanism between farm and retail nominal prices followed by the estimation of a measure of volatility and volatility spillover in the sector.

The retail prices contain missing observations corresponding to the periods during which no data was collected, namely the period from January 2001 to July 2001, which implies that six data points are missing. To avoid introducing bias into the analysis, the missing data points had to be calculated. The procedure to estimate the missing data points is discussed next.

5.2.1 Estimation of missing data

A sequential multiple imputation procedure similar to the one used in Raghunathan *et al.* (2001) was used to estimate the missing data. In this study, the consumer price index for meat and meat products was used to estimate the missing value. The imputation was based on the Bayesian approach implemented with a program written in MATLAB 2008. Thirty-two replications of the random draws were used to generate five imputed values of the missing data. It is recommended that after the imputation of the missing values, each completed data set is analysed separately by fitting a regression model. The point parameter estimate and the covariance matrix from the regression are then combined using Rubin's rule. The aim of this latter procedure is to select the best-fitting imputed data that could not be selected arbitrarily or through best guess. Due to the type of empirical approach undertaken in this study, a different method was followed to approximate the best imputed value by taking the mean of each data point for the five imputed values. The imputed missing values are shown in Appendix A2.

5.2.2 Descriptive statistics

The descriptive statistics of the monthly observations of the nominal price series were computed to give an indication of the frequency distribution of the data (Table 5.1). The skewness measures the asymmetry of the distribution around its mean. The skewness of a symmetric distribution, such as a normal distribution, is zero. Positive skewness means that the distribution has a long right tail, while negative skewness indicates a long left tail. Table 5.1 shows that the nominal farm price is normally distributed with a skewness of zero while the nominal retail price of chicken together with the prices of the other products are positively skewed.

A normally distributed series is bell-shaped. The kurtosis measures whether the shape of the distribution peaks or is flat. The kurtosis of a normal distribution is three. If the kurtosis exceeds three, the distribution is peaked (leptokurtic) relative to the normal; if it is less than three, the distribution is flat (platykurtic) relative to the normal. It can be seen from Table 5.1 that the nominal farm, sunflower and soybean prices are properly peaked relative to the normal compared to the retail and yellow domestic maize prices.

Another measure of the frequency distribution of data is the Jarque-Bera test, used to determine whether a time series is normally distributed. It measures the differences of the skewness and kurtosis of the series against those from the normal distribution. Under the null hypothesis of normality, the Jarque-Bera test statistics are chi-squared distributed with two degrees of freedom. Rejecting the null hypothesis is an indication that the series is not normally distributed. The test statistics cannot be rejected at 5 % for both nominal retail and farm prices, which implies that the two series are normally distributed. On the other hand, the prices of the other commodities deviate from the normality assumption.

Table 5.1 Descriptive statistics of the data[11]

STATISTICS	RETAIL	FARM	DMAZ[a]	DSOYB[b]	DSUNF[c]
Mean	18.20	11.36	1237.98	2438.69	2620.67
Median	17.96	11.41	1085.82	2333	2352.72
Maximum	26.86	15.70	2141.58	4698.65	5320.52
Minimum	11.78	7.88	582.48	1224.85	1554.09
Std. Dev.	4.17	1.82	425.48	821.44	949.28
Skewness	0.34	0.03	0.48	1.16	1.47
Kurtosis	2.42	2.63	2.07	3.87	4.12
Jarque-Bera	3.50	0.62	7.75	19.72	36.59
Probability	0.17	0.73	0.02	0.00	0.00
Sum	1892.92	1180.99	128749.80	187778.70	233239.70
Sum Sq. Dev.	1789.71	340.83	18646616.00	51282056	79298842.00
Observations	104	104.00	104.00	77	89.00

[a]DMAZ is the near-month domestic yellow maize spot SAFEX price; [b]DSOYB represents the domestic soybean spot SAFEX price; [c]DSUNF is the domestic sunflower seed spot SAFEX price.

5.3 STATIONARITY TEST

Visual inspection of the nominal price data in Appendix A3 shows that they are trended and appears to be non-stationary. To determine the data-generating properties of the individual data, two types of stationarity tests – the augmented Dickey-Fuller (ADF) test (Dickey-Fuller, 1979; 1981) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test (Kwiatkowski, *et al.*, 1992) – were performed. An important aspect of the stationarity test is the assumption about the exogenous variables to be included in the test and the optimal lag length. To determine whether to include an intercept and/or deterministic trends, an auxiliary test[12] was performed. OLS regression of the prices on a constant and a time trend was estimated. The results show that both exogenous variables have a significant influence on price and they were therefore included in the stationarity test. The lag length was selected using the data-dependent general-to-specific method proposed by Enders (2004). The maximum lag length to begin the test was computed from the equation $k_{\max} = \text{int}\left(12(n/100)^{0.25}\right)$. Optimal lag length was selected by minimising BIC. Firstly, the ADF test was performed in levels and in first difference. Both intercept and trend were included in the test. The results of the ADF test are shown in Table 5.2. The null hypothesis of unit root could not be rejected in levels, but was rejected in the first difference at 95 % confidence level. The test shows that prices are non-stationary in levels, but stationary in their first difference. The critical values are the MacKinnon (1996) one sided p-values computed using E-view statistical software.

[11] All prices are nominal.
[12] The results of the auxiliary test are not reported, but are available on request.

Table 5.2 ADF unit root test

Series	Lag length	ADF statistics	Critical value (95%)	Lag length	ADF statistics	Critical value (95%)
		Levels			First difference	
RETAIL	1	-1.4684	-3.4545	1	-6.6255	-3.4549
FARM	12	-1.9762	-3.4599	3	-6.5929	-3.4558
DMAZ	12	-2.3441	-3.4599	4	-4.1828	-3.4563
DSOYB	2	-0.7283	-3.4717	2	-4.7665	-34726
DSUNF	2	-1.1461	-3.4629	1	-6.2233	-3.4629

The KPSS test was then performed. Intercept and deterministic trends were included in the test. The lag length was selected by means of the data-dependent Andrews (1991) bandwidth method. The null hypothesis of the test is that the series are stationary against the alternative of unit root. The critical values for the level-stationary (no trend included) and first difference (with intercept and trend) tests for 1 %, 5 % and 10 % are (0.739, 0.463, 0.347) [a] and (0.216, 0.146 and 0.119)[b] respectively. The null hypothesis of level stationarity is rejected for all the prices. The first difference test is not rejected at all levels for all the prices. The results of the KPSS test show that the nominal retail, farm, grain and oilseed prices are non-stationary. The two tests, ADF and KPSS, show that the nominal poultry meat prices (retail and farm prices) and the selected grain and oilseed prices, i.e. the domestic SAFEX yellow maize, soybean and sunflower prices, are non-stationary[13].

Table 5.3 KPSS unit root test

Series	KPSS statistics*	
	Levels	First difference
RETAIL	1.0397	0.0688
FARM	0.4997	0.0418
DMAZ	0.4289	0.0731
DSOYB	3.6790	0.0729
DSUNF	2.0603	0.0828

***The critical value for the test is documented in Kwiatkowski *et al.* (1992:166). [a] Represents the critical values for the level-stationary KPSS unit root hypothesis, whereas [b] represents the critical values for the first-difference stationary KPSS unit null hypothesis.**

5.4 COINTEGRATION TEST

This section describes how the cointegration test was performed using different procedures. The aim was to compare the various approaches and choose the best-fitting error correction model. The reason for this comparison is that the cointegration test as a long-standing tool for investigating the long-run equilibrium relationship between variables needs to be undertaken through appropriate and comparable model selection criteria. Various approaches in conducting the cointegration test were discussed in Chapter 2. A widely applied cointegration test is the Engle and Granger (1987) test procedure. The cointegration test proposed by these authors has been criticised on the basis of their assumptions about the adjustment mechanism

[13] The unit root test is performed using E-views econometrics software.

of the error correction term. According to their cointegration test procedure, the adjustment mechanism is symmetric, implying that regardless of whether there is a positive or negative shock, market prices (economic agents) will respond in a similar way. Assuming that adjustment to the equilibrium relationship is asymmetric, Enders and Granger (1998) and Enders and Siklos (2001) suggested that Engle and Granger's (1998) model will be misspecified. They subsequently suggested an adjustment process that accounts for positive and negative errors in an error correction model. This asymmetric adjustment mechanism can be investigated by means of either the TAR model or the M-TAR model. For purposes of this study, both adjustment mechanisms were used to investigate retail-farm price relationships for a number of reasons.

Both the TAR model and the M-TAR model capture different adjustment processes. According to Enders and Granger (1998) and Enders and Siklos (2001), the TAR model captures asymmetrically deep movements in a series, while the M-TAR model is useful in capturing the possibility of asymmetrically sharp movements. For example, sharpness occurs when contractions are steeper than expansion, and deepness occurs when troughs are more pronounced than peaks. In the TAR and M-TAR adjustment processes, the absolute values of the adjustment coefficients measure the deepness or sharpness of the adjustment process. For example, in the TAR model, if the absolute value of $\rho_1 < \rho_2$, the series exhibits negative deepness (skewness) relative to its mean or trend. This implies that (a) more observations fall below the mean or trend than above, and (b) negative shocks to the series persist more than positive shocks. On the other hand, positive deepness occurs when the absolute value of $\rho_1 > \rho_2$, thus positive shocks persist more than negative shocks. In the M-TAR model the adjustment differs slightly. If a time series exhibits steepness, its first difference should exhibit negative skewness. For example, if the absolute value of $\rho_1 < \rho_2$ there will be less decay for positive than for negative of the error sequence ($\Delta\mu_{t-1}$). In that instance, the sharp decrease in the series should be larger but less frequent than increases (Abdulai, 2002), implying that increases tend to persist but decreases revert quickly to the equilibrium (attractor) (Enders & Siklos, 2001).

Since both deep and sharp movements can be found in one particular time series, it is better to choose the best-fitting model through appropriate model selection criteria. The results of the cointegration test obtained using the Johansen multivariate test, the Engle and Granger (1987) test, the TAR model and the M-TAR model are discussed next.

5.4.1 Johansen multivariate cointegration test

The Johansen multivariate vector autoregressive cointegration test (Johansen & Juselius, 1990) suggests estimating the cointegration ranks rather than assuming a fixed cointegration vector as in Engle and Granger (1987). The number of cointegrating ranks was investigated by means of this test procedure. The test is a maximum likelihood ratio test based on a maximal eigenvalue and trace of the stochastic matrix in the vector autoregression. Using eigenvalue, the hypothesis that r = 0 was tested against the alternative that r = 1. In the trace, the hypothesis of r = 0 against the alternative of (r+1) cointegrating vectors was tested. The lag order of two was selected for the vector autoregression using BIC. The assumption of both restricted and unrestricted intercept and no trend in the vector autoregression (VAR) cointegration test was undertaken. The result shows that restricting the intercept has a significant influence on the test results, because the trace and maximal eigenvalue statistics cannot reject the null hypothesis of no cointegration, implying that intercept should be included in the cointegration test. For this reason, only the results for the unrestricted test are reported. The Johansen cointegration test results are shown in Table 5.4. Both the maximal and trace eigenvalue statistics strongly reject the null hypothesis that there is no cointegration between the retail price (RP) and the farm price (FP) – that is, r = 0, while the hypothesis that there is at least one cointegrating relationship between the variables is not rejected at 95 %.

Table 5.4 Johansen multivariate cointegration test*

		Maximal Eigenvalues	
H0	Ha	Statistics	Critical value (95 %)
r = 0	r = 1	29.1514	14.88
r < 1	r = 2	0.2313	8.07
		Trace	
r = 0	r >=1	29.3828	17.86
r <= 1	r = 2	0.2313	8.07

*The test was computed using the MicroFit 4.1 statistical package.

5.4.2 Engle and Granger cointegration test

The order of autoregression was selected first, as described in section 4.4.3.1, with the procedure selecting AR(1). The Engle and Granger (1987) cointegration test was performed by fitting long-run equation (4.12) where y and x are the RP and FP respectively and μ is the disturbance term. The least squares residuals of (4.12) are measures of the equilibrium error

$$y_t - \alpha - \beta x_t \quad (5.1)$$

The parameter estimates obtained by fitting the ordinary least squares (OLS) of equation (4.12) are given in equation (5.2).

$$RP_t = -6.4671 + 2.1723 FP_t + \hat{\mu}_t \quad (5.2)$$

The t-test statistics are -7.7787 and 30.0772 for the intercept and farm price, respectively. The presence of a long-run cointegration relationship was tested using the ADF test. Firstly, the lag structure was determined by means of BIC, which selects two lag lengths. Equation (4.14) was then estimated by means of OLS regression. The null hypothesis of the test is that there is a unit root – no cointegration ($Ho: \rho = 0$) – against the alternative of stationarity ($Ha: \rho < 0$) – cointegration. The Engle and Granger (1987) cointegration test is shown in

Table 5.6. The estimated value of ρ is -0.3165 and the t-statistic for the null hypothesis of $\rho = 0$ is -4.995. The results show that the test satisfies the sufficient condition for stationarity (i.e. -2< ρ <0). The non-standard critical values for the Engle and Granger (1987) ADF test are 3.77, 3.17 and 2.84 at the 1 %, 5 % and 10 % significance levels. The absolute value of the t-statistics is greater than the critical values. The results indicate that the retail and farm prices are cointegrated. The diagnostic tests performed on the residuals were the Lagrange multiplier (LM) test, and the test for the presence of heteroskedasticity. The tests show that there is no residual serial correlation and that the errors are homoskedastic.

5.4.2.1 Parameter stability test

After fitting the OLS long-run equation (4.12) and prior to further analysis, the presence of a structural break in the cointegration relationship was investigated. The residual from the OLS regression of (4.12) was used for the test. The aim of the test was to determine the presence of a break in the residual, which represents equilibrium relations between the variables. Assuming that there is a structural shift in the cointegration relationship and this is not accounted for, the unit root and cointegration tests would be biased towards over-rejecting the hypothesis of unit root or no cointegration when it is appropriate to do so. To correct for the bias, appropriate dummy variables are incorporated into the unit root and cointegration tests in the presence of evidence of parameter instability. The dynamic linear programming algorithm of Bai and Perron (2003) was used to compute the estimates of the break points by globally minimising the residual sum of squares (RSS). The program sequentially examines different partitions of the data and searches for the RSS associated with the optimal partitions containing r breaks, thus allowing for multiple breaks. The break points are identified using different test statistics and critical values computed by the program. The test statistics are: (a) the $SupF$ test for the null hypothesis of no change versus the alternative of arbitrary number of changes, (b) the $SupF_T(k)$ test for l changes versus the alternative hypothesis of $(l+1)$ changes, (c) the double-maximum test for the null hypothesis of no structural breaks against the alternative of an unknown number of breaks – the double-maximum test is divided into two tests, the $UD_{\max}F_T$ and the $WD_{\max}F_T$, (d) the sequential procedure, and (e) the test according to information criteria.

The results of the structural-change tests are shown in Table 5.5. It can be seen from the results that none of the test statistics are significant. Therefore there is evidence to suggest that there is no structural change in the cointegrating relationship between farm-retail markets. The structural break test was also conducted on the individual prices used in the study. The results of the structural-break test on the individual prices are reported in Appendix A4. It can be seen from Table 5.5 that the $SupF_T(1)$ test for the null hypothesis of no breaks against the alternative of a single break is not significant for retail, farm and soybean prices, and the sequential procedure selects zero breaks for retail, farm and soybean prices. Determining the presence of a structural break for the domestic yellow maize (DMAZ) and sunflower oilseed (DSUNF) prices proved slightly difficult. The $SupF_T(k)$,

$UD_{\max}F_T$ and $WD_{\max}F_T$ are significant, but all the $SupF$ tests for the null hypothesis of no change versus the alternative of an arbitrary number of changes cannot be rejected. Therefore it is concluded that there is no structural break in the prices.

Table 5.5 Parameter stability test on the OLS cointegrating residuals of retail-farm prices

$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$	$UD\max$	$WD\max$
1.25	1.67	1.75	1.32	1.09	1.75	2.52
(8.58)	(7.22)	(5.96)	(4.99)	(3.91)	(8.88)	(9.91)
$SupF(2/1)$	$SupF(3/2)$	$SupF(4/3)$	$SupF(5/4)$	$Seq\ proc$		
2.14	0.71	0.31	0.04	zero		
(8.56)	(10.13)	(11.14)	(11.83			

Figures in parenthesis are the critical values from the dynamic programming algorithm of Bai and Perron (2003). The test statistics are evaluated at 5 % significance level.

Table 5.6 Cointegration estimates for the retail-farm price relationship

Test	Engle & Granger	TAR (r = 0)	M-TAR (r = 0)	M-TAR (r =-0.7264)[g]
Col.1	Col.2	Col.3	Col.4	Col.5
ρ_1	-0.3165 (-4.995)	-0.2730 (-3.282)[a]	-0.3594 (-4.256)	-0.3335 (-3.887)
ρ_2	Na	-0.3624 (-4.257)[b]	-0.2738 (-3.291)	-0.1267 (-0.826)
Φ^c	Na	12.7586	12.7832	7.5543
$\rho_1 = \rho_2{}^d$	Na	10.0118 (0.000)	10.0521 (0.000)	6.3845 (0.000)
BIC	-118.4872	-120.4546	-121.2101	-122.0477
$Lag\ lenght$	2	2	2	4
$LM\ (\chi^2)^e$	0.0490 (0.825)	0.1085 (0.742)	0.0223 (0.881)	1.6711 (0.196)
$Hetero\,(\chi^2)^f$	0.0624 (0.803)	0.0195 (0.889)	0.0812 (0.776)	0.1278 (0.721)
$Normality\ (\chi^2)^h$	3.7759 (0.151)	3.6065 (0.165)	3.9820 (0.137)	1.8858 (0.389)
R^2	0.2313	0.2364	0.2353	0.2555
$Adj\ R^2$	0.2156	0.2128	0.2119	0.2155
$Tsay$				25.0119
N	104	104	104	104

Notes: [a]Entries in this row represent the t-statistics for the null hypothesis test ($\rho_1 = 0$). [b]Entries in this row are the t-statistics for the null hypothesis ($\rho_2 = 0$). [c]Entries in this row are the sample values of the F-statistics for the null hypothesis of ($\rho_1 = \rho_2 = 0$) – the critical values for this test are tabulated in Enders and Siklos (2001) as the Φ and Φ^* distributions. [d]Entries in this row are the sample F-statistics for the null hypothesis that the adjustment coefficients are symmetric ($\rho_1 = \rho_2$). [e]Entries in this row are the Breusch-Godfrey Lagrange multiplier test of serial correlation. [f]Entries in this row are the White test for heteroskedasticity. [h]Entries in this row represent the Jarque-Bera normality test statistics.

5.4.3 Threshold autoregressive (TAR) model

The following steps were followed in fitting the TAR model: The residuals from the long-run OLS regression obtained by fitting equation (4.12) were used to specify the TAR models (4.18) and (4.19). In this model specification, the equilibrium relationship depends on whether the error sequence μ_{t-1} lies above or below the threshold. In this case, the TAR model was fit assuming that the threshold value is zero. To account for the positive and negative values of μ_{t-1}, the indicator variable was constructed to take the value of one if μ_{t-1} is greater than zero, otherwise zero. Equation (4.19) was then quantified using the indicator function. The BIC was used to select two lags for the TAR model. Equation (4.21) was then estimated using the OLS regression technique. The results of the TAR model estimation are shown in Table 5.6. As shown in the third column of the table, the point estimates of ρ_1 = -0.27301 and ρ_2 = -0.36243 suggest convergence to long-run equilibrium.

These results indicate that the necessary and sufficient conditions for stationarity are satisfied. According to Enders and Granger (1998), the sufficient condition for stationarity is that $-2 < (\rho_1, \rho_2) < 0$. Petruccelli and Woolford (1984:272) defined the necessary and sufficient condition as $\rho_1 < 0, \rho_2 < 0$ and $\rho_1\rho_2 < 1$ for any value of the threshold. Enders and Siklos (2001) rewrote the conditions as $\rho_1 < 0, \rho_2 < 0$ and $(1+\rho_1)(1+\rho_2) < 1$. Note that the sufficient conditions in Enders and Siklos (2001) and the conditions in Petruccelli and Woolford (1984) and in the revised version are all satisfied. The other property of the test is that convergence to equilibrium is faster (performance is better) when ρ_1 and ρ_2 are both negative. Where both ρ_1 and ρ_2 are negative, rapid convergence is implied. However, the adjustment is negatively skewed (deep) because the absolute value of $\rho_1 < \rho_2$. This means that negative shocks to the marketing margin persists more that positive shocks. Therefore autoregressive decay is faster when shocks to the series are positive.

Recall that if the linear combination of the retail price and farm price is not cointegrated, then there is no threshold. The null hypothesis of the test is: no cointegration, i.e. ($Ho: \rho = 0$), against the alternative of cointegration with TAR adjustment. The t-statistics and the sample values of the F-statistics were used for the tests, with the t-statistics being used to test the null hypothesis that $\rho_1 = 0$ and $\rho_2 = 0$. The F-statistics were used to test the null hypothesis that the joint distribution of ρ_1 and ρ_2 is zero (i.e. $Ho: \rho_2 = \rho_2 = 0$). The critical value for the test is tabulated in Enders and Siklos (2001). The largest of the t-statistics (t-max) is -3.2822, while the critical values reported in Table 2 of Enders and Siklos (2001) for the 10 %, 5 % and 1 % significance levels for one lagged change are (-1.91, -2.14 and -2.57). The absolute value of the t-statistics is greater than the tabulated critical values at all significance levels. This means that retail and farm prices are cointegrated. The sample value of the F-statistics was obtained from the post-regression Wald coefficient restriction test. The sample value of Φ = 12.7586 is greater than the 10 %, 5 % and 1 % critical values tabulated in Table 1 of Enders and Siklos (2001), and therefore the null hypothesis of no cointegration is rejected, implying that the linear combination of retail and farm prices is cointegrated. Since the two prices are cointegrated, the null hypothesis of symmetric adjustment (i.e. $\rho_1 = \rho_2$) can be tested using the F-distribution (Enders & Granger, 1998; Enders & Siklos, 2001). The sample value of the F-distribution is equal to 10.0118 with a p-value of (0.0000). The null hypothesis of symmetry is rejected at 1 % level of significance, which implies that the retail-farm relationship is asymmetric and threshold-driven.

The diagnostic test for model adequacy shows that there is no serial residual correlation and that the error variance is homoskedastic and normally distributed.

5.4.4 Momentum threshold autoregressive (M-TAR) model

Like the TAR models, the M-TAR models (4.23) and (4.24) were specified with the residual from the long-run OLS regression of (4.12). To account for possible serial correlation in the residual, extra lag changes of the error sequence were added and equation (4.21) was fit with specifications of (4.24). BIC was used to select two lags for the M-TAR model. The results of the M-TAR model estimation are shown in Table 5.6. As shown in the fourth column of the table, the point estimates of ρ_1= -0.35943 and ρ_2=-0.27382 suggest convergence to long-run equilibrium. The results indicate that the necessary and sufficient conditions for stationarity are satisfied. With regard to the adjustment mechanism implied by the M-TAR model, the absolute values of $\rho_1 > \rho_2$ and therefore there is less decay for negative than for positive discrepancies. This result is consistent with the result obtained with the TAR model in section 5.4.3.

For the cointegration test, the absolute value of t-max (-3.2915) is greater than Enders and Siklos' (2001) tabulated critical values at all significance levels for one lagged change. This means that cointegration is also confirmed as in the TAR model. The sample value of Φ=12.78322 is greater than the 10 %, 5 % and 1 % critical values; therefore the null hypothesis of no cointegration is rejected. The null hypothesis of symmetric adjustment (i.e. $\rho_1 = \rho_2$) was tested using the F-distribution from the OLS regression. The sample value of the F-distribution is equal to 10.0521 with a p-value of (0.0000). The null hypothesis of symmetry is rejected at 1 % level of significance. The diagnostic test shows that the M-TAR model is a consistent and efficient estimator of the retail-farm relationship.

5.5 THRESHOLD-CONSISTENT MODEL

According to the Granger representation theorem, if a linear combination of two I(1) series is cointegrated, there exists an error correction representation of the cointegrating variables. Since both the TAR and M-TAR models suggest that the retail-farm relationship is cointegrated and asymmetric, to determine whether adjustment follows a TAR or M-TAR model, Schwarz's BIC model was used to select the best-fit model. It can be seen from the Table 5.6 that according to Schwarz's BIC, the best-fit model is the M-TAR. Therefore, the M-TAR model was fitted and the threshold value was estimated using Chan's (1993) method.

The indicator variable was reconstructed on the assumption of each data point in the arranged residual being a potential threshold. After discarding 10% from the two extreme data points, a grid search algorithm for an optimal threshold was carried out with 80 % of the data. The optimal threshold was obtained by minimising the RSS of the arranged autoregression. The optimal threshold value was found to be (-0.7264). Using this threshold estimate, the M-TAR model was re-estimated. A model augmented by four lags was selected by means of Schwarz's BIC. The results of the M-TAR consistent estimate are given in the fifth column of Table 5.6. Due to the low power of the t-max statistics, the null hypothesis of no cointegration cannot be rejected. The sample value Φ^*-statistic for the test of ($\rho_1 = \rho_2 = 0$) is 7.5543 with a critical value of 6.56 at the 5 % level of significance, which rejects the null hypothesis of no cointegration. The null hypothesis of symmetric adjustment (i.e. $\rho_1 = \rho_2$) was tested using the F-distribution from the OLS regression. The sample value of the F-distribution is equal to 6.3845 with a p-value of (0.0000). The null hypothesis of symmetry is rejected at 1 % level of significance. This implies that the relationship between the retail and farm market channels is asymmetric and exhibits non-linear threshold behaviour.

To confirm non-linearity and threshold behaviour, Tsay's (1989) non-linearity test was performed. The F-statistics and the critical values of the test were calculated by means of the procedure described in section 4.4.3.2 of Chapter 4. The calculated F-statistics are shown in Table 5.6, column 5, row 14. The F-distribution $(F_2 : 93)$ with a test-statistic of 25.011 is greater than the tabulated critical values of 4.79, 3.07 and 2.35 at (1 %, 5 % and 10 %) significance levels respectively. The critical values were obtained from the F-distribution table reported in Gujarati (2003).

5.6 THRESHOLD ERROR CORRECTION MODEL

- **Adjustment to equilibrium shocks**

The cointegration relationship between farm-retail poultry prices has been investigated in the preceding sections. The results obtained through several approaches, namely the Johansen multivariate test, the Engle and Granger (1987) test and the TAR and M-TAR methods, show that the farm-retail poultry price series are cointegrated. The primary aim of investigating cointegration is to determine whether the variables have a long–run relationship such that the series are expected to move together in the long run. If the series do move together, another underlying concern is how the prices will adjust if there is an economic shock. According to Engle and Granger (1987), adjustments to equilibrium are best represented in an asymmetric error correction model. Therefore, to further examine the dynamics of the asymmetric relationship, an asymmetric error correction model was fit, as shown in equation (4.22).

The M-TAR model was selected as the best-fit model for the error correction estimation by minimising Schwarz's BIC. The ρ_1 and ρ_2 in equation (4.22) represent positive and negative adjustment coefficients. Thus, following equation (5.1), ρ_1 and ρ_2 are denoted as ECT^+ and

ECT^{-}, where $ECT_{t-1}^{+} = I(RP_{t-1} - 6.4671 - 2.1723FP_{t-1})$ and $ECT_{t-1}^{-} = (1-I)(RP_{t-1}) - 6.4671 - 2.1723FP_{t-1}$ The momentum Heaviside indicator I is specified according to whether the equilibrium error is above or below the estimated threshold. The OLS regression of the equation was estimated for both retail and farm prices as the dependent variable. The lag length was determined using the general-to-specific method, because the lag selection by means of Schwarz's BIC procedure produced values that increase with increasing observations. Equation (4.11) was used to determine the maximum lag to begin the test. This procedure selects the optimal lag corresponding to the regression with significant coefficients. A truncation lag length of 12 is significant, but the next (lag 11) is insignificant; therefore the lag order is set at 12 for both retail and farm equations. The results of the error correction specification are presented in Table 5.7 and Table 5.8.

Table 5.7 shows the result of the M-TAR error correction model with the retail price as the dependent variable. The asymmetric response of the retail price to positive and negative shocks to the marketing margin of producers is captured by the adjustment coefficients (ECT^{+} and ECT^{-}). ECT^{+} indicates the margin is above its long-run equilibrium value, whereas the opposite holds for ECT^{-}. The t-statistics for the adjustment coefficients are both statistically different from zero. The results indicate that retail prices respond to both positive and negative shocks, but ECT^{-} induces a significantly greater change in the retail price than ECT^{+} because it is greater in size. In other words, if the ECT^{-} is greater, it means that the producer margin is below its long-run equilibrium. If the producer margin is below its long-run equilibrium, this means, when producer prices increase, then retailers must react fast in response to the changes in producer price in order to return the equilibrium to normal because if the producer price, due to cost increases, rises, producer margins falls, and as a result producers will push the cost to the retailer. This will also affect the margin of the retailers. Whenever this happens, the retail price will adjust to correct the disequilibrium. Therefore ECT^{-} is said to induce a greater change in retail price than ECT^{+}.

The question is how long does it take for retail prices to completely correct the disequilibrium? Since this relationship was investigated on the basis of monthly data, it is expected that the disequilibrium would be corrected within one month. The results show that the contemporaneous coefficients, including the adjustment coefficients ECT^{+} and ECT^{-}, are significantly less than one, which implies that retail prices do not react completely within one month to producer price changes.

This lag in price adjustment can be due to several reasons; retailers have the choice to accept and adjust to producer prices changes or search for alternative prices. Because they do not have information about prices offered elsewhere due to the search cost involved, they would react to adjust to the producer price changes. They are expected to react instantaneously but because of the nature of the value chain they do not and hence there is a lag in the adjustment to equilibrium. The lag in adjustment is obtained by estimating the time it takes for the retail price to revert to equilibrium price (reaction time). Table 5.7 indicates that within one month, retail prices adjust so as to eliminate approximate 2.8 % of a unit-negative change in the deviation from the equilibrium relationship caused by changes in farm prices. This implies that the retailers must increase their marketing margin by 2.8% in order to response completely to a unit-negative change in farm prices. Also, Table 5.7 indicates that the retailers adjust to remove 2.7 % of a unit-positive change in farm prices and also requires an increase of 2.7% in the marketing margin to respond to this change. Even though retailers eliminate price shocks from producers at relatively the same rate, it can be deduced that adjustment towards the long-run relationship between producers and retailers is faster when changes in deviation are negative (i.e. producer prices rise that lowers the marketing margin) compared to positive (i.e. producer prices decline that increases the marketing margin) changes. In other words, given that ECT^- is greater than ECT^+ in absolute value, it means that when the marketing margin is below the long-run equilibrium, retail prices react faster than when margins are above the long-run equilibrium.

Table 5.7 Estimates of the M-TAR error correction model

Dependent Variable (ΔRP(t))				
Regressors	**Coefficients**	**Standard error**	**T-statistics**	**P-value**
Constant	-0.4911	0.3190	-1.5399	(0.129)
ΔRP(t-1)	-0.4368	0.1302	-3.3539	(0.001)
ΔRP(t-2)	-0.0134	0.1294	-1.0326	(0.306)
ΔRP(t-3)	-0.2267	0.1302	-1.7409	(0.087)
ΔRP(t-4)	-0.2102	0.1316	-1.5976	(0.115)
ΔRP(t-5)	0.0506	0.1333	0.3792	(0.706)
ΔRP(t-6)	0.0782	0.1377	0.5679	(0.572)
ΔRP(t-7)	-0.0979	0.1380	-0.7093	(0.481)
ΔRP(t-8)	-0.0523	0.1352	-0.3865	(0.700)
ΔRP(t-9)	-0.0791	0.1359	-0.5818	(0.563)
ΔRP(t-10)	0.0182	0.1290	0.14091	(0.888)
ΔRP(t-11)	-0.1330	0.1250	-1.0643	(0.291)
ΔRP(t-12)	-0.3908	0.1216	-3.2133	(0.002)
ΔFP(t-1)	0.4496	0.1761	2.5524	(0.013)
ΔFP(t-2)	0.3849	0.1633	2.3568	(0.022)
ΔFP(t-3)	0.5267	0.1718	3.0655	(0.003)
ΔFP(t-4)	0.2920	0.1733	1.6847	(0.097)
ΔFP(t-5)	0.3533	0.1744	2.0264	(0.047)
ΔFP(t-6)	0.4902	0.1797	2.7274	(0.008)
ΔFP(t-7)	0.1519	0.1827	0.8314	(0.409)
ΔFP(t-8)	0.3274	0.1808	1.8112	(0.075)
ΔFP(t-9)	0.0731	0.1780	0.4108	(0.683)
ΔFP(t-10)	0.0713	0.1819	0.3921	(0.696)
ΔFP(t-11)	0.0406	0.1761	0.2308	(0.818)
ΔFP(t-12)	0.4367	0.1884	2.3181	(0.024)
ΔFP	0.2575	0.1644	1.5666	(0.122)
ECT+	0.0271	0.0147	1.8452	(0.0700)
ECT-	0.0281	0.0150	1.8744	(0.066)
R^2	0.4852			
R^2bar	0.2646			
		Diagnostic Test		
Serial Correlation			1.5546	(0.212)
Normality			2.7302	(0.255)
Heteroskedasticity			0.2827	(0.595)
ARCH			1.8145	(0.178)
Wald			36.9426	(0.001)

This finding reveals that retail prices react more rapidly but not completely to increases in upstream (producer) prices than to decreases – that is, the reaction is quicker when producer prices rises to squeeze the marketing margin than when they decline to stretch the margin.

This type of asymmetric relationship is termed positive price asymmetry and is more harmful to consumers than negative asymmetry[14].

Table 5.8 Estimates of the M-TAR error correction model

Dependent Variable (ΔFP(t))				
Regressors	**Coefficients**	**Standard error**	**t-statistics**	**p-value**
Constant	0.1626	0.24344	0.6681	(0.507)
ΔRP(t-1)	0.0919	0.1057	0.8698	(0.388)
ΔRP(t-2)	-0.0408	0.0980	-0.4162	(0.679)
ΔRP(t-3)	0.0151	0.1002	0.5111	(0.880)
ΔRP(t-4)	0.0892	0.1003	0.8889	(0.377)
ΔRP(t-5)	0.0658	0.1005	0.6580	(0.513)
ΔRP(t-6)	0.0142	0.1038	0.1372	(0.891)
ΔRP(t-7)	-0.1846	0.1016	-1.8165	(0.074)
ΔRP(t-8)	-0.0735	0.1014	-0.7252	(0.471)
ΔRP(t-9)	-0.0887	0.1019	-0.8703	(0.387)
ΔRP(t-10)	-0.0529	0.0968	-0.5464	(0.587)
ΔRP(t-11)	0.0800	0.0943	0.8486	(0.399)
ΔRP(t-12)	0.1521	0.0968	1.5713	(0.121)
ΔFP(t-1)	0.1047	0.1385	0.7560	(0.452)
ΔFP(t-2)	-0.2096	0.1254	-1.6717	(0.100)
ΔFP(t-3)	-0.1322	0.1375	-0.9611	(0.340)
ΔFP(t-4)	-0.2108	0.1306	-1.6147	(0.111)
ΔFP(t-5)	-0.5146	0.1352	-0.3807	(0.705)
ΔFP(t-6)	-0.2637	0.1390	-1.8969	(0.062)
ΔFP(t-7)	-0.0855	0.1378	-0.6209	(0.537)
ΔFP(t-8)	0.0973	0.1389	0.7005	(0.486)
ΔFP(t-9)	-0.1739	0.1323	-1.3146	(0.193)
ΔFP(t-10)	0.2706	0.1326	2.0405	(0.046)
ΔFP(t-11)	0.0646	0.1323	0.4888	(0.627)
ΔFP(t-12)	0.3599	0.1405	2.5569	(0.013)
ΔRP	0.1456	0.0930	1.5666	(0.122)
ECT+	-0.0053	0.0113	-0.4696	(0.64)
ECT-	-0.0005	0.1158	-0.0415	(0.967)
R^2	0.5799			
R^2bar	0.3999			
		Diagnostic Test		
Serial Correlation			0.6551	(0.416)
Normality			0.1798	(0.914)
Heteroskedasticity			1.9323	(0.165)
ARCH			1.5346	(0.216)
Wald			11.7705	(0.547)

- **Causality**

It should be noted that the response of retail prices to positive or negative changes in producer prices is not instantaneous but rather distributed over a time lag. For this reason, the response of retail prices to both contemporaneous and lagged changes in producer prices was investigated. The results show that on average, contemporaneous and lagged changes in producer prices induce a significant response from retail prices thus, signifying a contemporary impact asymmetric relationship. In order to determine the direction of this causal influence, the Granger causality test was performed by testing the joint null hypotheses that current and lagged changes in producer prices do not affect retail prices. In the farm price equation (Table 5.8) the contrary is tested. The results of the Granger causality test are shown in the second panel of Table 5.7 and Table 5.8. Using Wald test statistics, the null hypothesis is rejected for the retail price equation (Table 5.7), but is not rejected in the producer price

[14] The result and interpretation of the Asymmetric price transmission (APT) is based on producer and retail price data only, it does not include input or output costs.

equation (Table 5.8). The results show that there is unidirectional causality running from farm to retail prices. This implies that there a distributed lag effect asymmetric relationship between farm-retail prices. This finding is consistent with findings elsewhere (see Abdulai, 2002; Goodwin & Holt, 1999; Goodwin & Piggott, 2001; Kirsten & Cutts, 2006).

Compared with the retail price results presented in Table 5.7, the adjustment coefficients ECT^{+} and ECT^{-} in the producer price equation are not statistically significant. This implies that the producer price does not respond to long-run negative and positive changes in the marketing margin. The reason is that the ability to store meat is limited and therefore any temporary change in price does not affect the farmer's response because of the inelastic supply of livestock products. This situation is not the same with retailers who immediately respond to price increases or decreases by adjusting their prices. For this reason, the flow of price expectation (causality) in the long-run is transmitted from producers to retailers and seldom vice versa.

Other categories of asymmetric price transmission identified in this study are, (i) equilibrium adjustment path asymmetry- adjustment to equilibrium depends on whether the equilibrium term is above or below the equilibrium level, (ii) momentum equilibrium path asymmetry- an asymmetric adjustment exhibits more momentum in one direction than the other and (iii) regime equilibrium adjustment path asymmetry- threshold variable is defined by the equilibrium error correction term.

- **Diagnostic test**

A number of tests for model adequacy were performed to show that the M-TAR error correction model is consistent and that the parameter estimate is valid under contemporary statistical inference. These tests are the Breusch-Godfrey Lagrange multiplier (LM) test of serial correlation, the Jarque-Bera test of normality, the White test of heteroskedasticity, and the autoregressive conditional heteroskedasticity (ARCH) test. The diagnostic tests are shown in the lower panels of Table 5.7 and Table 5.8. All diagnostic tests show that there is no violation of the classical linear regression assumption; hence the model fits the data.

5.7 CONDITIONAL PRICE VOLATILITY

The basic aspect in measuring volatility is to separate the predictable component of the price process from the unpredictable part. The reason is that since the predictable component constitutes price variability, which the agents can anticipate from one period to another, it should be differentiated from volatility, which constitutes the unpredictable component of the future price process.

The first step in identifying the unpredictable process is to examine the stochastic component of the price series in order to determine the process that generated the data. If the data was generated by a trend-stationary process, the effect of shocks on future realisations is temporary, whereas a difference-stationary process elicits permanent effects. The most widely used method to determine whether prices are trend- or difference-stationary is to carry out a unit root test. However, this test has low power in small samples and also performs poorly if the underlying series have structural breaks. Therefore, to account for this, a structural stability test on the prices must first be conducted. The results of the structural stability test conducted for this study are shown in Table 5.5. The results indicate that there is no structural break in any of the prices series studied. The unit root hypothesis was then examined, as indicated in section 5.4. The results of the unit root test indicate that all the price series are trend-stationary.

After determining the time-series property, the Box-Jenkins methodology (Box & Jenkins, 1976) was used for model identification, estimation and diagnostics. The first step in such model identification is to determine the order of the autoregressive process used in the conditional volatility measurement. The ARIMA representation was adopted since it is an important forecasting tool and has the combination of three important components of time-series modelling, namely the autoregressive (AR) component, the integrated time-series component, and the moving average component. A combination of these three components makes up the ARIMA (p,d,q) process. The order of integration d is the number of times a difference-stationary series needs to be differenced to make it stationary. The unit root test reported in section 5.3 indicates that all the series are integrated of the order I(1), hence they are differenced once. The p is the AR(p) order, which indicates the number of times the AR process is lagged. The moving average component is a measure of the orthogonality of the disturbance term. The error term is lagged q times to render it orthogonal.

The Box-Jenkins methodology (Box & Jenkins, 1976) was used together with Schwarz's BIC to select the values of (p,q). Schwarz's BIC is preferred over Akaike's information criterion (AIC) because according to Hannan (1980), it provides consistent order-estimation in the context of linear ARIMA models. The autocorrelation and partial autocorrelations are first examined. The process involves fitting an ARIMA process and examining the correlogram to determine the ARIMA orders. As a rule of thumb, if the autocorrelation function dies off smoothly at a geometric rate and the partial autocorrelations are zero after one lag, then a first-order AR model is identified. Alternatively, a first-order MA process is identified if the autocorrelations are zero after one lag and the partial autocorrelations decline geometrically. To serve as a guide, the minimum Schwarz's BIC are used simultaneously to identify the ARIMA orders. Different ARIMA orders are identified for the selected price series. The ARIMA orders are shown in Table 5.10, panel A, column 6.

5.7.1 GARCH effect

A test for conditional error variance in the ARIMA process is a necessary condition for fitting volatility models. If the estimated ARIMA process does not have GARCH errors, it has constant variance and covariance, and hence it is time-invariant. If there is a GARCH error, the volatility varies with time. An LM test was used to test for the presence of autoregressive conditional heteroskedasticity (ARCH) / generalised autoregressive conditional heteroskedasticity (GARCH) effects in the ARIMA process. OLS of the best-fitting ARIMA process was estimated and the post-regression residuals used for the LM test. The null hypothesis of the test is that there is no ARCH/GARCH effect in the residual of the estimated ARIMA process. The LM test is asymptotically distributed chi-square with the degrees of freedom equal to the number of lags (q). In addition to the LM test, an F-test for the joint significance of the residuals was computed. The results of the LM test and the F-test are shown in Table 5.9. The null hypothesis is rejected at all conventional significance levels.

Table 5.9 Test of ARCH/GARCH/EGARCH effect

Price Series	F-test	LM test
DMAZ	1.92188	9.26752
	(0.0982)[a]	(0.0988)
DSUNF	6.34551	24.22005
	(0.0000)	(0.0000)
DSOYB	2.36023	10.90975
	(0.04965)	(0.05319)
RETAIL	5.9550	5.73275
	(0.0164)	(0.0166)
FARM	4.40689	4.30530
	(0.0383)	(0.0380)

[a] The figures in parenthesis are the probability values.

The results show that the OLS regressions assuming the ARIMA process of the selected agricultural products, namely the retail and farm poultry prices, the domestic spot SAFEX yellow maize (DMAZ) price, the domestic sunflower (DSUNF) price and the soybean (DSOYB) price, have non-constant errors, i.e. they are heteroskedastic. The price process of the commodities was investigated further to determine whether the error process is conditionally heteroskedastic. The process is conditionally heteroskedastic if the unconditional or long-run variance of the price processes may be constant (which is rare), but there are periods in which the variance is relatively high (volatile). A measure of the degree of volatility and whether the volatility in these commodities spills over to other commodities was investigated. In order to accomplish this task, the next step was to select the best-fit conditional volatility model. The EGARCH model as discussed in Chapter 2 and Chapter 4 was adopted. Firstly, the appropriate order of the EGARCH model was selected by fitting the EGARCH (1,1) EGARCH (2,1) and EGARCH (1,2) models. The EGARCH (1,1) model was selected by minimising Schwarz's BIC.

5.7.2 Model estimation

The empirical estimation of price volatility was conducted in two steps. In the first step, an estimate of the changing conditional variance in the prices was determined. In the second step, it was determined whether there is significant volatility spillovers between farm and retail prices and whether the price volatility in the major poultry feed components of yellow maize, sunflower oilseed and soybean significantly spills over to farm and retail prices.

To estimate the changing conditional variance of the prices, a conditional mean and variance model of the prices was fitted and the conditional standard deviation derived as the square root of the conditional variance was obtained. All models were determined to be best fit by the EGARCH (1,1) model. The EGARCH (1,1) model for the conditional variance was fitted assuming an ARIMA representation as shown in equation (4.30) in Chapter 4. The models were estimated by the method of maximum likelihood techniques under the assumption that the residual errors are independently and identically normally distributed draws from the generalised error distribution (GED) density function. The log-likelihood function for the GED is given by

$$l_t = -\frac{1}{2}\log\left(\frac{\Gamma(1/\tau)^3}{\Gamma(3/\tau)(\tau/2)^2}\right) - \frac{1}{2}\log\sigma_t^2 - \left(\frac{\Gamma(3/\tau)(y_t - X_t^{'}\theta)^2}{\sigma_t^2\Gamma(1/\tau)}\right)^{\tau/2} \tag{5.3}$$

where the tail parameter $\tau > 0$. The GED is normally distributed if $\tau \geq 2$, and is fat-tailed if $\tau < 2$, while $y_t - X_t^{'}\theta$ represents the residual from the mean equation. The parameters of the EGARCH model were estimated by means of an iterative algorithm. The Marquardt algorithm and the Berndt, Hall, Hall and Hausman (1974) algorithm are the most commonly used. However, the latter algorithm converges more rapidly and accurately and was therefore selected for this analysis.

The EGARCH (1,1) model was fitted considering two conditions. Firstly, the conditional volatility was calculated without a seasonal component, and secondly the effect of seasons on the volatility of the prices was considered. The seasonal component was incorporated into the EGARCH model following the procedure discussed in Chapter 4, the aim being to compare the two options since volatility in agricultural commodities is highly associated with seasonality. The results indicate that there is no remarkable difference between the two results; therefore, only the results of the EGARCH model with a seasonal component are reported.

5.7.2.1 Conditional volatility estimates

The results of the EGARCH (1,1) model estimation with a seasonal component are given in Table 5.10. Panel A, column 4, in Table 5.10 reports the unconditional coefficient of variation computed by dividing the standard deviation of the nominal prices by their means. The aim of computing the coefficient of variation is to show that using approaches that do not cater for the time-varying predictable component overstates volatility. For instance, the volatility implied by the coefficient of variation for all the prices is larger in value compared to that implied by the conditional standard deviation of the conditional variance calculated using the EGARCH (1,1) model (Table 5.10, panel A, column 5). This is because the removal of the time-varying predictable component from the series decreases volatility. It should be noted, however, that the time-varying volatility cannot be captured as a single value but is rather represented graphically. Dehn (2000) suggests that the median of the conditional standard deviation can be used as measures of volatility. The median estimate of the conditional volatility is used in this instance. The results show that the magnitude of volatility in the retail and farm poultry prices for the period 2000M1-2008M8 is 1.82 % and 2.8 % respectively (Table 5.10, panel A, column 5, rows 3 & 6). The farm price is more volatile compared to the retail price. The volatility implied by the conditional variance of the domestic yellow maize price for the same period is 6.4 %. The conditional volatility was computed for different time periods in order to determine any changes in the volatility within the periods under review. The results show that the volatility implied by the conditional standard deviation of the retail prices fluctuates when different periods are considered. For instance, the volatility in the poultry retail price increases from 1.82 % to 1.93 % and decreases to 1.66 % when considering different time periods whereas the farm price volatility declines slightly but steadily from 2.78 % and 2.61 % to 1.72 % in the same period (Table 5.10, panel A, column 5).

To complement the results obtained with the median estimate of the conditional volatility, a graphical representation of the conditional standard deviation of the conditional variance is presented in Appendix A5. This appendix shows the plots of the conditional standard deviation obtained by fitting the EGARCH model with seasonal components. The plots show that the volatility distribution for most of the commodities is relatively leptokurtic. This implies that major changes in the price process follow major changes in volatility and vice versa. The volatility in the farm price peaks in October 2002, November 2003 and November 2007 relative to other years. The periods of high volatility in the retail price of poultry correspond to May 2002, November 2002, May 2006 and January 2006. The volatility depicted in these plots corresponds to the periods when there were high food prices.

The results of the mean and the variance component of the EGARCH model are reported in Table 5.10, panel B. The results show that most of the ARIMA parameters in the mean equation are significant[15]. The regularity conditions require that all the inverted roots of the ARIMA process and the ARIMA coefficients should be inside the unit circle; hence the condition is fulfilled because all the ARIMA coefficients in the mean equation are less than unity, and the sum of all the inverted roots[16] of the AR and MA processes are within the unit circle (less than one).

In the variance equation, volatility persistence is measured by coefficient b. Recall from the preceding chapters that if the coefficient is significant, there is significant evidence of persistence of shocks. The smaller the absolute value of b, the less persistent volatility is after a shock. If the value of b approximates unity, shocks persist into the future. The results show that volatility in the farm price and in the domestic yellow maize, sunflower and soybean prices is significant. There is no significant volatility persistence in the retail price, and the absolute value of the coefficient is relatively low compared to other prices. Even though there is significant volatility persistence in the farm price, the absolute value of the

[15] The statistical significance of the estimated coefficients is calculated from the standard normal z-distribution tabulated in Gujarati (2003) using the z-statistics obtained from the maximum likelihood regression output.
[16] The inverted roots of the AR and MA processes are not reported, but will be made available on request.

coefficient is relatively small, implying that volatility persistence into the future decays faster. The absolute value of the volatility persistence parameter of the domestic maize, sunflower and soybean prices is high, suggesting that volatility in these markets persists. This implies that once a shock occurs, it takes a long time to be eliminated.

The persistence in price can also be assessed according to its half-life. Half-life is the time it takes for half of the shocks to be eliminated. The half-life for the shocks on the different prices is shown in the last row of Table 5.10, panel B. It is shown that it takes less than one month (0.41 and 0.73 respectively) for half of the shocks to the individual retail and farm prices to be eliminated. The half-life of shocks occurring in the other commodity markets are 4.9 for the domestic yellow maize market, 12.02 for the sunflower market, and 2.47 for the soybean market. This implies that once a shock occurs to the domestic yellow maize, sunflower and soybean markets, it takes about 4.9, 12.02, and 2.47 months respectively for half of the shocks to decay.

The impact of season on the conditional volatility estimates of the prices was then investigated. The seasonal deterministic components incorporated into the EGARCH model are reported in Table 5.10, panel C. There is no evidence of a strong seasonal influence on the conditional volatility of the prices, because only a few coefficients of the sum of the trigonometric functions are statistically significant. Even though these trigonometric functions are not strongly significant, their inclusion improves the fit of the EGARCH model and therefore they should not be ignored. Strong seasonality is not observed, because chicken products are produced throughout the year due to improved technology and production practices. Hence, the volatility associated with seasonal sales smoothens as demand is met with regular market supply.

Table 5.10: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (Panel A)

Series name	Period	Coefficient of variation	Conditional standard deviation	Process of the price series
Col. 1	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**
	2000M1-2008M8	0.2290	0.0182	A RIMA(0,1,1)
RETAIL	2002M1-2008M8	0.1657	0.0193	ARIMA(1,1,0)
	2004M1-2008M8	0.1487	0.0166	ARIMA(1,1,0)
	2000M1-2008M8	0.1602	0.0278	ARIMA(8,1,0)
FARM	2002M1-2008M8	0.1074	0.0261	ARIMA(5,1,0)
	2004M1-2008M8	0.1052	0.0172	ARIMA(5,1,0)
	2000M1-2008M8	0.3437	0.0644	ARIMA(1,1,2)
DMAZ	2002M1-2008M8	0.3126	0.0587	ARIMA(0,1,1)
	2004M1-2008M8	0.3449	0.0573	ARIMA(1,1,0)
	2001M4-2008M8	0.3620	0.0556	ARIMA(2,1,0)
DSUNF	2002M1-2008M8	0.3606	0.0518	ARIMA(3,1,0)
	2004M1-2008M8	0.3884	0.0504	ARIMA(1,1,0)
DSOYB	2002M4-2008M8	0.3370	0.0641	ARIMA(0,1,1)
	2004M1-2008M8	0.3883	0.0653	ARIMA(2,1,0)

Table 5.10: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (Panel B – monthly data)

PARAMETERS	FARM	RETAIL	DMAZ	SUNF	SOYB
			Mean Equation		
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**
Constant	0.0290 (0.1346)	0.0068* (0.0012)	0.0150 (0.5055)	0.01661 (0.2824)	0.00441 (0.4897)
AR(1)	0.0206* (0.0034)		0.8849* (0.0000)	0.42468* (0.0016)	
AR(2)	-0.0242** (0.0254)			0.02681 (0.3757)	
AR(3)	-0.01063 (0.3489)				
AR(4)	-0.0002 (0.9802)				
AR(5)	0.0254** (0.0367)				
AR(6)	-0.0273** (0.0171)				
AR(7)	0.0041 (0.6729)				
AR(8)	0.0109** (0.0629)				
MA(1)		0.0096 (0.9489)	-0.4602** (0.0142)		0.24977* (0.0000)
MA(2)			-0.2527 (0.1879)		
MA(3)					
			Variance Equation		
Constant	-5.37757 (0.1541)	-9.5279* (0.001)	-10.7247* (0.0000)	-0.32600* (0.0000)	-0.91875* (0.0000)
a	-0.31086 (0.4202)	0.5683*** (0.0594)	0.3840** (0.0201)	0.01318 (0.9443)	-0.48139* (0.0039)
b	0.3862** (0.0645)	-0.18214 (0.6335)	-0.8679* (0.000)	-0.94414* (0.0000)	0.75567* (0.0000)
γ	0.8222* (0.0044)	0.1235 (0.4415)	-0.0193 (0.8394)	0.00079 (0.9954)	-0.43860* (0.0020)
Half-live	0.73	0.41	4.90	12.06	2.47

Figures in parenthesis are the p-values. The asterisks, *, **, *** represent statistical significance at the 1 %, 5 % and 10 % significance levels.

Table 5.10: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (Panel C - Trigonometric seasonality terms)

PARAMETERS	FARM	RETAIL	DMAZ	SUNF	SOYB
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**
COS 1	1.9473 (0.7436)-	-0.577*** (0.0631)	-0.0565 (0.5657)	0.14770 (0.3532)	0.34652 (0.304)
COS 2	-1.5732 (0.6614)	-0.4754 (0.1331)	0.0951 (0.5716)	-0.10157 (0.5851)	0.6946*** (0.0828)
COS 3	0.6099 (0.6022)	0.3992 (0.1998)	-0.1529 (0.2576)	0.02742 (0.8727)	-0.15174 (0.6506)
SIN 1	-0.6314 (0.5305)	-0.2467 (0.5811)	0.1985 (0.218)	-0.24236 (0.1993)	-0.11456 (0.7294)
SIN 2	0.4955 (0.7196)	-0.2662 (0.5651)	-0.3324*** (0.1018)	-0.09791 (0.5763)	-0.01965 (0.9654)
SIN 3	-0.9242 (0.2887)	0.5123** (0.0443)	0.11692 (0.376)	0.3248*** (0.0952)	-0.31674 (0.3481)

Figures in parenthesis are the p-values. The asterisks, *, **, *** represent statistical significance at the 1 %, 5 % and 10% significance levels.

5.7.2.2 Model specification tests

The results of the EGARCH model are reliable only if the model is correctly specified. If the EGARCH model is correctly specified, the condition for the stationarity of the EGARCH model specified in Chapter 4, section 4.5.6, must be met. To verify that these conditions are fulfilled several inferential and diagnostics procedures are undertaken.

Test for stationarity of estimated parameters. The significance of the estimated EGARCH model and whether the coefficients of the estimated AR and MA components fall within the unit circle are some of the conditions for stationarity of the model. Other conditions are that the sum of the inverted roots of the ARIMA model and the volatility persistence parameter is less than one. These conditions have been discussed previously.

Test for remaining serial correlation in the mean equation. The orthogonality condition implied by the correct specification of the EGARCH model requires that the distribution of the standardised residuals is serially uncorrelated. Therefore a test for the remaining serial correlation in the mean equation must be checked. If the mean equation is correctly specified, none of the Ljung-Box Q-statistics in the correlogram of autocorrelation and partial autocorrelation of the standardised residuals would be significant. The test is chi-square distributed with a degree of freedom equal to the number of pre-specified lags. One-quarter of the total sample is chosen as the optimal lag length, which gives a lag order total of 26 for the test. The null hypothesis of the test is that the joint Q-statistics are equal to zero. Rejecting the null hypothesis implies that the sequence of standardised residuals is serially correlated and that the model of the mean is not correctly specified. The results for the test of serial correlation in the standardised residual are reported in Table 5.10, panel D, row 3. The Ljung-Box Q-statistics are not statistically different from zero for all the tests. This implies that there is no serial correlation in the standardised residual and that the mean equation is correctly specified.

Table 5.10: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (Panel D - Model specification test Diagnostics)

PARAMETERS	FARM	RETAIL	DMAZ	SUNF	SOYB
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**
Ljung-Box [26]	26.279 (0.448)	14.355 (0.448)	22.887 (0.467)	14.791 (0.927)	8.3297 (0.999)
Ljung-Box [26]	21.556 (0.713)	17.681 (0.856)	18.913 (0.706)	18.034 (0.801)	12.863 (0.978)
F-test	0.2202 (0.9796)	0.4777 (0.8484)	1.1076 (0.3657)	0.98641 (0.4482)	0.49420 (0.8961)
LM [7]	1.6626 (0.9761)	3.5146 (0.8337)	7.7734 (0.3530)	7.00190 (0.4287)	3.05861 (0.8795)
Jarque-Bera	0.7188 (0.6981)	0.3681 (0.8319)	3.008 (0.2222)	5.1755*** (0.0752)	47.6843* (0.0.00)
GED	1.6369* (0.0005)	2.0190* (0.0033)	5.2355*** (0.0986)	6.0263*** (0.0909)	1.12611* (0.0001)
LogL	218.9806	257.806	143.0353	128.1189	106.7061

Test for remaining ARCH in the variance equation. Recall that before the EGARCH model was fit, an (LM) test for the presence of ARCH/GARCH effect revealed an ARCH/GARCH error in the residuals. After fitting the EGARCH model to measure conditional volatility, it became appropriate to check for the model's stationarity – that is, whether all the conditional errors had been removed. If the EGARCH model is correctly specified, there should not be any remaining errors in the variance of the model. This test verifies whether this condition is satisfied. The Ljung-Box Q-test is used to verify this. One-quarter of the total sample size was used as the optimal lag length. The results for the test of remaining ARCH/GARCH errors in the squared standardised residual are reported in Table 5.10, panel D, row 4. As in the test for the correct specification of the mean equation, the results show that the Q-statistics cannot be rejected at all the pre-specified lags. This implies that there are no remaining ARCH/GARCH errors in the variance of the EGARCH model and that the variance model is correctly specified.

Test for additional ARCH in the standardised residual. This LM test is used to determine whether the standardised residuals exhibit additional ARCH/GARCH effects. Like the Ljung-Box test, this test is used to check whether the variance equation is correctly specified. If the variance equation is correctly specified there should be no ARCH/GARCH left in the standardised residuals. The null hypothesis is that there is no ARCH/GARCH up to the specified number of lag order in the residual. The Engle (1982) test statistics were used, computed as the total number of observations in the test sample multiplied by the coefficient of determination (R^2), known as the Obs*R-squared test statistics. The test statistics are asymptotically distributed chi-square with degrees of freedom equal to the number of residual lags. The results of the LM test are reported in Table 5.10, panel D, row 6. The null hypothesis of no ARCH/GARCH effect in the residual cannot be rejected at 5 % level of significance.

Test for omitted variables in the variance equation. This is an F-test for omitted variables in the variance equation. The F-test is used to test the hypothesis of joint significance of all lagged squared residuals. The null hypothesis is that there is no omitted variable in the variance equation. The results are reported in Table 5.10, panel D, row 5. The null hypothesis is not rejected for all the tests. This signifies that there is no omitted variable in the variance equation of the EGARCH model.

Test for normality of standardised residuals. The Jarque-Bera test statistics are used to test the hypothesis that the standardised residuals are normally distributed. If the standardised residuals are normally distributed, the Jarque-Bera test statistics should not be rejected. The results regarding the normality of the standardised residuals are reported in Table 5.10, panel D, row 7. The results show that with the exception of the soybean price, all the prices are normally distributed. Another test for the normality of the standardised residuals is the GED tail parameter of the GED error distribution. If the tail parameter < 2, the distribution of the standardised residuals is fat-tailed rather than normal. The standardised residuals are normally distributed if the tail parameter ≥ 2. The results of the GED distribution test are presented in Table 5.10, panel D, row 8. The value of the GED tail parameter indicates that the standardised residuals are normally distributed with the exception of the soybean price, which deviates from normal.

5.7.3 VOLATILITY SPILLOVER

Section 5.7.2.1 reports the estimates of the conditional volatility in farm, retail and grain prices. Three important aspects of market relationships are investigated in this section, namely: (a) Whether there is a significant volatility spillover effect or price influence between these markets; (b) Whether the influence (if present) is asymmetric and, if so, (c) Whether the asymmetric volatility persists in the future. The major focus falls on the bivariate farm-retail relationship, but because the grains and oilseeds are inputs in the poultry-feed industry, the question of whether there is a significant influence on the price expectation between the different commodities is considered. A bivariate AR(P) EGARCH (1,1) model is used to model this relationship. Different AR(P) processes are fit for different bivariate relationships. Following the specifications of the bivariate EGARCH (1,1) model described in Chapter 4, the results of the bivariate relationship between the market prices are presented in Table 5.11.

The results of the mean equation of the EGARCH (1,1) model, as presented in Table 5.11, panels A and B, suggest that there is a significant bivariate relationship between the market prices investigated. Intuitively, this implies that market influence could flow either way. The volatility spillover parameter a is used to measure the direction of the influence. If the parameter is significant for one market linkage and insignificant for the alternative, then volatility spillover or market influence exists in one direction (unidirectional). The relationship could be bidirectional, whereby volatility or market influence is transferred in either direction. The results show that the bivariate linkage between RETAIL-FARM is significant whereas the relationship between FARM-RETAIL is not significant (Table 5.11, panel C, rows 4 & 5, and column 3). This implies that there is significant volatility spillover from the farm to the retail poultry market channel and not vice versa. This is consistent with the results of other researchers (see Buguk *et al.*, 2003; Rezites, 2003). This is also consistent with the findings in the price transmission analysis between the two market channels reported in section 5.6 of this chapter where unidirectional market price influence (Granger causality) is found to flow from the farm to the retail market of the poultry sector and not vice versa.

The results for the volatility spillover test between farm and retail poultry prices and the poultry feed (grain and oilseed) materials are presented in Table 5.11, panel C. The results show that there is a significant unidirectional volatility spillover from the domestic yellow maize price to the farm and retail market prices. This implies that changes in the price of yellow maize have a significant spillover effect on the retail and farm poultry market prices. Market influence also flows from the sunflower oilcake price to the retail market price. The soybean oilcake price has the least impact, because there is no significant volatility spillover between the soybean price and the retail and farm market prices. This finding is consistent with the expectation, because the yellow maize price is expected to have more influence on the poultry price compared to the price of oilcake. This is because the inclusion rates of these materials into poultry feeds differ. According to a report of the Food Price Monitoring Committee (FPMC, 2003), the inclusion rate of maize in the total production of feed rations is about 50-60 %, Sunflower oilcake makes up 0-5% while soybean oilcake makes up 20-35% of the volume. These three feed components make up at least 70% of the poultry feed ration. Poultry feed is formulated on a least cost linear programming basis, hence the inclusion rate depends on the types of raw materials and the nutrient component need of the ration. The nutrient requirement of poultry feeds varies. For example the nutrient requirement of broiler is high thus its feeds can contain up to 20 raw materials (Bredenham, 2010).

5.7.4 Volatility persistence

Volatility persistence between the markets is measured by coefficient b. This coefficient has the same interpretation as previously discussed. With regard to this coefficient, significant volatility persistence is found to exist when the retail-farm linear relationship is considered but not when farm-retail linear combination is considered. This is because the farm market price exerts more influence over retail price and not vice versa, such that the effect persists in the future.

A significant volatility persistence effect also exists between retail-sunflower prices where more influence flows from the sunflower price to the retail price and not vice versa.

Table 5.11 Maximum likelihood estimates of the bivariate EGARCH (1,1) model for volatility spillover: Monthly data [2000M1-2008M8]

Panel A

						Mean equation				
Parameters		**Constant**	**AR(1)**	**AR(2)**	**AR(3)**	**AR(4)**	**AR(5)**	**AR(6)**	**AR(7)**	**AR(8)**
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**	**Col. 7**	**Col. 8**	**Col. 9**	**Col. 10**	**Col. 11**
FARM-RETAIL	FARM		0.0076	0.00218	-0.0193*	-0.0233*	0.0063	-0.0148**	-0.0091	
		0.01053*	(0.1171)	(0.7096)	(0.0009)	(0.0000)	(0.3710)	(0.0112)	(0.1466)	
	RETAIL	(0.0000)	0.0074**	0.0082***	-0.0052	0.0026	0.0008	-0.0080	-0.0135*	
			(0.043)	(0.0949)	(0.1956)	(0.5493)	(0.8685)	(0.1770)	(0.0069)	
RETAIL-FARM	FARM		0.0243*							
		0.00754*	(0.0000)							
	RETAIL	(0.0000)	-0.0068							
			(0.1059)							
FARM-DMAZ	FARM		0.00367	-0.01616	-0.01091	-0.01019	0.02979***	-0.02289***	0.00418	0.01564
		0.05784*	(0.6655)	(0.2085)	(0.4155)	(0.3925)	(0.0636)	(0.0971)	(0.7681)	(0.1227)
	DMAZ	(0.0046)	0.00010*	0.00007	0.00004	0.000019	-0.000036	0.000013	0.000008	0.0000062
			(0.0035)	(0.1929)	(0.5044)	(0.7314)	(0.5597)	(0.8423)	(0.8859)	(0.8486)
DMAZ-FARM	FARM	-0.01059	0.03484	-0.02041	-0.01134					
			(0.1991)	(0.6848)	(0.6306)					
	DMAZ	(0.8783)	0.00017***	-0.00261***	0.00007					
			(0.0949)	(0.0633)	(0.5077)					
FARM-SUNF	FARM	0.10347	0.000230	-0.01741	0.00384	-0.01789**	0.019230*			
			(0.7554)	(0.1854)	(0.7589)	(0.0273)	(0.0001)			
	SUNF	(0.0000)	0.00005*	0.000012	0.000034	0.000022	0.00002***			
			(0.0000)	(0.4634)	(0.1935)	(0.3336)	(0.1009)			
SUNF-FARM	FARM		0.020834*	-0.00728*	-0.01199					
		-0.00081	(0.0000)	(0.0000)	(0.354)					
	SUNF	(0.9938)	0.000172*	-0.00026*	0.00008***					
			(0.0000)	(0.0000)	(0.0948)					
FARM-SOYB	FARM		0.01005	-0.01995***	-0.00665	-0.0235**	0.02863*			
		0.129205	(0.235)	(0.0885)	(0.6209)	(0.0421)	(0.0005)			
	SOYB	(0.0078)	0.00008*	-0.00006**	0.000007	0.00004	-0.00005***			
			(0.0001)	(0.0437)	(0.8321)	(0.3116)	(0.0926)			
SOYB-FARM	FARM		0.012222	0.003668						
		-0.13237	(0.4048)	(0.8061)						
	SOYB	(0.0283)	0.00009*	-0.00012*						
			(0.0000)	(0.0000)						

Panel B **Mean equation, continued: Monthly data [200M1-2008M8]**

Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8	Col. 9	Col. 10	Col. 11
RETAIL-DMAZ	RETAIL	0.0071	-0.0013 (0.1015)							
	DMAZ	(0.4436)	0.00002 (0.0115)							
DMAZ-RETAIL	RETAIL	-0.0366	0.02391 (0.2162)	-0.0179 (0.3604)						
	DMAZ	(0.4017)	0.0002* (0.0036)	-0.0003* (0.0017)						
RETAIL-SUNF	RETAIL	0.01196***	-0.001269 (0.029)							
	SUNF	(0.0539)	0.000008** (0.0154)							
SUNF-RETAIL	RETAIL	0.013127	0.007589 (0.6780)	-0.00488 (0.7920)						
	SUNF	(0.6666)	0.000017* (0.0000)	-0.00019* (0.0000)						
RETAIL-SOYB	RETAIL	-0.00247	-0.000172 (0.8114)							
	SOYB	(0.8161)	0.000005 (0.1280)							
SOYB-RETAIL	RETAIL	-0.05279	0.00001* (0.0003)	-0.00019* (0.0000)	0.00012* (0.0006)	0.00005* (0.1073)				
	SOYB	(0.2341)	0.11023 (0.2748)	-0.00695*** (0.1009)	0.00099 (0.9432)	0.00170 (0.8775)				

Table 5.11 Panel C	Variance equation: Monthly data [2000M1-2008M8]			
SPILLOVER	**CONSTANT**	**a**	**γ**	**b**
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**
RETAIL-FARM	-0.2052 (0.2793)	-0.2303*** (0.0591)	0.1454*** (0.0736)	0.9494* (0.0000)
FARM-RETAIL	-6.0700*** (0.0587)	-0.0734 (0.9000)	0.6235*** (0.0612)	0.1415 (0.7484)
FARM-DMAZ	-6.8091** (0.0393)	-0.5485*** (0.0946)	0.4598*** (0.0923)	0.0361 (0.9335)
DMAZ-FARM	-8.0532* (0.000)	0.2984 (0.1179)	0.1363 (0.2938)	-0.4812*** (0.0614)
RETAIL-DMAZ	-7.8211* (0.000)	0.5595*** (0.0833)	0.3112*** (0.0980)	0.0560 (0.8141)
DMAZ-RETAIL	-7.7991* (0.0016)	0.2685 (0.2419)	0.1603 (0.2872)	-0.4249 (0.3737)
FARM-SUNF	-13.2218* (0.0000)	0.234347 (0.3707)	0.3541*** (0.0655)	-0.702235 (0.0000)
SUNF-FARM	-10.9136* (0.0000)	-0.182575 (0.2767)	0.131953 (0.1492)	-0.9529* (0.0000)
FARM-SOYB	-2.821247 (0.2760)	0.201026 (0.5496)	0.148789 (0.4747)	0.6526** (0.0470)
SOYB-FARM	-5.1353*** (0.0998)	-0.6358 (0.1559)	-0.2153 (0.4716)	-0.0360 (0.9481)
RETAIL-SUNF	-0.7503** (0.0169)	-0.3689** (0.0323)	0.3817* (0.0010)	0.8647* (0.000)
SUNF-RETAIL	-8.1847* (0.0000)	-0.0694 (0.5383)	0.0607 (0.4067)	-0.4559* (0.0013)
RETAIL-SOYB	-0.5906* (0.0002)	-0.2637 (0.2172)	0.3402** (0.0255)	0.8983* (0.0000)
SOYB-RETAIL	-3.8287 (0.4506)	-0.3321 (0.5386)	-0.2542 (0.4304)	0.2395 (0.8087)

5.7.5 Asymmetric spillover

The results of the asymmetric volatility spillover between the farm and retail market channels are shown in Table 5.11, panel C. It can be seen that the asymmetric spillover coefficient γ is positive and statistically significant at 10 % level of significance. This implies that the spillover effect that flows from the farm to the retail market is asymmetric. That is, the response to rising prices (positive shock) at any production and marketing stage (farm or retail) differs from the response to price declines (negative shock). The sign of the coefficient (positive) indicates that positive shocks increase volatility whereas negative shocks decrease volatility. An investigation into the impact of volatility in animal feed materials (maize and oilseeds) on the poultry farm and retail prices shows that the volatility spillover from the domestic maize price to the farm price (FARM-DMAZ), from the domestic maize price to the retail price (RETAIL-DMAZ) and from the sunflower price to the retail market price (RETAIL-SUNF) is positive and asymmetric.

Any positive shock from a market channel with significant market influence will increase volatility in the alternate market, whereas any negative shock will decrease volatility.

5.7.6 Diagnostic statistics

The diagnostic tests on the standardised residuals of the EGARCH (1,1) model in this section follow the same interpretation as the tests performed in section 5.7.2.2. The results of the model adequacy and specification tests are reported in Table 5.11, panel D. The results show that there is no remaining serial correlation in the mean equation of the EGARCH model. There is also no additional ARCH/GARCH effect in the standardised residuals, nor is there any omitted variable in the variance equation. This implies that the mean and variance equations of the EGARCH model are correctly specified. The test for normality of the standardised residuals shows that the market price linkages are normally distributed, as implied by the Jarque-Bera test statistics and the GED parameter. However, the bivariate relationship between SOYB-FARM market prices slightly deviates from the normality assumption.

Table 5.11 Panel D Model specification tests: Monthly data [2000M1-2008M8]

Parameters	Ljung-Box	Ljung-Box	F-test	LM	J-Bera	GED	Logl
Col. 1	**Col. 2**	**Col. 3**	**Col. 4**	**Col. 5**	**Col. 6**	**Col. 7**	**Col. 8**
FARM-RETAIL	15.157 (0.938)	20.279 (0.73)	0.8003 (0.5723)	4.9140 (0.5548)	1.2470 (0.5361)	1.7671* (0.0000)	262.151
RETAIL-FARM	26.03 (0.406)	14.535 (0.952)	0.7256 (0.6302)	4.4853 (0.6113)	4.2452 (0.1197)	0.8970* (0.0000)	220.962
FARM-DMAZ	27.106 (0.404)	24.306 (0.558)	0.6727 (0.6945)	4.8900 (0.6734)	1.0950 (0.5784)	1.9806* (0.0093)	225.864
DMAZ-FARM	21.678 (0.706)	11.975 (0.991)	0.7105 (0.6632)	5.1388 (0.6430)	3.5000 (0.1738)	8.6795 (0.4057)	131.719
RETAIL-DMAZ	22.003 (0.689)	11.511 (0.994)	0.6557 (0.7087)	4.7605 (0.6892)	2.5697 (0.2767)	4.2911** (0.0125)	130.096
DMAZ-RETAIL	18.502 (0.857)	18.608 (0.853)	0.9539 (0.4699)	6.7705 (0.4532)	2.9638 (0.2272)	1.6303* (0.0000)	255.700
FARM-SUNF	28.237 (0.347)	17.981 (0.876)	0.2942 (0.9539)	2.2316 (0.9456)	0.0108 (0.9946)	1.6490* (0.0004)	197.787
SUNF-FARM	14.054 ((0.972)	15.381 (0.950)	0.7458 (0.63401)	2.2316 (0.9459)	0.0108 (0.9946)	1.6490* (0.004)	197.786
FARM-SOYB	24.65 (0.539)	20.134 (0.785)	0.9204 (0.4977)	6.6009 (0.47156)	0.3040 (0.8590)	2.1763** (0.0264)	170.377
SOYB-FARM	23.761 (0.590)	22.217 (0.677)	0.7798 (0.60667)	5.6706 (0.5786)	5.4700 (0.0647)	1.0249* (0.0011)	101.122
RETAIL-SUNF	19.211 (0.827)	34.572 (0.121)	0.6446 (0.7176)	4.7151 (0.6947)	0.4705 (0.7904)	1.9983* (0.0017)	219.672
SUNF-RETAIL	17.774 (0.884)	18.888 (0.841)	1.3446 (0.2423)	9.2487 (0.2353)	3.1143 (0.2107)	3.4657* (0.0000)	120.228
RETAIL-SOYB	14.543 (0.965)	30.901 (0.232)	0.5550 (0.78913)	4.1317 (0.764480	0.3782 (0.8277)	1.9016** (0.0136)	180.680
SOYB-RETAIL	16.037 (0.935)	20.857 (0.749)	13.8363 (0.2296)	9.4442 (0.2223)	3.5292 (0.1713)	1.0071* (0.002)	96.6381

5.8 SUMMARY

In this chapter, the empirical results of the application of the procedures used to investigate price and volatility spillover in the poultry retail and farm market channels, as discussed in Chapter 4, are presented.

Firstly, the long-run cointegration relationship between farm-retail market channels was investigated by means of the TAR and M-TAR procedures. The results show that the farm-retail relationship is cointegrated. This culminates in a threshold behaviour that is estimated to be asymmetric. Adjustment to the equilibrium relationship between the market channels shows that there is less decay for negative than for positive discrepancies. This implies that the impact of negative economic shocks to the marketing margin will persist to a greater extent than positive shock.

The results of volatility transfer (spillover) between retail and farm prices show that there is significant volatility spillover from the farm to the retail market channel, but not vice versa. This is also consistence with the market influence (Granger causality) found to flow from the farm to the retail market within the cointegration and error correction framework investigated by means of the M-TAR model.

CHAPTER 6

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

Escalating food prices have increasingly been a major concern of governments and consumers alike globally and in South Africa. Many reasons have been mentioned why food prices increased over the past decade. During the 2001/02 the exchange rate has been cited as being the main reason for commodity and food prices to increase significantly above their long run equilibrium levels in South Africa. More recently the hike in food prices in 2007/08 was a result of, amongst others, an increasing demand for commodities for industrial purposes (e.g. biofuels), climate events in certain part of the world, high energy costs (oil) and responses by governments. At the same time market price volatility has been more visible. A concern in this regard is that market price volatility, especially the unforeseen price variations in response to adverse and spontaneous exogenous or endogenous shocks has important consequences for the welfare of consumers and producers of agricultural products. A further concern is the phenomenon of volatility spillover between markets. The question arises as to whether there is enough evidence to suggest that there has been volatility spillovers from one commodity market channel, e.g. between farm to retail unit or vice versa, in an effort to explain volatility in different market channels. This is important since it will affect policy responses by, for example, governments or business behaviour by chain players.

This study investigated the transmission of volatility (volatility spillover) within the South Africa vertical poultry (broiler) supply chain. An important aspect in the transmission of volatility is the possibility of unequal (asymmetric) price transmission from one market channel to another, e.g. from upstream (producer) to downstream (retailers) or vice versa. Therefore a secondary aspect of this study is to examine asymmetry in the price and volatility transmission between the markets. This implies examining whether the perception about price and volatility transmission at the farm-retail level is correct – that is, whether the upstream market channel of agricultural commodities has the power to asymmetrically influence prices at the retail levels.

6.2 LITERATURE REVIEW

The literature review focussed on theories, assumptions and the approaches used by economists and agricultural economists to study asymmetric price and volatility transmission mechanisms.

In the literature, a vertical market relationship has been defined according to whether market exchange is based on open market operations or through internal organisation by the firms. Firms tend to engage in vertical relationships due to the need to reduce the transaction costs involved in market exchange, thereby enjoying the benefit of reduced total cost due to economies of scale. The important question is whether firms transfer the cost savings as reduced prices. Firms pass on cost increases easily – while being reluctant to reduce prices during cost decreases due to the adjustment cost involved in doing so.

Adjustment cost refers to the cost incurred in the process of changing nominal prices of goods, printing catalogues, dissemination of information about price changes, and cost of inflation. Considering these costs, firms do not adjust their prices easily even when their transaction costs decline because in most instances they presume the decline is temporary. Moreover, if they reduce their price when costs decline it will send a wrong signal to rational consumers who will assume that market conditions have improved and hence may want to explore the market by engaging in searching for a better price. In practise, this is not always the case because consumers often do not have full knowledge of the prices offered by other firms further away and may not engage in search behaviour due to the cost involved in doing so.

Firms may be reluctant to reduce prices because of lack of local rivalry and competition in an uncompetitive market economy. If firms enjoy monopoly powers, they will not reduce prices when their costs decline because they have no local rivalry and competitors to engage them in a price war. In such an instance, firms are said to possess market power and have oligopolistic anti-competitive tendencies to exert control over the market. These and other factors are the underlying causes of asymmetric price transmission in a commodity market. However, identifying the cause of asymmetry and empirically measuring it has recently become a cause for concern because a variety of often unreliable empirical tests for asymmetric price transmission exist in the literature. For example, earlier approaches failed to account for the long-run cointegration relationship between economic agents (Farrell, 1952; Houck, 1977; Peltzman, 2000; Tweeten & Quance, 1969; Ward, 1982; Wolffram, 1971; Zhang *et al.*, 1995). In contrast to earlier approaches, recent studies consider the cointegration relationship in an error correction framework. In the cointegration and error correction specification, cointegration ensures the presence of long-run equilibrium while the error correction term measures deviation from the equilibrium relationship. This is consistent with the Granger representation theorem of Engle and Granger (1987). Further improvement of the method used to quantify asymmetric price and volatility transmission has resulted in the use of threshold adjustment mechanisms and the exponential generalised autoregressive conditional heteroskedasticity (EGARCH) model.

Two types of threshold adjustment models have been suggested in the literature. These are the threshold autoregressive (TAR) model of Engle and Granger (1987) and the momentum threshold autoregressive model (M-TAR) suggested by Enders and Granger (1998). With the Engle and Granger (1987) approach, namely the TAR model, adjustment is symmetric, while the approach taken by Enders and Granger (1998), namely the M-TAR model assumes asymmetric adjustment such that adjustment in one direction has more momentum than the other. Other than price adjustment, the risk and uncertainty caused by price volatility is also a concern. Studies have shown that volatility influences market expectations. For example, Buguk, Hudson and Hanson (2003) showed that volatility in one market channel influences price expectations in the alternate market and that the relationship is often asymmetric. In other words, volatility may spillover from one market channel to another. For this purpose, price and volatility transmission were investigated in this study. Threshold models were used to account for price transmission and equilibrium adjustments, while the exponential generalised autoregressive conditional heteroskedasticity (EGARCH) model was used to measure conditional volatility.

6.3 INDUSTRY OVERVIEW

The poultry sector has experienced some significant changes since the liberalisation and deregulation of the agricultural sector. It is now exposed to demand and supply shocks and also to competition from both local and international markets. A major challenge facing the broiler industry is the lack of an adequate productive base, proper support services and sound market infrastructure. Other challenges include climatic, environmental and structural or institutional changes that affect the competitiveness, productivity and efficiency of the sub-sector.

The per capita consumption of broiler meat is increasing compared to red meat. This is attributed to increasing household disposable incomes and the fact that the broiler industry is becoming more competitive and efficient in terms of production. The situation can also be attributed to the fact that broiler meat is relatively less expensive than other meat types and hence appeals to a wider consumer range.

There is a high level of concentration in the broiler industry. The two largest firms in the broiler industry, namely Rainbow and Astral, account for a 54 % market share. These firms have also consolidated their market power by forming vertical market linkages. Most of the broiler firms either have links with feed mills or are part of or a subsidiary of other broiler production firms. The conglomerate in the broiler sub-sector makes it difficult for new entrants to be successful; hence there is barrier to entry into the broiler sub-sector.

6.4 METHODOLOGY

The long-run relationship between the farm price and the retail price in the broiler sector was investigated in this study. The aim was to determine the presence of an equilibrium relationship between the prices. If an equilibrium relationship could be found between the prices, then it would be possible to establish how the prices would adjust in the presence of an economic shock. Cointegration was examined by means of four different approaches, namely the Johansen multivariate test (Johansen & Juselius, 1990), the Engle and Granger two-step approach (Engle

& Granger, 1987), the threshold autoregressive (TAR) model, and the momentum threshold autoregressive (M-TAR) model. Once the cointegrating relationship had been confirmed, the error correction model assuming M-TAR representation was used to analyse the inter-market relationship. The EGARCH model was then used to measure volatility and volatility spillover.

6.5 MAJOR CONCLUSIONS DRAWN FROM THIS STUDY

6.5.1 Threshold cointegration

The results of the threshold cointegration test show that a linear combination of the farm and retail broiler prices is cointegrated. This implies that, even though the two prices may deviate from each other in the short-run, in the long-run they will move together. Following the Granger representation theorem, the error correction model was estimated using the best-fit M-TAR model selected by means of Schwarz's Bayesian information criterion (BIC). It should be recalled that changes in farm prices causes disequilibrium in the farm-retail market relationship. Because there is a long-run cointegration relationship between the two prices (confirmed by cointegration test), the retail price must respond quickly to restore the equilibrium relationship. The results of the error correction specification show that retail prices do not react completely within one month to changes in the producer price. This is attributed to the fact that due to adjustment cost amongst other reasons, market agents do not respond instantaneously to economic shocks but rather the response is distributed over time.

These results also show that within one month, the retail prices adjust so as to eliminate approximate 2.8 % of a unit-negative change in the deviation from the equilibrium relationship caused by changes in farm prices. This implies that the retailers must increase their marketing margin by 2.8% in order to respond completely to a unit-negative change in the farm price. Also, the channel will adjust to remove 2.7 % of a unit-positive change in the farm price and also requires an increase of 2.7% in the marketing margin to respond to this change. Thus it can be deduced that adjustment towards the long-run relationship between producers and retailers is faster when changes in the deviation are negative compared to positive changes. When the marketing margin is below the long-run equilibrium (i.e. when producer prices rise to lower the marketing margin), retail prices react faster than when margins are above long-run equilibrium (i.e. when producer prices decline to increases the marketing margin).

In other to determine the direction of market influence between the farm-retail prices, a Granger causality test was conducted. The result shows that the direction of market influence is unidirectional, running from farm to retail market channel with no evidence of reverse causality feedback. The result shows that retailers do adjust to shocks in the producer prices, while the effects of retail market shocks are largely confined to retail markets. This finding is consistent with results obtained elsewhere.

6.5.2 Estimation of Conditional volatility

The estimation of conditional volatility shows that the use of the coefficient of variability as a measure of volatility is not appropriate because it overstates volatility. The conditional standard deviation of the conditional variance is a more appropriate measure, because it removes the time-varying predictable component from the series, thereby decreasing volatility. The median of the conditional volatility was used as a point estimate. The results show that the magnitude of volatility in the retail and farm prices in the poultry industry for the period 2000M1-2008M8 is 1.82 % and 2.8 %, respectively. The farm price is more volatile than the retail price. The volatility in the farm price is found to approximate the volatility implied by the adjustment shocks in the farm-retail price relationship investigated with the M-TAR error correction model.

6.5.3 Asymmetric volatility spillover

This study also investigated whether there is asymmetric volatility spillover between the farm and retail market marketing channels in the broiler industry. This is similar to the market influence investigated by considering the adjustment to equilibrium between the prices. The results show that there is significant asymmetric volatility spillover from the farm to the retail market and not vice versa, that is, the response to rising prices (positive shocks) at any production and marketing stage differs from the response to a price decline (negative shocks). This implies that retailers rely heavily on market information at the production level in forming their market expectations. An investigation into the impact of the prices of the major broiler feed materials, namely yellow maize, sunflower and soybean, shows that there is a volatility spillover from the yellow maize price to farm and retail prices. This implies that any change in the price of yellow maize will have a significant impact on the retail and farm prices. Market influence also flows from the sunflower oilcake price to the retail market price.

6.5.4 Volatility persistence

The study has shown that price shocks were found to spillover from farm to retail market. In order to determine the nature of autoregressive decay of the shock, volatility persistence was investigated. The aim was to examine whether the price shock is temporary or have permanent effects. The result shows that significant price shocks arising from farm to retail market persist, that is, it has long-term effects, while no significant persistent shock was found to flow from retail to farm prices. This confirms the results obtained previously that market influence only flows from the farm to retail level and not vice versa.

6.6 RECOMMENDATIONS

High transaction cost, requirements in terms of capital investment in infrastructure, access to sufficient cash flow facilities, the high level of technical know-how required at the different levels of production, processing and retailing, as well as financial and biological risks inherent to the poultry industry are major barriers to entry for new entrants. It is therefore no surprise that the poultry industry is characterised by a high level of value chain concentration, and hence is also open to the potential abuse of market power. Given the finding of this study that there is downward stickiness in prices when upstream (producer) prices decline (i.e. asymmetric price transmission), the perception could easily be created that downstream role players such as processors and retailers are misusing their market power. One possible mechanism to address the current state of concentration is for government to provide incentives to lower the barriers to entry. It is therefore recommended that government launch a cluster based incentive programme to lower entry barriers into the poultry industry. Such an approach could potentially include (i) preferential access to financial resources through parastatals such as the Land Bank and institutions such as the Industrial Development Corporation and the Development Bank of South Africa or provide the appropriate guarantees for these institutions to increase their willingness to provide financial tools to new entrants; (ii) recapitalisation of existing small firms; and (iii) provision of efficient and targeted support services, not only to producers, but also to downstream entrepreneurs. The key challenge will be to implement such incentives in a properly coordinated and synchronised manner to achieve the necessary scale economies required to ensure the profitability of new entrants. The aforementioned will not necessarily result in eliminating concentration in the poultry value chain, but will definitely add to the level of competition. In addition to the aforementioned a tightening of anti-competition laws is required.

This study also found that market influence flows from producers to the retailers with no feedback causality effects. This implicitly suggests that the flow of information in the poultry value chain is not optimal. In other words retailers do not have sufficient access to information about what happens at primary production level in order to allow them to plan retailing activities properly. In an imperfect market, information flow is limited and costly, usually to the detriment of consumers and producers, especially in a market characterised by a high level of concentration. It is therefore vitally important for industry role players to understand each others information needs and as an industry ensure that such information is available. Cognisance should however be taken that certain information exchange practises could lead to the abuse of market power, and hence it will be important that the competition authority is consulted.

The fact that this study has pointed out that there exist unidirectional volatility spillover from the input sector that affects producer and retail broiler prices emphases that government policies that could potentially affect input prices need careful consideration. An example is the use of trade policy instruments to ensure sufficient production of commodities such as maize and soybean locally to cushion volatility spillover effects from international commodity markets. Moreover, this study provides sufficient evidence that value chains that are highly integrated in order to achieve economy of scale benefits require holistic approaches when, for example considering changes in trade policy or programmes to enhance food security.

6.6.1 Recommendations for further study

This study investigated price and volatility spillover only in the broiler sector of the poultry industry. It is recommended that the study be extended to accommodate all the meat sectors, including the other poultry-meat sectors and the red-meat industry. This will give a broader picture of price and volatility transmission in the South African meat industry as a whole. This is important for a holistic policy intervention in the broader meat industry.

Lastly, further analyses of price transmission should be carried out with a data set that has a higher frequency of data points. This will provide better insight into the pricing behaviour and actions of role players, which is necessary to ensure greater transparency required to increase the level of competition in the poultry industry.

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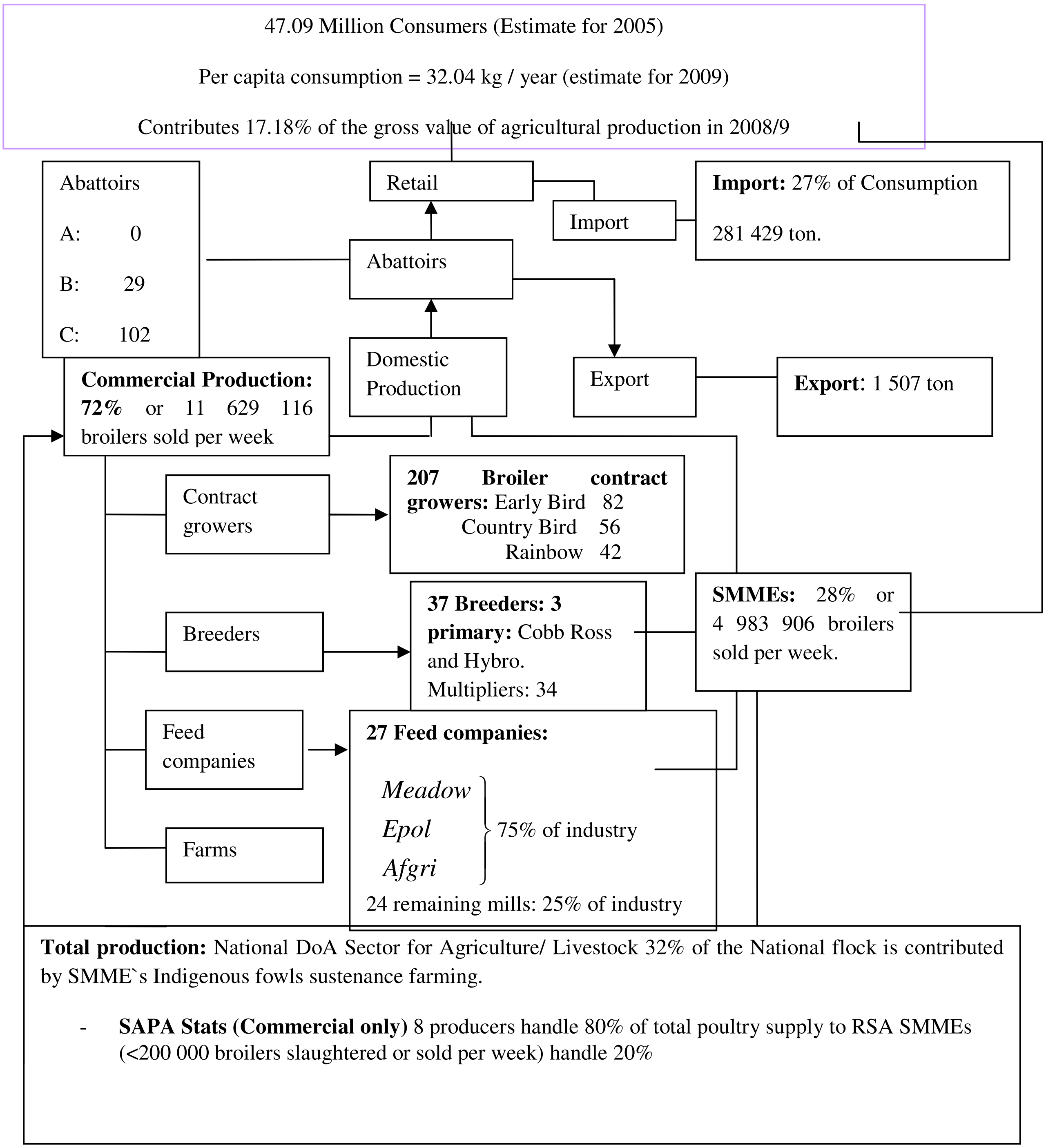
APPENDICES



Appendix A.1 Poultry value chain

Source: DAFF (2009)

APPENDIX A2 Imputed missing data sets for the retail broiler price

Appendix A2 Imputed missing data sets for the retail broiler price

Impute 1	Impute 2	Impute 3	Impute 4	Impute 5
20.66	20.35	20.4	20.25	20.93
20.09	21.06	20.09	20.5	18.94
19.93	20.8	20.65	19.54	19.57
21.96	21.27	21.85	19.98	21.77
20.65	20.68	19.95	20.38	20.56
21.13	21.07	20.54	21.91	21.95

APPENDIX A3 Visual plot of nominal prices

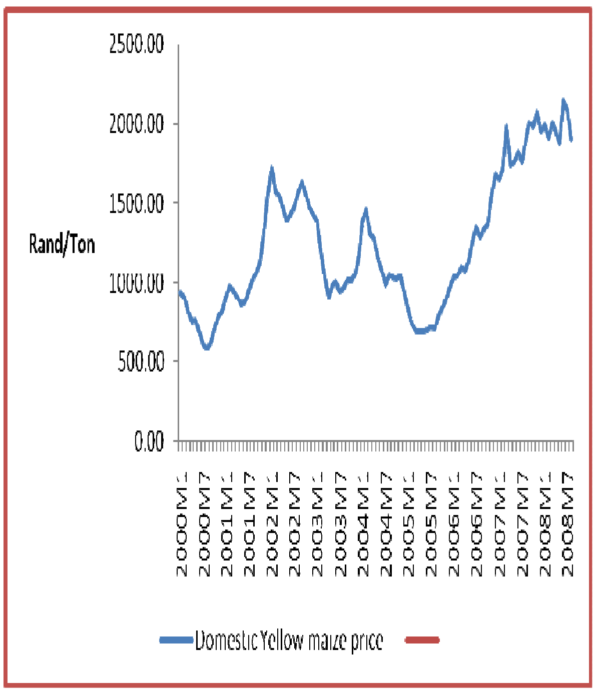


Figure A3.1 Domestic maize price
Source: SAFEX (2009)

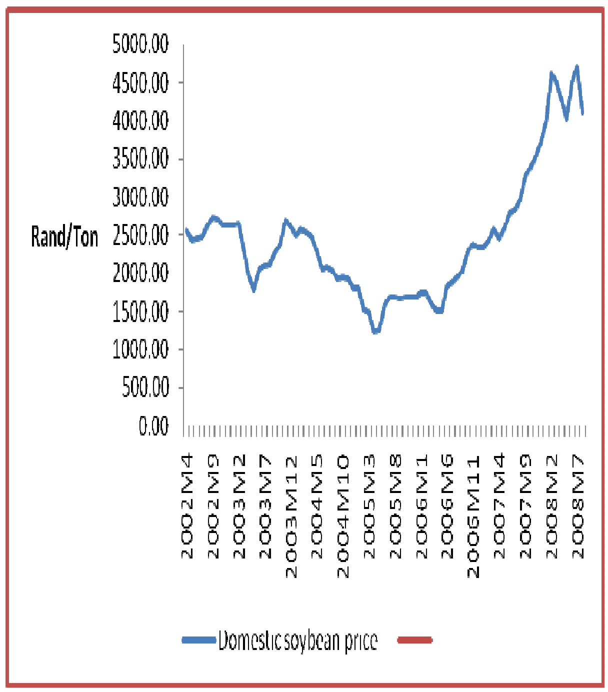
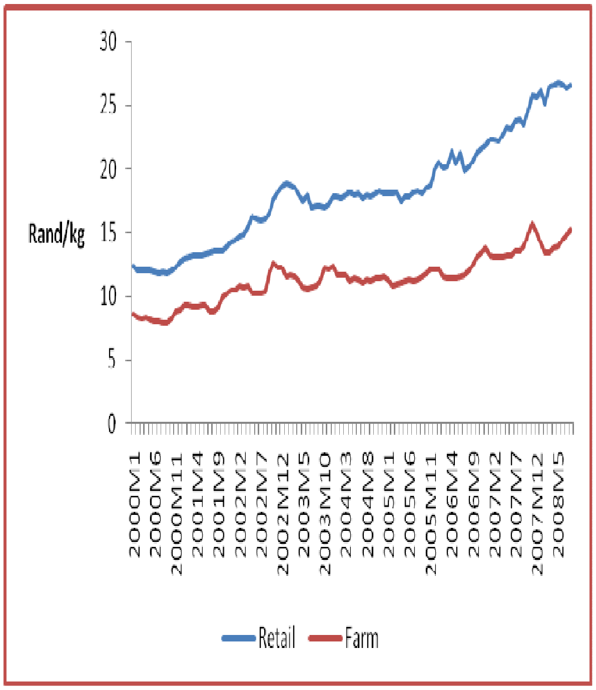
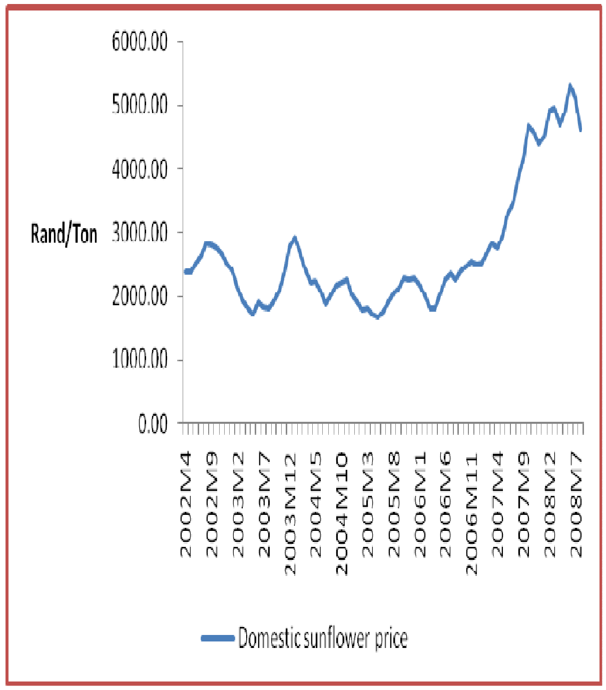


Figure A3.2 Domestic soybean price
Source: SAFEX (2009)





(Figure A3.3) Poultry farm-level and retail prices **(Figure A3.4) Domestic sunflower price**

Source: Department of Agriculture, Forestry and Fishery **Source: Statistics South Africa**

APPENDIX A4 Parameter stability test on price series

	RETAIL	FARM	DMAZ	DSUNF	DSOYB
$SupF_T(1)$	2.31 (7.04)	0.026 (8.58)	43.84* (8.58)	28.47* (8.58)	6.08 (8.58)
$SupF_T(2)$	20.83* (6.28)	6.62 (7.22)	108.93* (7.22)	43.87* (7.22)	11.37* (7.22)
$SupF_T(3)$	43.94* (5.21)	5.85 (5.96)	45.87* (5.96)	39.47* (5.96)	25.96* (5.96)
$SupF_T(4)$	27.24* (4.41)	4.46 (4.99)	34.85* (4.99)	33.87* (4.99)	18.30* (4.99)
$SupF_T(5)$	23.43* (3.47)	4.14 (3.91)	37.79* (3.91)	30.93* (3.91)	15.65* (3.91)
$UD\max$	43.94* (8.88)	6.63 (8.88)	108.93* (8.88)	43.87* (8.88)	25.95* (8.88)
$WD\max$	63.26* (9.91)	9.09 (9.91)	129.45* (9.91)	67.88* (9.91)	37.37* (9.91)
$SupF(2/1)$	17.23* (8.58)	9.17* (8.58)	1.33 (8.58)	0.69 (8.58)	0.28 (8.58)
$SupF(3/2)$	12.08* (10.13)	0.76 (10.13)	1.13 (10.13)	0.64 (10.13)	1.20 (10.13)
$SupF(4/3)$	1.04 (11.14)	0.52 (11.14)	0.024 (11.14)	0.17 (11.14)	1.48 (11.14)
$SupF(5/4)$	0.23 11.83)	0.72 (11.83)	0.00 (11.83)	0.00 (11.83)	0.056 (11.83)
Sequential proc	**zero**	**Zero**	**One** **BD= 2006M11**	**One** **BD=2007M6**	**Zero**

Figures in parenthesis are the critical values. The test statistics are evaluated at 5 % significance level.

APPENDIX A5 Conditional volatility of market price

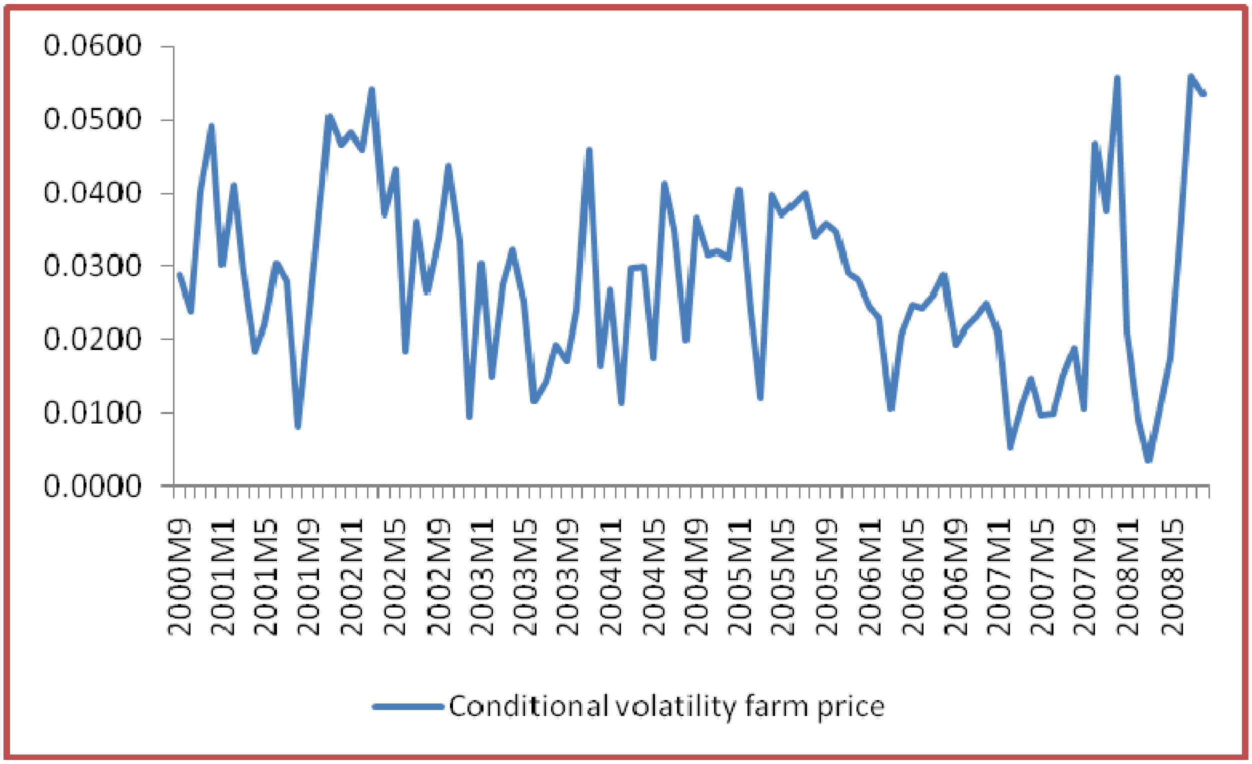


Figure A5.1: Conditional volatility in farm price with seasonal component for monthly data 2000M1-2008M8

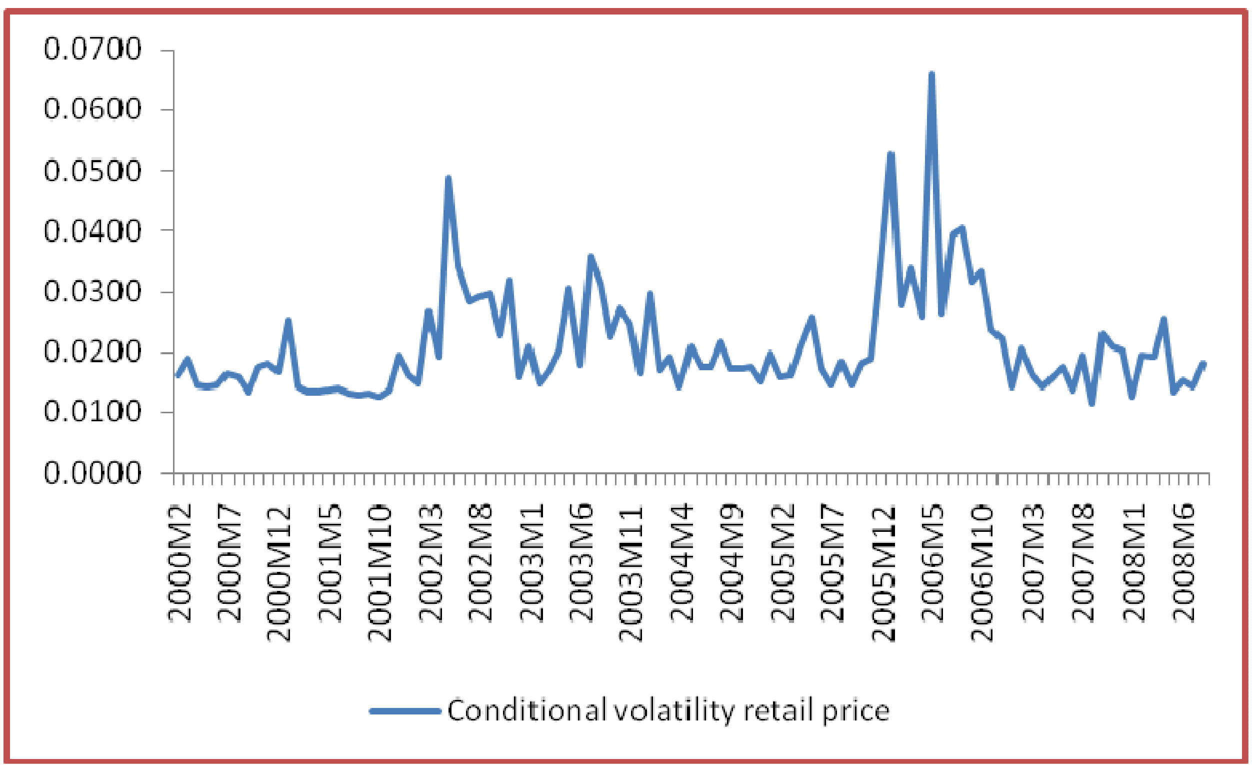


Figure A5.2: Conditional volatility in retail price with seasonal component for monthly data 2000M1-2008M8

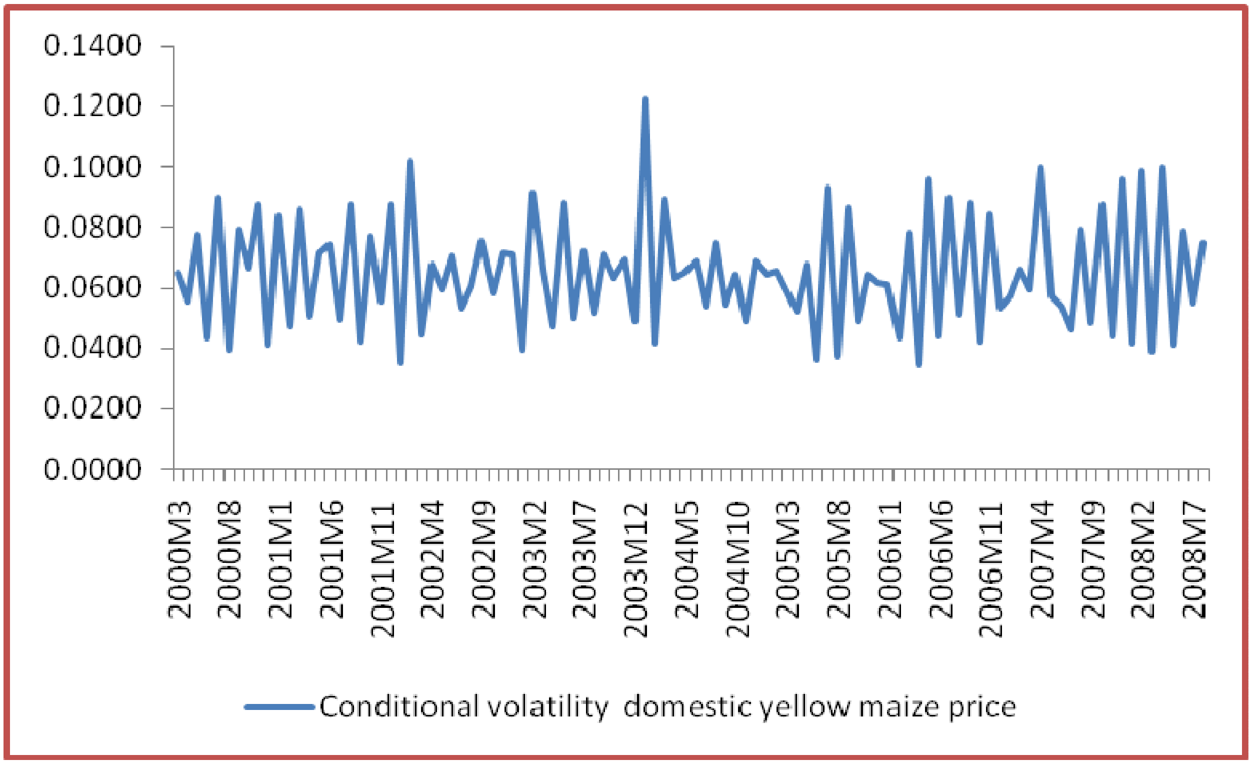


Figure A5.3: **Conditional volatility in domestic maize price with seasonal component for monthly data 2000M1-2008M8**

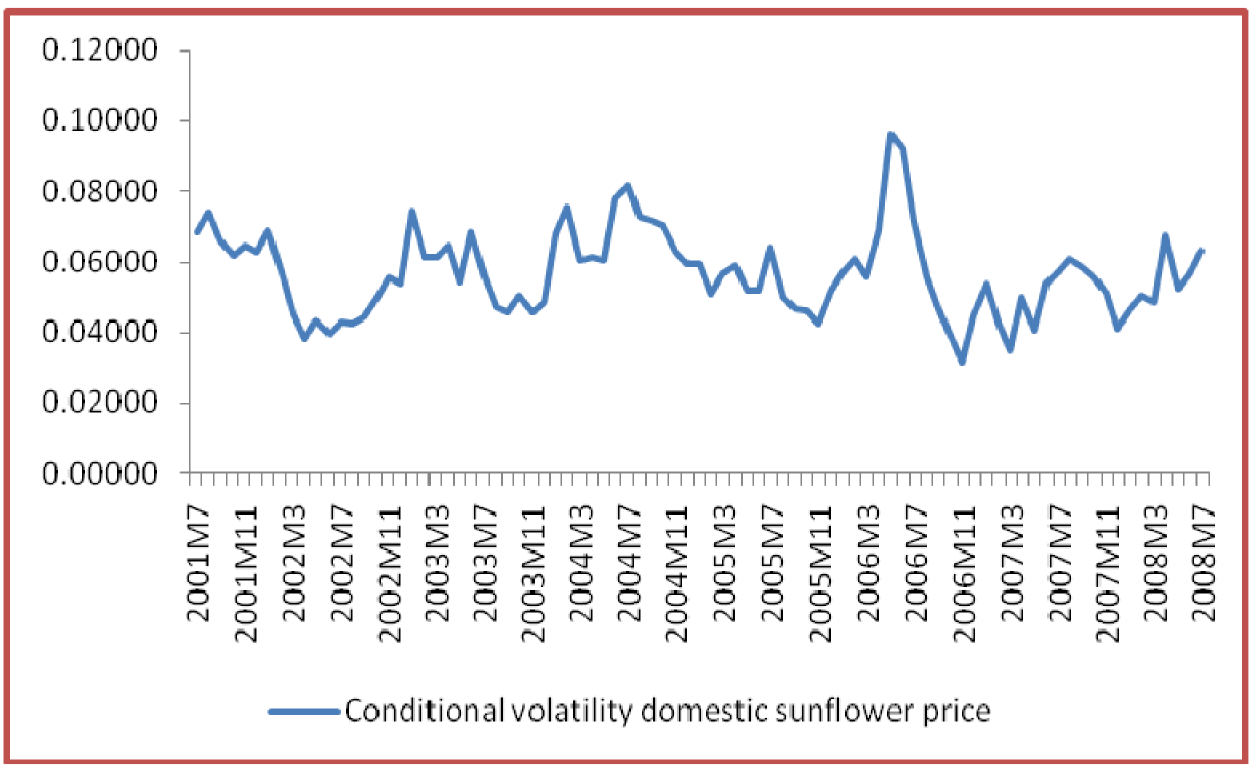


Figure A5.4: **Conditional volatility in domestic sunflower price with seasonal component for monthly data 2001M4-2008M8**

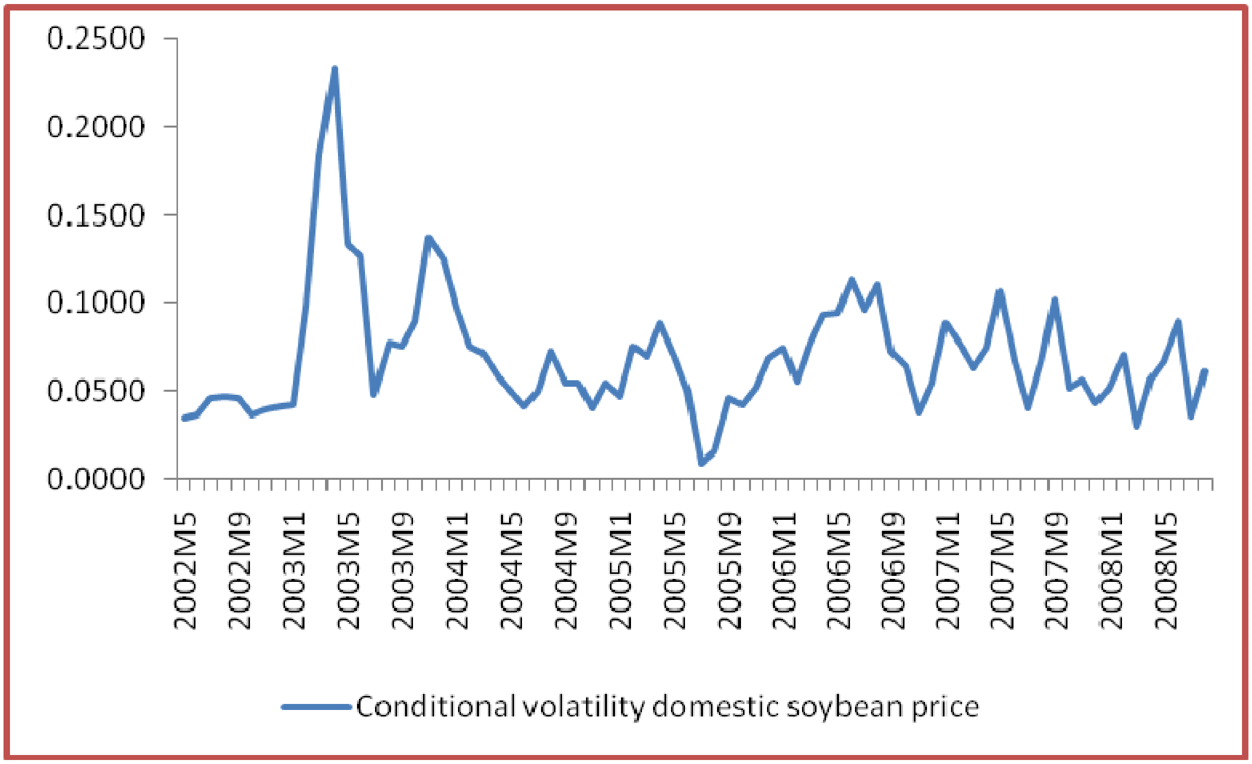


Figure A5.5 Conditional volatility in domestic soybean price with seasonal component for monthly data 2002M4-2008M8