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

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Abstract

This study investigated asymmetric price and volatility spillover in the broiler value chain. The data used for the study includes farm and retail broiler monthly prices dated from January 2000 to August 2008. 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 price volatility and the volatility spillover effect between retail and farm prices. Price asymmetry was found between farm and retail prices with retail prices responding more rapidly (with a lag) to negative than positive changes in farm price. 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 response completely to a unit-negative change in farm prices. The 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, with significant asymmetric volatility spillover from the farm to retail level of the value chain. This implies that the response to positive shock at any production and marketing stage differs from the response to a negative shock.

1 Introduction

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 of 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 farm-retail value chain. The 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, but at the same time the broiler industry is one of the agricultural sub-sectors with the highest levels of concentration and vertical integration. Given the vertical linkages and market power in this agricultural sub-sector, it will be reasonable to hypothesise that there will be asymmetric price and volatility transmission (or volatility spillover).

Volatility spillover has been found to exist between the input markets (feed) and the output markets (wholesale cart fish) in the United State 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 level of the broiler value chain 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 level of the value chain influences another level. The volatility spillover effects have not yet been investigated in any meat supply chain in South Africa.

2 Overview of the South African poultry (broiler) industry

The poultry industry is estimated to be the largest agricultural sub-sector, contributing significantly to the total gross value of agricultural production. During 2008/2009 period, the total gross value of agricultural production in South Africa was R130.7 billion; the poultry industry had the largest contribution of R22.5 billion, representing 17.18 % of the total gross value of agricultural production (DAFF, 2010a). More poultry meat is being consumed than other meat categories. According to a report by Meyer *et al.* (2008), poultry has the highest percentage contribution to the national aggregate meat expenditure, contributing a 16.7% share of the meat and meat product basket.

The broiler sub-sector constitutes the largest proportion of the poultry industry. It is estimated that the broiler industry makes up more than 80% of the turnover in the poultry industry (National Department of Agriculture, National Agricultural Marketing Council and Commark Trust, 2007). Since 1991/92 broiler meat has surpassed beef as the principal meat type in the food basket of South Africans (NDA, 2006). This can be attributed to, amongst other factors, the increase in the average disposable income of consumers and the fact that average broiler meat prices are lower compared to other meat sources.

As mentioned this industry is characterised by high levels of concentration and vertical integration. Broiler firms either have links with feed mills or are part of or are a subsidiary of other broiler production units, thus creating a network of production and marketing linkages. For example, the Astral Foods Group has links with Meadow Feeds, while Rainbow has links with Epol. 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. Apart from being highly integrated the sector is also concentrated. The two largest producers, namely Rainbow and Astral, together account for approximately 54 % of the market share.

3 Data used in the analysis

The analysis 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 prices represent the average carcass price in cents/kg slaughter weights. The farm price was obtained from the National Department of Agriculture, Forestry and Fisheries (DAFF, 2009), while the retail price was obtained from Statistics

South Africa (2009). Only nominal prices were used in the analysis. 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 were missing. To avoid introducing bias into the analysis, the missing data points were imputed using a sequential multiple imputation procedure similar to the one used in Raghunathan *et al.* (2001). The imputation was based on the Bayesian approach implemented with a program written in MATLAB 2008. The imputed missing values are shown in **Appendix A1.**

4 Methodology

The analysis was conducted in two steps. Firstly, price transmission in the farm-retail prices was investigated. Secondly, volatility and volatility spillover in the broiler value chain were quantified. The rest of this section discusses the methodological approaches followed.

4.1 Measuring price transmission

The paper employed the threshold cointegration approach to test for a cointegration relationship between farm-retail prices with asymmetric adjustment. Cointegration was examined by means of three different approaches, namely the Engle and Granger two-step approach (Engle & Granger, 1987), the threshold autoregressive (TAR) model, and the momentum threshold autoregressive (M-TAR) model. The aim of using different approaches was to compare the various approaches and choose the best-fitting error correction model.

4.1.1 Engle and Granger cointegration approach

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

$$y_t = \alpha + \beta x_t + \mu_t \tag{1}$$

where y and x are the retail and farm prices, respectively, and μ is the disturbance term. The least square residuals of (1) 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 is estimated from the equations

$$\Delta\mu_t = \rho\mu_{t-1} + e_t \tag{2}$$

$$\Delta\mu_t = \rho\mu_{t-1} + \sum_{i=1}^{n} \lambda_i \Delta\mu_{t-1} + e_t \tag{3}$$

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 (2) is augmented with an extra lag, and equation (3) is estimated (Enders, 2004).

4.1.2 TAR cointegration approach

Following equation (2), the TAR cointegration and adjustment process is specified as

$$\Delta\mu_t = \begin{cases} \rho_1\mu_{t-1} + \varepsilon_t & if\ \mu_{t-1} \geq r \\ \rho_2\mu_{t-1} + \varepsilon_t & if\ \mu_{t-1} < r \end{cases} \tag{4}$$

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:

$$\Delta\mu_t = I_t\rho_1(\mu_{t-1} - r) + (1 - I_t)\rho_2(\mu_{t-1} - r) + \varepsilon_t \tag{5}$$

where I_t is the Heaviside indicator function such that

$$I_t = \begin{cases} 1 & if\ \mu_{t-1} \geq r \\ 0 & if\ \mu_{t-1} < r \end{cases} \tag{6}$$

Using the TAR model (5) and (6), the null hypothesis of unit root (no cointegration) is tested against the alternate of threshold cointegration. Enders (2004) demonstrated that a high order of the error sequence $\{\mu_t\}$ can be estimated if the residuals are correlated. In this instance, equations (6) and (7) are estimated instead of equations (4) and (5).

$$\Delta\mu_t = I_t\rho_1(\mu_{t-1} - r) + (1 - I_t)\rho_2(\mu_{t-1} - r) + \sum\nolimits_{i=1}^{p}\beta_i\Delta\mu_{t-1} + \varepsilon_t \tag{7}$$

4.1.3 M-TAR cointegration approach

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 allow 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. In this instance, following equation (5), the M-TAR model is given as

$$I_t = \begin{cases} 1 & if\ \Delta\mu_{t-1} \geq r \\ 0 & if\ \Delta\mu_{t-1} < r \end{cases} \tag{8}$$

where I_t is the Heaviside indicator function. This model is used to capture the asymmetrically sharp or 'steep' movements in the autoregressive series.

4.1.4 Error correction model

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

$$\begin{aligned} \Delta y_t &= I_t \rho_1 (\mu_{t-1} - r) + (1 - I_t) \rho_2 (\mu_{t-1} - r) \\ &\quad + \sum_{i=0}^{k} \beta_i \Delta x_{t-i} + \sum_{i=1}^{k} \xi_i \Delta y_{t-i} + \ldots\ldots\ldots\ldots\ldots \sum_{=1i}^{k} \phi_{ni} \Delta x_{n,t-i} + \varepsilon_t , \end{aligned} \tag{9}$$

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.

4.2 Measuring price volatility

For purposes of comparison, both the naïve and the orthodox methods of measuring volatility were considered.

4.2.1 Unconditional volatility

The naïve approach treats all price movement as unpredictable implying that past realisations of price and volatility have no influence on the current and future realisations (Moledina *et al.*, 2003). It does not control for the predictable component of the price evolution process, and hence it does not distinguish between unpredictable and predictable components of the process. Examples of the naïve approach is the use of unconditional standard deviation or the coefficient of variation as a measure of volatility.

4.2.2 Conditional volatility

Since the unpredictable component of volatility is not observable, Dehn (2000) and Moledina *et al.* (2003) suggests modelling the predictable elements using an approach that is capable of distinguishing between unpredictable and predictable components. One of these approaches is the EGARCH model. It is adopted in this study because other members of the autoregressive conditional heteroskedasticity (ARCH) family have limitations. For example, generalised ARCH (GARCH) model imposes non-negativity constraints on the parameters of the model. 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 given by the equations.

$$\log(\sigma_t^2) = \exp\left[\psi + \sum_{i=1}^{q} a_i g(z_{i-1}) + \sum_{k=1}^{p} b_k \log\left(\sigma_t^2\right) + \right] \tag{10}$$

$$g(z_t) \equiv \theta z_t + \gamma\left[\,| z_t | - E\,| z_t |\,\right] \tag{11}$$

where σ_t^2 is the variance of the residuals from the mean equation. The fitted values of σ_t^2 are the conditional variances whose square root is the measure of conditional volatility.

The EGARCH (1,1) model was fitted assuming an ARIMA specification. The Box-Jenkins procedure (Box & Jenkins, 1976) was used in the identification of the EGARCH models. A test of the GARCH effect was first carried out to determine the presence of any GARCH errors. Then the orders of the ARIMA and EGARCH models were selected by minimising Schwarz's BIC. The appropriate EGARCH model was selected by fitting the EGARCH (1,1) EGARCH (2,1) and EGARCH (1,2) models and then the EGARCH (1,1) model was selected by minimising Schwarz's BIC.

The EGARCH (1,1) model was 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

$$l_t = -\frac{1}{2}\log\left(\frac{\Gamma(1/\tau)^3}{\Gamma(3/\tau)(\tau/2)^2}\right) - \frac{1}{2}\log\sigma_t^2 - \left(\frac{\Gamma(3/\tau)(y_t - X_t^{'}\theta)^2}{\sigma_t^2\Gamma(1/\tau)}\right)^{\tau/2} \tag{14}$$

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 Marquardt algorithm and the Berndt, Hall, Hall and Hausman (1974) iterative algorithm was used to estimate EGARCH (1,1) model. 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 (15).

$$s_t = \sum_{i=1}^{k} \left[\phi_i \cos(2\pi d_t /12) + \phi_i \sin(2\pi d_t /12) \right] \tag{15}$$

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[4].

4.2.3 **Measuring volatility spillover**

A bivariate EGARCH spillover model was fitted 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 volatility spillover between the two market levels was measured from the AR(p)-EGARCH(1,1) model.

Mean equation

$$rp_{1,t} = \delta_{1,0} + \sum_{i=1}^{k} \delta_{1,1i} rp_{1,t-1} + \sum_{i=1}^{k} \delta_{1,2i} fp_{2,t-1} + \xi_{1,t} \tag{16}$$

$$fp_{2,t} = \delta_{2,0} + \sum_{j=1}^{r} \delta_{2,1j} rp_{1,t-1} + \sum_{j=1}^{r} \delta_{2,2j} fp_{2,t-1} + \xi_{2,t} \tag{17}$$

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

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

Variance equation

$$\log(\sigma_{1,t}^2) = \exp\left[\psi_{1,0} + a_{1,1} g(z_{1,t-1}) + a_{1,2} g(z_{2,t-1}) + \sum_{k=1}^{p} b_{1,k} \log(\sigma_{1,t-1}^2) \right] \tag{18}$$

$$\log(\sigma_{2,t}^2) = \exp\left[\psi_{2,0} + a_{2,1} g(z_{1,t-1}) + a_{2,2} g(z_{2,t-1}) + \sum_{k=1}^{p} b_{2,k} \log(\sigma_{2,t-1}^2) \right] \tag{19}$$

$$g(z_{1,t}) = | z_{1,t-1} | - E(| z_{1,t-1} |) + \gamma_1 z_{1,t-1} \tag{20}$$

$$g(z_{2,t}) = | z_{2,t-1} | - E(| z_{2,t-1} |) + \gamma_2 z_{2,t-1} \tag{21}$$

$$z_{1,t} = \xi_{1,t} / \sigma_{1,t} \tag{22}$$

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

$$z_{2,t} = \xi_{2,t} / \sigma_{2,t} \tag{23}$$

$$\sigma_{1,2,t} = \rho_{1,2}\sigma_{1,t}\sigma_{2,t} \tag{24}$$

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 (16) and (17) 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. Equation (18) specifies the conditional variance from the mean equation (16) as a function of its own lagged standardised residual ($z_{i1,t}$) and the standardised residual from equation (16), ($z_{2,t}$), while the same applies to equation (19). 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 (18) and (19). 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 $\ln(0.5)/\ln(b)$.

5 Results and discussions

5.1 Price transmission model

The descriptive statistics of the monthly observations of the nominal price series show that the prices are normally distributed (Appendix A2).

5.1.1 Unit root 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. The results of the ADF (Appendix 4) and KPSS (Appendix A5) tests show that the farm and retail prices are integrated (non-stationary).

5.1.2 Cointegration test

After fitting the OLS long-run equation (1) and prior to further analysis, the presence of a structural break in the cointegration relationship was investigated. The result shows that there are no structural breaks in the price series.

Following the outcome of the stability test, the Engle and Granger (1987) test was then carried out. The presence of a long-run cointegration relationship was tested using the ADF test. Firstly, the lag structure was determined by means of Schwarz's BIC, which selects two lag lengths. Equation (3) was then estimated by means of OLS regression. The Engle and Granger (1987) cointegration test is shown in Table 1. The absolute value of the t-statistics is greater than the critical values tabulated in Engle and Granger (1987) therefore rejecting the null hypothesis of no cointegration.

The TAR model was fitted by assuming that the threshold value r is zero. Equation (7) augmented with additional lag was estimated using the OLS regression technique. The results of the TAR model estimation are shown in Table 1. 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. 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 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. 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.

Table 1 **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
$LM\left(\chi^2\right)^e$	0.0490 (0.825)	0.1085 (0.742)	0.0223 (0.881)	1.6711 (0.196)
$Hetero\left(\chi^2\right)^f$	0.0624 (0.803)	0.0195 (0.889)	0.0812 (0.776)	0.1278 (0.721)
$Normality\left(\chi^2\right)^h$	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.

The results of the M-TAR model estimation are shown in Table 1. With regard to the adjustment mechanism implied by the M-TAR model, the absolute values of $\rho_1 > \rho_2$ and therefore like in the TAR model, there is less decay for negative than for positive discrepancies. 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 null hypothesis is rejected at 1 % level of significance.

5.1.3 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 1 that 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 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 1. 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, 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 null hypothesis 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 as shown in Tsay (1989). The calculated F-statistics are shown in Table 1, 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). The diagnostic tests show that there are no violations of assumptions of classical regressions.

5.1.3 M-TAR error correction

The M-TAR error correction model was fitted with the estimated optimal threshold value. The OLS regression of the M-TAR model 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. This procedure selects the optimal lag corresponding to the regression with significant coefficients. A truncation lag length of 12 was significant, but the next (lag 11) was 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 2 and Table 3. Table 2 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^-). The ECT^+ indicates that 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 other 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^+. However, 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 suppose to react instantaneously but because of the nature of the value chain they don't 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 2** 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 2** indicates that the retail prices 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.

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[5].

[5] 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.

Table 2 Estimates of the M-TAR error correction model

Dependent Variable ($\Delta RP(t)$)				
Regressors	**Coefficients**	**Standard error**	**T-statistics**	**P-value**
Constant	-0.4911	0.3190	-1.5399	(0.129)
$\Delta RP(t-1)$	-0.4368	0.1302	-3.3539	(0.001)
$\Delta RP(t-2)$	-0.0134	0.1294	-1.0326	(0.306)
$\Delta RP(t-3)$	-0.2267	0.1302	-1.7409	(0.087)
$\Delta RP(t-4)$	-0.2102	0.1316	-1.5976	(0.115)
$\Delta RP(t-5)$	0.0506	0.1333	0.3792	(0.706)
$\Delta RP(t-6)$	0.0782	0.1377	0.5679	(0.572)
$\Delta RP(t-7)$	-0.0979	0.1380	-0.7093	(0.481)
$\Delta RP(t-8)$	-0.0523	0.1352	-0.3865	(0.700)
$\Delta RP(t-9)$	-0.0791	0.1359	-0.5818	(0.563)
$\Delta RP(t-10)$	0.0182	0.1290	0.14091	(0.888)
$\Delta RP(t-11)$	-0.1330	0.1250	-1.0643	(0.291)
$\Delta RP(t-12)$	-0.3908	0.1216	-3.2133	(0.002)
$\Delta FP(t-1)$	0.4496	0.1761	2.5524	(0.013)
$\Delta FP(t-2)$	0.3849	0.1633	2.3568	(0.022)
$\Delta FP(t-3)$	0.5267	0.1718	3.0655	(0.003)
$\Delta FP(t-4)$	0.2920	0.1733	1.6847	(0.097)
$\Delta FP(t-5)$	0.3533	0.1744	2.0264	(0.047)
$\Delta FP(t-6)$	0.4902	0.1797	2.7274	(0.008)
$\Delta FP(t-7)$	0.1519	0.1827	0.8314	(0.409)
$\Delta FP(t-8)$	0.3274	0.1808	1.8112	(0.075)
$\Delta FP(t-9)$	0.0731	0.1780	0.4108	(0.683)
$\Delta FP(t-10)$	0.0713	0.1819	0.3921	(0.696)
$\Delta FP(t-11)$	0.0406	0.1761	0.2308	(0.818)
$\Delta FP(t-12)$	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)

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. In other 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 3) the contrary was tested. The results of the Granger causality test are shown in the second panel of Table 2 and Table 3. Using Wald test statistics, the null hypothesis is rejected for the retail price equation (Table 2), but is not rejected in the producer price equation (Table 3). The results show that there is unidirectional causality running from farm to retail prices. This finding is consistent with findings elsewhere (see Abdulai, 2002; Goodwin & Holt, 1999; Goodwin & Piggott, 2001; Kirsten & Cutts, 2006).

Table 3 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)

Compared with the retail price results presented in Table 2, the adjustment coefficients ECT^+ and ECT^- in the producer price equation in Table 3 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.

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 2 and Table 3. All diagnostic tests show that there is no violation of the classical linear regression assumption; hence the model fits the data.

5.2 Measuring volatility

The results of the EGARCH (1,1) model estimation with a seasonal component are given in Table 4 & 5. Table 4A (column 4) shows the unconditional coefficient of variation. 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 4A**,** column 4). 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 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 4A, column 4, rows 3 & 6**).** The farm price is more volatile compared to the retail price. 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 broiler 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 4A, column 4).

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 A6. 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 the prices 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 4B. The results show that most of the ARIMA parameters in the mean equation are significant[6]. In the variance equation, volatility persistence is measured by coefficient b . The results show that there is significant volatility persistence in the farm price 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

[6] 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.

in the farm price, the absolute value of the coefficient is relatively small, implying that volatility persistence into the future decays faster.

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 4B. 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 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 Appendix A7. 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. Diagnostic tests shows the EGARCH model is adequate for the data (Appendix A8)

Table 4 A: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices

Series name	**Period**	**Coefficient of variation**	**Conditional standard deviation**	**Process of the price series**
Col. 1	**Col. 2**	**Col.3**	**Col.4**	**Col. 5**
	2000M1-2008M8	0.2290	0.0182	ARIMA(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)

Table 4 B: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (monthly data)

	Mean equation	
PARAMETERS	**FARM**	**RETAIL**
Col. 1	**Col. 2**	**Col. 3**
Constant	0.0290 (0.1346)	0.0068* (0.0012)
AR(1)	0.0206* (0.0034)	
AR(2)	-0.0242** (0.0254)	
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)
MA(2)		
MA(3)		
	Variance Equation	
Constant	-5.37757 (0.1541)	-9.5279* (0.001)
a	-0.31086 (0.4202)	0.5683*** (0.0594)
b	0.3862** (0.0645)	-0.18214 (0.6335)
γ	0.8222* (0.0044)	0.1235 (0.4415)
Half-live	0.73	0.41

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

5.2.1 Volatility spillover

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 different value chain levels; (b) whether the influence (if present) is asymmetric and, if so, (c) whether the asymmetric volatility persists in the future. The results of the bivariate EGARCH model are presented in Table 5. The volatility spillover parameter a is used to measure the direction of market influence. The results show that the bivariate linkage between RETAIL-FARM is significant whereas the relationship between FARM-RETAIL is not significant (Table 5, column 3, rows 4 & 5). This implies that there is significant volatility spillover from the farm to the retail broiler 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 value chain levels discussed ealrier where unidirectional market price influence (Granger causality) was found to flow from the farm to the retail market and not vice versa.

5.2.2 Volatility persistence

Volatility persistence between the markets is measured by coefficient b. This coefficient has the same interpretation as previously discussed. Significant volatility persistence was found to exist when the retail-farm linear relationship is considered, but not when the farm-retail linear combination was considered. This is because the farm level prices exert more influence over retail prices and not vice versa, such that the effect persists in the future.

5.2.3 Asymmetric spillover

The results of the asymmetric volatility spillover between the farm and retail market channels are shown in Table 5. 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. 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. Diagnostic tests show that the mean and variance equations are correctly specified.

Table 5 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)

6. Conclusions and recommendations

This study investigated asymmetric price transmission and whether there is volatility in the farm-retail price relationship and the degree by which price uncertainty in one market influences another market. The results show 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 also reveal 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 magnitude of adjustment implied by the adjustment shocks in the farm-retail price relationship investigated with the M-TAR error correction model.

The results also reveal 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.

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 that often creates barrier to entry into the industry. The government should strive to lower entry barriers by launching cluster-based incentive programmes. 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. It will be worthwhile to increase access to agricultural information systems amongst the role players in order to reduce information bottlenecks which are prevalent in a typical highly concentrated value chain.

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Appendix A

Appendix A1: 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 A2: Descriptive statistics of the data

STATISTICS	RETAIL	FARM
Mean	18.20	11.36
Median	17.96	11.41
Maximum	26.86	15.70
Minimum	11.78	7.88
Std. Dev.	4.17	1.82
Skewness	0.34	0.03
Kurtosis	2.42	2.63
Jarque-Bera	3.50	0.62
Probability	0.17	0.73
Sum	1892.92	1180.99
Sum Sq. Dev.	1789.71	340.83
Observations	104	104.00

Appendix A3: Visual plot of nominal prices

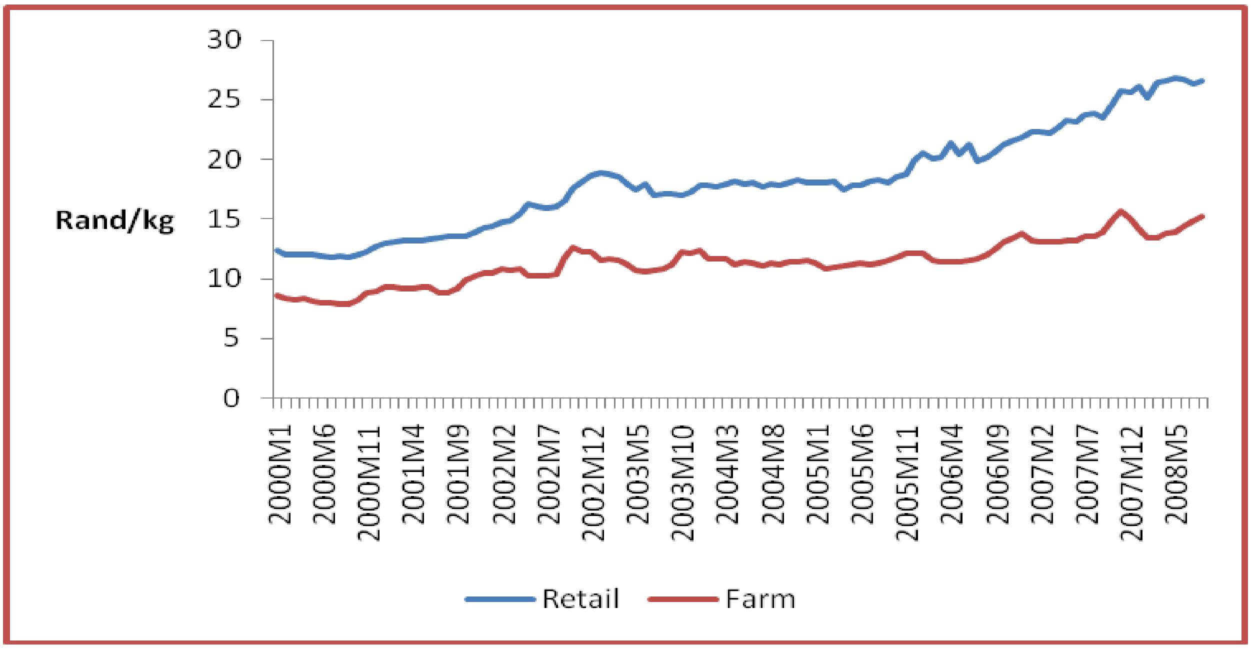

Figure A3.1: Poultry farm-level and retail prices
Source: DAFF (2009)

Appendix A4: 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

Appendix A5: KPSS unit root test

Series	**KPSS statistics***	
	Levels	**First difference**
RETAIL	1.0397	0.0688
FARM	0.4997	0.0418

*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.

Appendix A6: Conditional volatility of market price

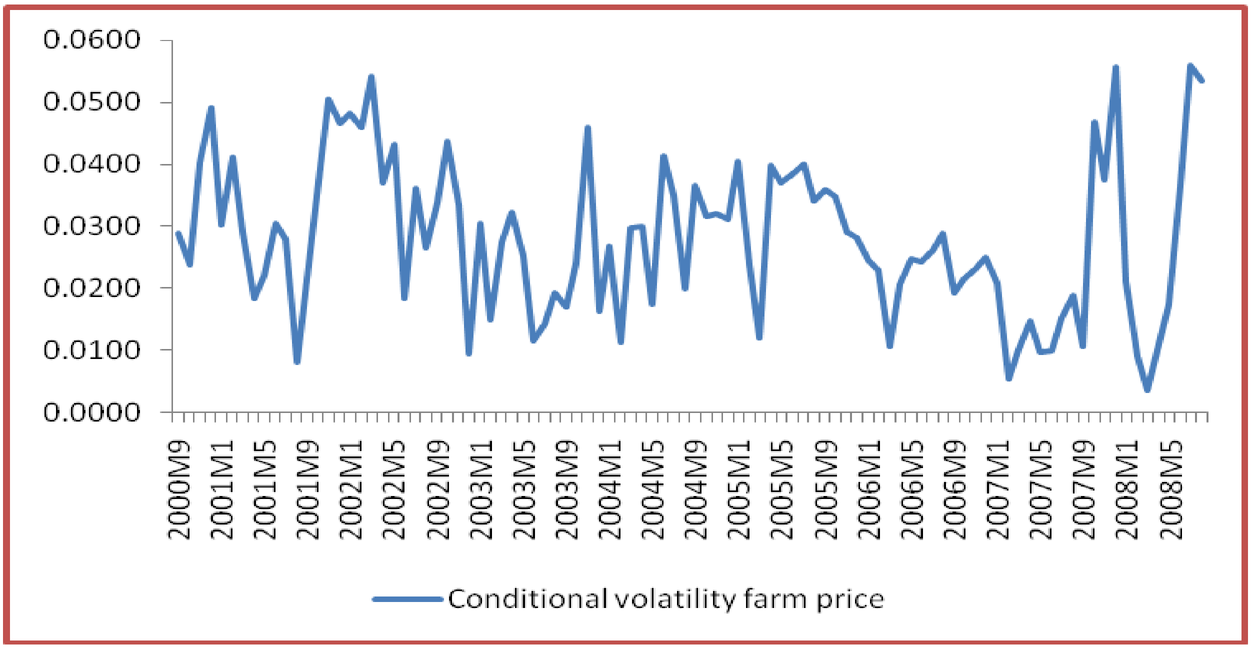

Figure A6.1: Conditional volatility in farm price with seasonal component for monthly data 2000M1-2008M8

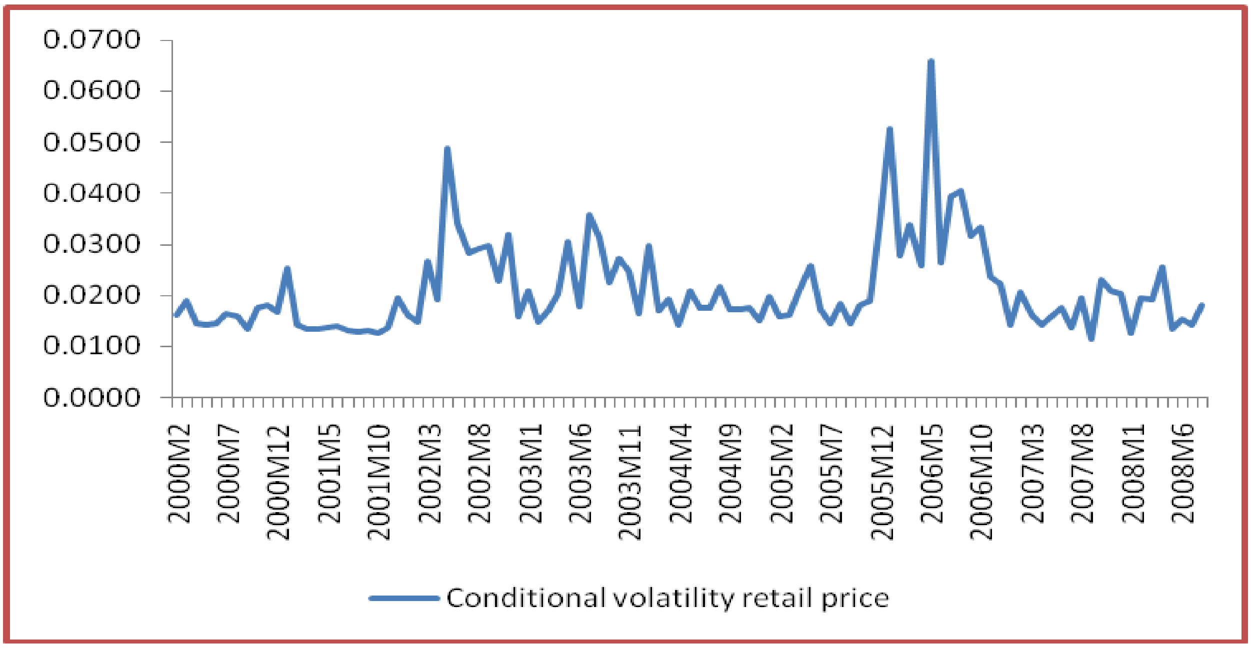

Figure A6.2: **Conditional volatility in retail price with seasonal component for monthly data 2000M1-2008M8**

Appendix A7: Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (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.

Appendix A8: **Maximum likelihood parameter estimates for monthly seasonality in the volatility of prices (Panel D - Model specification test Diagnostics)**

PARAMETERS	FARM	RETAIL
Col. 1	**Col. 2**	**Col. 3**
Ljung-Box [26]	26.279 (0.448)	14.355 (0.448)
Ljung-Box [26]	21.556 (0.713)	17.681 (0.856)
F-test	0.2202 (0.9796)	0.4777 (0.8484)
LM [7]	1.6626 (0.9761)	3.5146 (0.8337)
Jarque-Bera	0.7188 (0.6981)	0.3681 (0.8319)
GED	1.6369* (0.0005)	2.0190* (0.0033)
LogL	218.9806	257.806