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Analysing Price Risk and Volatility in the Namibian Sheep Market: A Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) Approach

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Abstract

The objective of this paper is to analyse sheep producer's supply response under price risk and volatility using data from January 2000 to December 2013. Different Autoregressive Conditional Heteroscedastic (ARCH) processes were compared and TGARCH (1, 1) model was selected and used to estimate expected price and price volatility effects. The study found positive inelastic short-run supply price elasticity of 0.2184 for the Namibian sheep industry. The long-run own-price supply elasticity is more elastic than in the short-run (0.6817). The findings also show that the expected price volatility (-0.1385) has a negative and statistically significant effect on producer's supply response, this implies that sheep supply declines as the price volatility increases. The volatility effects were found to be negatively asymmetric and persistent which implies that producers tend to respond more intensely in the case of a negative shock that reduces their margin than a positive shock. Sheep producer's attitude towards risk can be said to be averse, this hypothesis was confirmed by calculating the relative marginal risk premium which is 0.0257. The value is close to zero and may suggest no strong departure from relative risk neutrality or marginal cost pricing.

Keywords: Volatility, asymmetric effects, persistence, elasticity, risk, price expectation

1. Introduction

It is assumed that producers, when making production decisions, have control over output and that they know the commodity output price with certainty. In reality, especially in the livestock sector, the situation is different, because significant time lag exists between breeding decision and the realization of output (Tomek and Robinson 1990). Consequently, and firstly, the prevailing price at the time of sale may differ from the price that was expected at the time the decision to produce was made due to seasonal price fluctuations and secondly, the actual production may not even be equal to future planned production due to perishability, weather and disease constraints.

Implicitly, the shortfall between what the producer plan to get and what they actually get is a measure of the risk (volatility) and the uncertainty involved in agricultural livestock production. If risk expectation is high between when decision to produce is made and the actual sale, the producer will be reluctant to supply at certain prices, otherwise, they are motivated to expand production (Tomek and Robinson 1990). Most importantly, it should be noted that livestock farmer's willingness or reluctance to sell their animal at any given price is a function of the perceived value they attach to them irrespective of the prevailing circumstances. The reason being that sheep is often regarded as both a consumption and capital goods. In-as-much-as they are needed for economic reasons; they serve as a store of value. Therefore, there could be negative (positive) reaction by producers to higher (lower) levels of price uncertainty. If expected price risk is negative, it implies that elasticity of supply for sheep in response to price uncertainty is negative; as such producers are regarded as risk averse.

The question is, does price uncertainty have a significant effect on Namibian sheep producer's supply response? If so, what is the magnitude and sign of the impact? Price expectation and volatility effects have been at the centre of economic research for many years. Various studies have shown that price expectation and volatility effects influence production decision and aggregate supply response (Aradhyula and Holt 1989; Holt and Aradhyula 1998, 1990; Holt and Moschini 1992; Rezitis and Stavropoulos 2008, 2009a, 2009b, 2012). The producer tends to align future price and volatility expectations with past sales in a form of adaptive expectation; such that, given information set, their expectation of the distribution of future prices is a function of past realisations (Nerlove 1956; Nerlove and Bachman 1960). As a result, producer's supply response to price risk and uncertainty is based on the hypothesis that quantity produced depends on input prices and their expectation of output price.

The objective of this study is to investigate price expectation and price volatility response in a rational expectation context for aggregate producers' supply response in the Namibian sheep market. Sheep market is chosen for this study because of the following reasons: (a) sheep market is not as developed as beef market in Namibia, as such, the price-supply relationship in this sub-sector is important for stakeholders, (b) no known study has measured price expectation and volatility effects in the Namibian sheep industry, (c) sheep production constitutes major source of income for many, as such, knowledge of price risk is important. (d) Information obtained in this study about the supply response in the sheep industry will serve as a useful guide for policy makers. In the context of the above reasons, this study incorporates future price and volatility expectations in the aggregate supply response of the Namibian sheep market model in order to determine their effects on output supply.

2. Conceptual model

In the literature, econometrics model is most widely used to identify price expectation and risk response by simply including expected price and risk term in the supply equations. The typical model is used not only to determine producer's response to price expectation or risk but also to ensure that the risk they respond to is time variant. This is because it is important to characterize the time pattern of the unobserved expectation and conditional variance. Nevertheless, a variety of time-invariant models has been applied to model risk aversion and price variability. For instance, adaptive expectation models have been applied to model risk premier by Just (1976); Mbaga, and Coyle (2003). Antonovitz and Green (1990) applied a static ARIMA model to U.S beef supply; Pagan and Ullah (1988) used instrumental variable estimator to estimate risk term. Other models of time invariant nature were used by Roe and Antonovitz (1984) and Reynolds and Gardiner (1979). The problem is that the conditional and unconditional variances associated with these models are time-invariant

Engle (1982) proposed autoregressive conditional heteroscedasticity (ARCH) model which can be used to model time-varying conditional variance. Bollerslev (1986) generalised the ARCH model now called GARCH by allowing the conditional variance of the error process to be an autoregressive integrated moving average (ARIMA) process.` In the GARCH model, the conditional variance depends not only on the past values of the unpredictable error process but also on a moving average of the past conditional variance. Several authors have evaluated the effects of price uncertainty in agricultural supply response using the GARCH and multivariate GARCH models (Aradhyula and Holt 1989; Holt and Aradhyula 1990; Holt and Moschini 1992; Rezitis and Stavropoulos 2008, 2009a, 2009b; 2012). Although the GARCH model has been widely used to model changing conditional variance, it has some limitations (Nelson 1991). According to Nelson (1991), 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. 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. In other words, GARCH has no allowance for asymmetry.

In order to test if the data support asymmetric price and volatility effects, ARCH models that allow asymmetric effects of news (innovations or unexpected changes) in the price and volatility processes are specified. To save space, out of the various members of ARCH family, five asymmetric models were estimated, tested and only the best fit was chosen to explain the effects of expected price and volatility on the supply response of sheep producers. The aim is to compare asymmetric results using different ARCH models. The selected asymmetric models are, the exponential GARCH (EGARCH) model proposed by Nelson (1991), the Threshold GARCH by Zakonian (1994) and Glosten, Jagannathan, & Runkle, (1993), the asymmetric power ARCH by Ding, Granger and Engle (1993), the EGARCH-in-mean model (EGARCH-M) by Nelson (1991), and the Asymmetric component GARCH (ACGARCH) model by Engle and Lee (1999). TGARCH (1, 1) was found to the best fit for the data; therefore, it was used to characterize the time-varying conditional mean and variance of expected price and volatility in aggregate producer-price equations. Unlike the symmetric GARCH, the possibility of asymmetric price volatility effects is determined using maximum likelihood estimators in a TGARCH model. Asymmetric volatility effects were estimated and interpreted as the observed differences in the volatility effects between a decrease and an increase in prices of the same magnitude. Positive asymmetry suggests that sheep producers react faster to price increases than decreases in prices of the same magnitude – an indication of market power. Negative asymmetric price volatility suggests that sheep producer have a weak market position and cannot increase the price to exploit the market, but can decrease price to stay in it.

The rest of the paper is organized as follows: First, the Namibian sheep industry is briefly reviewed in section 3. The review highlights the structure and the importance of the sheep sub-sector. Second, the method used in the study is described in section 4, followed by the description of the data and the model specification in section 5. Empirical results are then presented in section 6, and lastly, closing remarks are given in the concluding section 7.

3. The Namibian sheep market

The agricultural system in Namibia is dualistic. There are the established commercial sector and the resource-poor small-scale farmers. The record of commercial agriculture shows that the sector contributed 3.2% to GDP in 2015, of which the livestock contributed 1.9% (Namibian Statistical Agency 2015). The red meat sub-sector contributes more than 80% to the total contribution in the livestock sector, making it an import sub-sector. The contribution of the commercial sector drives the entire agricultural economy with relatively less impact on the rural and emerging sector.

Climatic factors are major impediments to agricultural production. This is because there is an often erratic rainfall and sporadic occurrence of drought. Large stock production subsists well in the Northern part of the country which has higher annual rainfall, good vegetation but more disease-prone. Livestock subsists well in the central region, while in the more arid and less disease-prone southern part, extensive sheep and goat rearing predominates. Marketing of sheep is mainly main-stream, but there is a significant informal and speculative exchange transactions occurring in the remote areas of the country.

Small stock livestock is either marketed to local butchers, export abattoirs or exported live to South Africa. Sheep is marketed in the local abattoirs, butcheries, and auction pens located at strategic points across the country. Export of live sheep dominated Namibian sheep market until 2006 when export ratio on live sheep was introduced. Under the export ratio trade policy framework, out of every six sheep exported one is slaughtered locally. This affected export sales as more sheep were marketed domestically (See appendix Figure A2). Most of the Namibian market outlets have low throughput and lack the required accreditation for export, hence, few export abattoirs exit. Because of the structure and size of the domestic market, almost 70-80% of Namibian livestock production is exported live to South Africa until 2006. The share of sheep to the total small stock marketed increased from 25-86% during the period of 1999 to 2011. In 2014, the export share of live sheep and goats was 33% compared to 31% in 2013. The local slaughtering of sheep increased especially after the implementation of the Small Stock Marketing Scheme (SSMS) in 2004 (Meat Board of Namibia 2012). The total number of sheep marketed showed an average annual growth trend of 1.7% in the same period. The average utilisation of local slaughter capacity for sheep at the export abattoirs was 57% in 2008, 65% in 2009, 61% in 2010 and 55% in 2011 (Meat Board of Namibia 2012).

Appendix Figure A1 shows the quantity of sheep supplied to the market between Jan 2012 and December 2013. It can be seen that most sheep are marketed via the export abattoir. The most export sales were during the March, April, and May periods. Export sales were highest in March 2012 and 2013. Implying that March, April, and May are the peak periods for sheep export market. Export sales of live sheep to South Africa occur across the months. Sales are recorded in dry months (June, July, and August) as much as in rain months (February, March, and April). As such, the highest export sales to South Africa during 2013 period occurred in April and June. The domestic sales to local non-export abattoirs occur almost at any time of the year. This can be seen from the even distribution of the sales. Most formal (export) marketing of small livestock is mainly sheep because goat sale is seasonal main target market for goat sale being Eastern Cape and Kwazulu-Natal markets.

4. Methodology

The empirical model for sheep supply response is specified in this study as a function of expected price and its conditional variance and a vector of independent variables consisting of inputs prices, time which stands for technology, and rain as additional factors of production. The equation is represented as follows:

$$y_t = a_o + a_1 P_t^e + a_2 h_t + a_3 x_{1t} + e_{it} \tag{1}$$

Where y_t is the sheep supply, P_t^e is the expected price, h_t is the expected price variance which measures volatility, $x_{1t}^{'}$ is a vector of independent variables and e_{1t} is a mean zero normally distributed error term with variance σ. The GARCH (p, q) model generates the variables P_t^e and h_t with the following price expectations:

$$P_t|\Omega_{t-1} = c_o + \sum_{i=1}^{n} c_i P_{t-1} + e_{2t} \tag{2}$$

and,

$$h_t = c_0 + \sum_{i=1}^{q} a_i \varepsilon_{2t-1}^2 + \sum_{i=1}^{p} b_i h_{t-1} \tag{3}$$

$e_{2t} \mid \Omega_{t-1} \sim N(0, h)$, where e_{2t} is a discrete stochastic error and Ω_{t-1} is the information set available to the producer at the time $(t-1)$ when the decision to produce was made. The regularity condition is observed if:

$$c_0 > 0, \quad a_i > 0, \quad i = 1,....,q, \quad b_i \geq 0, \quad i = 1,.....p, \quad \sum a_i + \sum b_i < 1 \tag{4}$$

Due to possible cross-equation correlation between (e_{1t} and e_{2t}) in equations (1) and (2), using P_t^e and h_t generated from a stochastic model such as GARCH as regressors in equation (1) will result in a biased estimate of the parameters of the supply model. Therefore, a non-linear iterative maximum likelihood estimation (MLE) procedure was suggested by Pagan (1984).

4.1 The asymmetric models

4.1.1. The EGARCH

The asymmetric conditional variance models are extensions of the basic ARCH and GARCH models. For example, the variance equation of the EGARCH model is given as:

$$\log(h_t^2) = \omega + \sum_{j=1}^{q} b_j \log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{i=1}^{p} a_i \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - E\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \right| \tag{5}$$

or simply,

$$\log(h_t^2) = \omega + b\log(\sigma_{t-1}^2) + \gamma\varepsilon_{t-1} + a\big[|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|\big] \tag{6}$$

Where, ω, b, γ *and* a are parameters to be estimated. The EAGARCH model is asymmetric because of the inclusion of $\gamma\varepsilon_{t-1}$ with the asymmetric coefficient γ which captures the impact of asymmetric price changes. If γ is insignificant, positive and negative shock have the same effect on volatility. If $\gamma = 0$ and $a > 0$, the innovation in $\log(h_t^2)$ is positive (negative) when the magnitude in $\gamma\varepsilon_{t-1}$ is larger (smaller) than its expected value. If γ is < 0, and $a = 0$, negative shock increases volatility more than a positive shock of the same magnitude. Put differently, this implies that the innovation in the conditional variance $\log(h_t^2)$ - a measure of volatility, is positive (increases), when there is a negative shock; otherwise it is negative (decreases) when there is a positive shock. The persistence of a shock is measured by the absolute value of b .In equation (3) and (4), the regularity condition in the EGARCH model requires that $0 < b < 1$. If the unconditional variance is finite, the absolute value of $b < 1$. If the coefficient is significant, there is a significant evidence of persistence of shock. The smaller the absolute value of b , the less persistent volatility will be after a shock. If the value of b 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).

4.1.2. The EGARCH-M

The EGARCH model is similar to the EGARCH-M model as specified in equations (5) and (6). The EGARCH-M model differs from the EGARCH model by allowing the conditional mean to depend directly on the conditional variance or the standard deviation. This is accomplished by including the standard deviation or conditional variance term in the conditional mean model.

4.2.3. The symmetric power GARCH

The symmetric power TARCH /GARCH model introduced by Ding, Granger, and Engle (1993) is regarded as a standard deviation GARCH model, where the standard deviation is modelled rather than the variance as follows:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} b_j \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} a_i (|\varepsilon_{t-1}| - \gamma_i \varepsilon_{t-1})^{\delta} \tag{7}$$

The introduction of a power term to an ARCH or GARCH model results into a power TARCH/GARCH, the power parameter δ is estimated instead of being imposed to cater for clustering of volatility. The parameter γ captures asymmetry, where $\delta > 0, |\gamma_i| \leq 1$. In the APGARCH, like other asymmetry models, asymmetry is present if $\gamma_i \neq 0,$.

4.1.4. The asymmetric component GARCH

The asymmetric component GARCH (ACGARCH) model was designed to account for long-run volatility dependencies. It is a combination of component model and the asymmetric TARCH model.

$$\sigma_t^2 - m_t = a(\varepsilon_{t-1}^2 - m_{t-1} + \gamma(\varepsilon_{t-1}^2 - m_{t-1})d_{t-1} + b(\sigma_{t-1}^2 - m_{t-1}) \tag{8}$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \theta_1 z_{1t} \tag{9}$$

The m_t is the time varying long-run volatility, z and d are exogenous and dummy variables respectively. The introduction of threshold effects introduces asymmetry into the component model.. The parameter $\gamma > 0$ indicates the presence of transitory asymmetry effects in the conditional variance.

4.1.5. The Threshold GARCH

The Threshold GARCH model independently developed by Zakonian (1994) and Glosten *et al* (1993) is specified respectively as:

$$\sigma_t = \omega + a \mid \varepsilon_{t-1} \mid + \gamma \mid \varepsilon_{t-1} \mid \mathrm{I}\ (\varepsilon_{t-1} < 0) + b\sigma_{t-1} \tag{10}$$

$$\sigma_t^2 = \omega + a \mid \varepsilon_{t-1}^2 \mid + \gamma \mid \varepsilon_{t-1}^2 \mid \mathrm{I}\ (\varepsilon_{t-1} < 0) + b\sigma_{t-1}^2 \tag{11}$$

The TGARCH allows asymmetry effect into GARCH model by separating the impact of past shock using an indicator variable, I. Where $\mathrm{I}_t = \mathrm{I}\ \ if\ \ \varepsilon_{t-i} > 0,$ and 0 otherwise, (See Table 1). The negative shock (bad news), $\varepsilon_{t-i} > 0,$ and the positive shock (good news), $\varepsilon_{t-i} < 0$ have different effects on conditional variance. A positive shock has (a) impact and contributes $a\varepsilon_{t-i}^2$ to h_t, while a negative shock has a larger impact, ($a_i + \gamma_i$) with $\gamma_i > 0.$ If $\gamma_i > 0$, negative shock ($\varepsilon_{t-1} < 0$) increases volatility more than a positive shock ($\varepsilon_{t-1} > 0$) of the same magnitude, if $\gamma_i \neq 0,$ the impact is asymmetric. The regularity (sufficient) condition to ensure strict positive conditional variance is that $\omega > 0,$ $a > 0,$ $b > 0,$ and $(a + y) > 0$. The TGARCH model was used in this study to estimate the producer-price model.

The summary of the model framework for the selected ARCH models is given in Table 1. In all the selected models, asymmetric term γ is incorporated into the ARCH component of the model to distinguish between effects of positive (good news) and negative (bad news) innovations (shocks) to the conditional variance.

5. Data and model specification

The data used in this study are the monthly sheep supply data, the producer price of sheep, the maize spot price and rainfall data from years 2000 to 2013. Sheep supply data was obtained from the meat board of Namibia. It consists of the total number of sheep supplied to the market to the export abattoirs, butcheries, and the numbers exported to the neighbouring countries. The producer price was also sourced from the meat board. It is the average carcass producer price measured in Namibian dollar per kilogramme (N$/kg). There was a huge constraint in getting the input data; as a result, maize spot price was used as a proxy for input prices. Maize price was used because maize is a major component of animal feed which constitutes a large part of input cost. The South African futures exchange (SAFEX) yellow maize spot price was used. The spot price was approximated to the Namibian price by multiplying the spot price with the distance between Windhoek and Johannesburg. Rainfall was included in the model because it is an important parameter in supply response. Monthly rainfall data was sourced from the Namibian Meteorological Services. All the variables are log transformed, and all prices were deflated with consumer price index obtained from the Namibian Statistical Agency.

The empirical model is based on the producer-price models representing the producer-price structure of the Namibian sheep market. The assumptions are that: (i) producers form expectations about endogenous variables in a manner consistent with rational expectation hypothesis, (ii) producers are risk averse, and that, (iii) sheep price is a major source of uncertainty in the sheep market. Considering the above assumptions, price expectation, price volatility and the level of risk (whether producers are averse, neutral, or seeking) were investigated. Following the supply model (1), the sheep supply response equation is specified as:

$$QSB = a_0 \sum_{i=1}^{12} a_{it} D_{it} + a_{13} EPPS_t + a_{14} PPSV_t + a_{15} Ymaz_{t-8} + a_{23} QSS_{t-8}$$

$$+ a_{31} Rn_{t-1} + a_{32} Tm_T + \varepsilon_{1t} \qquad (12)$$

Where QSS_t is the quantity of sheep supplied to the market in period t. Seasonal dummies D_{it} are used to account for seasonality in sheep production. The data is monthly; therefore 12 seasonal dummies are included. The EPPS and PPSV are the expected producer price and the producer price volatility respectively. The two variables capture farmer's price expectations and the conditional variance which is a measure of volatility. As mentioned previously, input cost is captured by yellow maize price, $Ymaz_t$ which is a major component of sheep input price. Production lags are also included; For instance, the production cycle of sheep in Namibia is about 231 days (including preparations (30 days), oestrus cycle (21 days) and gestation period (180 days), therefore, seven lag structures were used to take care of the lags in sheep production because producers may not be able to adjust production to the desired level during the year. Lastly, one period lag of rain was included to represent the impact of rain as a factor of production in the sheep industry, while, one lag of time stands for technical change.

5.1. Price and conditional variance equation

An autoregressive order AR (7) was used for the real producer price equation, representing the price of sheep in the period $t-i$, where $i = 1...2,...7$. The real producer price equation is given by

$$PPS_t = \alpha_0 + \sum_{i=1}^{7} \alpha_i PPS_{t-i} + \alpha_8 Tm_T + \varepsilon_{2t} \qquad (13)$$

Where PPS_t is the real producer price of sheep in time t, Tm_T is a time trend which stands for technical change, PPS_{t-i} is the real producer price at time $t-1$, where $i = 1,..........7$. Seven periods was indicated because the production cycle in sheep was determined to be 7 months.

The conditional variance model is given by equation (10). The TGARCH orders were selected by minimizing Akaike information criteria (AIC), Swartz-Bayesian Information Criteria (SIC) and Hannan-Quinn Information Criterion (HQC). According to the three model selection criteria, TGARCH (1, 1) fits the data most; therefore, producer-price models of equation (10), (12) and (13) were estimated simultaneously with the TGARCH model using Full Information Maximum Likelihood (FIML) estimation procedure implemented with E-views (version 9.5) statistical package. Following the function $f(y_t, x_t, \psi) = \varepsilon_t$, where y_t is a vector of endogenous variables, x_t is a vector of exogenous variables, the FIML finds the vector of parameters ψ by maximizing the likelihood under the assumption that ε_t is independently and identically distributed multivariate random variable with a covariance matrix Σ. Under the normality assumption, the log-likelihood is given as:

$$\log L = -T/2\log|\Sigma| + \sum_{t=1}^{T}\log\|\delta f_t / \delta y_t'\| - 1/2\sum f_t'\Sigma^{-1} f_t \qquad (14)$$

The expected price $EPPS_t$ in equation (12) was obtained from equation (13). This represents the future expectation of farmers which they formed using producer price at $t-1$. The conditional variance term in equation (7) is obtained from the conditional variance component of the TGARCH (1, 1) model. Additional cross-equation restrictions are imposed by the TGARCH (1, 1) model. One of the assumptions is that the unconditional errors are normally distributed and the Marquardt logarithm is used to obtain the maximum likelihood estimates of the system represented by the supply equation (12) and price equation (13).

6. Empirical results

The descriptive statistics of the data used in the producer-price model is shown in the Appendices Table A1. The results show that the producer price of sheep (PPS), the producer price of sheep volatility (PPSV), the quantity supplied of sheep carcasses (QSSC) and the yellow maize (Ymaz) are not normally distributed while the expected producer price of sheep (EPPS) is normally distributed. The datasets are all positively skewed except EPPS with kurtosis not far from normal.

Stationarity test was performed to determine the time series property of the variables. This was conducted using three different unit root tests; (a) the Augment Dickey-Fuller, (b) the Kwiatkowski-Phillips-Schmidt-Shin test, and (c) the Elliott-Rothenberg-Stock (DF-GLS) test. Intercept and trend components were included in the tests. The tests show that the PPS, QSS and Ymaz datasets are non-stationary in levels (Appendices Table A2). The results justify the inclusion of intercept and time trend in the models.

The parameter estimates for the risk-responsive sheep supply equation (12) is shown in Table 2. Recall that the best performing model according to AIC, SIC, and the HQC is the TGARCH model (Table 2); therefore, further empirical result interpretations will be based on the parameters obtained with TAGRCH producer-price model. The result for the producer response to price expectation was as expected. The result shows that the short-run price elasticity given by the estimated coefficient of EPPS has a positive sign, i.e, 0.2184. As the sign indicates the expected sheep price increases induces Namibian sheep producers to sell more of their sheep in the short-run as prices expectations increases. This is consistent with what is obtained elsewhere, for example, see Rezitis and Stavropoulos (2009 b). The long-run price elasticity of sheep supply is 0.6817 (Table 4). This indicates that the elasticity of sheep supply increases in the long-run as price expectation increases. Producers will tend to supply more sheep to the local abattoir in the long run. The more lucrative export market in South Africa will be patronized as the producers gain more knowledge of the export market in the long-run.

The estimated sheep short-run price volatility (PPSV) is -0.1385. It is significant at one percent level of significance and has the expected negative sign indicating that price volatility has a negative effect on producer supply response. This risk effect is regarded as the marginal risk effect. This result indicates that increase in expected price volatility by one percent decreases sheep supply by 0.14%. This is an indication that price volatility is an important risk factor for the sheep industry. Therefore, price volatility should be considered when forming an expectation about future production and prices. The historical path of the conditional volatility for sheep is shown in figure 1. The figure shows that volatility peaks in February, March, and April. This result is expected because sheep sale tends to increase during the festive months; it declines and picks up again from February, March, and April when the obligation for school fees and other household debts such as vacation increases. The average and median values of sheep volatility are calculated to be 0.0786 and 0.0752 respectively. Both values indicate a volatility value of 7.8% and 7.5% respectively. The calculated long-run price volatility is 22.97%. The result shows that price volatility in the long-run is more elastic than short-run volatility.

The sum of the magnitude of feed cost represented by $Ymaz_{t-i}$ is estimated to be -0.1046. The result has the expected sign, which signifies negative effect on sheep supply. Maize forms a major part of input cost; as a result, increases in maize price are expected to affect feed cost and indirectly affect sheep supply. The lagged quantity of sheep supplied, QSS_{t-i} shows the magnitude of adjustment to the production level. If adjustment is high, the value will approximate zero, otherwise, production does not adjust properly. The value of the estimated lagged production is 0.7121. The value is large, signifying that actual (current) production adjusts slowly to the required future (new) desirable production level. Its coefficient is comparatively larger than the coefficient of price expectation, an indication that though producers respond to expected price changes, they are as well influenced by past supplies

The sign of the coefficient for technical change, $Time_{t-1}$ is positive and statistically significant at 10% level, indicating a significant technical transformation in the sheep industry. However, the magnitude of the coefficient is small, which suggest that there have not been a complete transformation in the sector. This can be attributed to low capacity utilization identified in the previous section. The result shows that seasonal effects also increase the vulnerability of sheep producer. It can be seen from Table 2 that all the dummy coefficients for seasonal effects are statistically significant, implying strong seasonal effects in the sheep industry.

Previously, the marginal or incremental risk effect, the PPSV, was determined to be negative and statistically significant. In keeping with the notion that negative sign implies negative reaction by producers, sheep producer may be regarded in this instance as risk averse. The question is what is the ratio of the marginal risk in relation to the expected price? To answer this question, the relative marginal risk premium (RMRP) was estimated as the negative of the ratio of the variance and price elasticity of supply (see Holt and Moschini, 1992; Holt and Aradhyula, 1998). It is regarded as the percentage departure from marginal cost pricing (Holt and Moschini, 1992). Equation (14) was used to estimate RMRP.

$$-\frac{\eta_\sigma}{\eta_p} = \frac{\lambda y \sigma^2}{\bar{p}} \tag{14}$$

where $\lambda y \sigma^2$ is the risk premium, η_p is the point price elasticity of supply and η_σ is the supply elasticity with respect to price variance, the $(\bar{p}, \sigma^2)$ are the *ex-ante* mean and variance of price from the producer-price model. If RMRP is positive, producers are risk averse, if it is less than zero, producers are risk seeking, and if it is equal to zero, producers are risk neutral; a small and infinitesimal value of RMRP, that is, a value equal to or close to zero is not different from risk neutrality. The estimated mean value of RMRP is 0.0257. It is positive, meaning producers are risk averse and it is close to zero, implying there is no strong departure from risk neutrality or marginal cost pricing. The calculated RMRP series ranges from a minimum of 0.10% to a maximum of 7.96% during the sample period, the average being 2.57%. The result confirms the earlier findings that sheep producers are risk averse.

The empirical result from the price and variance equation is shown in Table 3 under the column TGARCH(1, 1). Similar to the results from the supply model reported in Table 2, most of the parameters of the lagged producer price of sheep (PPS) in the conditional mean model are significant. In the conditional variance model, the result of asymmetry effect of expected price volatility and persistence is presented. The value of the volatility persistence parameter b, is 0.7096. It is statistically significant at one percent. The magnitude of the parameter is high, an indication that price volatility in the sheep market is persistent. If volatility is persistent, any shock to conditional variance takes a long time to die out. The asymmetric parameter γ is positive, (i.e., 0.9152) and statistically significant at ten percent level of significance. This implies that there is a negative and significant asymmetric price effect in the sheep market, as a result; a negative shock in price causes more volatility than a positive shock of the same magnitude. An example of a negative shock is the unexpected rise in the input cost that reduces producer's market margin. This suggests that the sheep producers' have a weak market position. If they have a strong market position, they can manipulate the market by increase price to adjust to the increased cost.

The result so far shows that the prediction of sheep supply and the conditional variance (volatility) under the producer and price models is plausible, signifying the models are correctly specified as indicated in the Table appendices Table A3, however, further evidence is required to determine their performance (Holt and Moschini 1992). The predictive power of the model was determined by (a) regressing observed (actual) prices on the predicted (fitted) prices for the conditional mean, (b) regressing the observed squared deviations from the estimated expected prices on the estimated conditional variance (volatility). The result for the prediction of the conditional mean is unbiased and consistent, with R^2, 0.9476 (Table 5). The F-statistics for the Wald coefficient restriction test do not reject the hypothesis that the values of the intercept and slope coefficients are zero and one respectively. This implies that the ability to predict price is high. On the other hand, the result for the prediction of conditional variance was not as expected. The R^2 is low; 0.0075 and the F-statistic for the Wald test was rejected at one percent level of significance (Table 5).

Recall that the conditional variance model was determined to be asymmetric with persistent shocks. Given the low predictive power exhibited by the model in predicting volatility, a diagnostic test for asymmetry was performed using the test proposed by Engle and Ng (1993). The aim is to determine the validity of the asymmetric result obtained. The tests are; (a) sign bias test (SBT), (b) the negative sign bias test (NSBT) , (c) the positive sign bias test (PSBT) and (d) the joint test (JT). The SBT was carried out by regressing squared standardized residual on a constant and on S_t^- , where, $S_t^- = 0, if\ \varepsilon_{t-1} = 0, 0$ otherwise[1]. The null for the SBT test evaluates whether positive and negative innovations (shocks) have a different (asymmetric) effect on future volatility from the prediction of the model (Glosten, Jagannathan, and Runkle, 1993). It also shows whether other variables other than the ones specified in the producer-price model can be used to predict volatility. If the null is rejected, asymmetry effect does not exist in the model, therefore, it is misspecified. The NSBT is a regression of standardized squared residual on a constant and on $S_t^- \varepsilon_{t-1}$. The test investigates whether larger negative shocks are correlated with larger biases in predicted volatility, that is, it shows the different effects that large and small negative shocks have on volatility which was not predicted by the volatility model (Engle and Ng 1993; Fornari 1997; and Rohan 2009). For the PSBT test, the squared standardized residual was regressed on a constant and

[1] Note that ε_{t-1} is the residual innovation (shock) whose impact on h_t^2 is being evaluated.

on $S_t^+ \varepsilon_{t-1}$, where, $S_t^+ = 1 - S_t^-$.The test shows whether large positive innovations are correlated with larger biases on the predicting volatility. The joint test JT is the combined tests involving the SBT, NSBT, and PSBT. Table 6 presents the diagnostic test for asymmetry. None of the test statistics on the coefficients of the SBT, NSBT, PSBT, and the JT tests were significant, signifying the rejection of the null hypothesis in all cases. This is an indication that the producer-price model is correctly specified and that there is an asymmetric volatility effect in the Namibian sheep market.

Since asymmetric price volatility was confirmed with the diagnostic tests, the low predictive power of the conditional variance model can be attributed to the long production planning horizon. According to Holt and Moschini (1992), the predictive power of conditional variance model declines as the planning horizon[2] increases, hence the unbiased conditional estimates may rapidly become biased like the unconditional estimates from time-invariant models.

The diagnostic tests for the TGARCH (1, 1) model are presented in appendix Table A3. The results show that there is no serial residual correlation and heteroskedasticity in the residual of the TGARCH model. The null hypothesis of no serial residual correlation was not rejected at 1, 5, 10, 20, 25, 30 and 35 lags for both supply and price equation. The null for the ARCH test is that the residuals are homoskedastic. In the Lagrange Multiplier test shown in Appendix Table A3, the null was not rejected meaning that the residuals are homoskedastic.

7. Conclusion

The study investigated sheep producer’s supply response under price volatility risk. The magnitude and sign of impacts were estimated and the implications for producer’s response were outlined. The result was based on aggregate sheep supply data ranging from 2000M1 to 2013M12. Various approaches used to specify conditional variance and volatility were compared and the Threshold GARCH (1, 1) model was selected using various model selection criteria.

The result shows that sheep producers take future price increase as temporary, therefore, in the short-run; they are induced to supply their animals to the market instead of withholding

[2] Because monthly dataset was used, a period is a month. There are twelve months production lags, hence, 12 production horizons.

them. The long-run own-price elasticity of sheep supply is greater than the short-run, an indication that in the long-run due to the possible diversification and the development of more lucrative export market producers would supply more sheep to the market.

The producer response to risk was negative and statistically significant. In keeping with the notion that negative sign implies negative reaction by producers, Namibian sheep producer may be regarded as risk averse. Further investigations into their risk profile were carried out by calculating the relative marginal risk premium (RMRP). The result of the RMRP confirms that Namibian sheep producers are risk averse. Examination of the effects of price volatility shows that sheep producers have weak market position due to the presence of a negative asymmetric price effect. Producers seem to respond more intensely to a negative price shock which increases price volatility than a positive shock of the same magnitude. The effects were found to be persistent.

The effects of input price, rainfall, and impact of technical change were also investigated. The results show that input cost had a significant influence on sheep supply. This is not surprising given that Namibia is a net importer of livestock feed, high feed costs affect sheep supply. The findings also show that technological advancement enhanced sheep supply under strong seasonal effects.

Table 1 The summary of the properties of the selected ARCH models

	Conditional variance	C	GARCH Term	ARCH Term		Regularity condition	Null hypothesis	Asymmetric condition
EGARCH	$\log(h_t^2)$	ω	$b\log(\sigma_{t-1}^2)$	$\gamma\varepsilon_{t-1}$	$a[\lvert\varepsilon_{t-1}\rvert]-E\lvert\varepsilon_{t-1}\rvert$	$\omega>0,\ 0\le b\le 1$	$\gamma<0$	$\gamma\neq 0$
TGARCH	h_t	ω	$b\sigma_{t-1}$	$\gamma\lvert\varepsilon_{t-1}\rvert \mathrm{I}(\varepsilon_{t-1}<0)$	$a\varepsilon_{t-1}$	$\omega>0, 0\le b\le 1$	$\gamma<0$	$\gamma\neq 0$
APGARCH	h_t^δ	ω	$b\sigma_{t-1}^\delta$	$a(\lvert\varepsilon_{t-1}\rvert-\gamma\varepsilon_{t-1})^\delta$		$\delta>0, \lvert\gamma\rvert\le 1$		$\gamma\neq 0$
EGARCH-M	$\log(h_t^2)$	ω	$b\log(\sigma_{t-1}^2)$	$\gamma\varepsilon_{t-1}$	$a[\lvert\varepsilon_{t-1}\rvert]-E\lvert\varepsilon_{t-1}\rvert$	$\omega>0,\ 0\le b\le 1$	$\gamma<0$	$\gamma\neq 0$
ACGARCH	$\sigma_t^2-m_t$		$b(\sigma_{t-1}^2-m_{t-1})$	$\gamma(\varepsilon_{t-1}^2-m_{t-1})d_{t-1}$	$a(\varepsilon_{t-1}^2-m_{t-1})$	$\omega>0, 0\le b\le 1$	$\gamma<0$	$\gamma>0$

Note, if $\gamma\neq$, asymmetry condition is present. γ can take positive (negative) value, however, typically, it is normally negative. m_t takes the place of ω in the component model. C stands for constant.

Table 2 Maximum Likelihood Estimation of Sheep Supply Response

Variables	TGARCH (1 1)	EGARCH (1 1)	EGARCH-M	APARCH (1 1)	CGARCH (1 1)
EPPS	0.2184*** (0.0004)	0.2996*** (0.0000)	-28.9830*** (0.0000)	0.2649 (0.1170)	0.2694* (0.0737)
PPSV	-0.1385*** (0.0023)	-0.0064* (0.0587)	0.1042 (0.2230)	-0.0051 (0.9620)	-0.0037 (0.6657)
Ymaz(t-1)	-0.2204*** (0.0000)	-0.1930*** (0.0000)	-0.3772*** (0.0000)	-0.2144 (0.1877)	-0.2203*** (0.0000)
Ymaz(t-2)	0.1158*** (0.0000)	0.0720*** (0.0000)	-0.3527*** (0.0000)	0.0843 (0.5895)	0.1011*** (0.0000)
QSS(t-1))	0.4198*** (0.0000)	0.4917*** (0.0000)	0.2513*** (0.0000)	0.4372*** (0.0000)	0.4929*** (0.0000)
QSS(t-2)	0.2923*** (0.0000)	0.2748*** (0.0000)	0.5385*** (0.0000)	0.3150*** (0.0000)	0.2737*** (0.0000)
Rain(t-1)	0.0001 (0.1766)	-0.0001*** (0.0000)	0.2742*** (0.0000)	0.0000 (0.7290)	0.0000 (0.6660)
Time(t-1)	0.0016* (0.0257)	0.0017*** (0.0000)	0.0000 (0.5387)	0.0017** (0.0203)	0.0017* (0.0155)
Dummy1	3.8716*** (0.0000)	3.8174*** (0.0000)	0.0016*** (0.0001)	4.1307*** (0.0000)	3.8154*** (0.0000)
Dummy2	3.9409*** (0.0000)	4.1007*** (0.0000)	7.9889*** (0.0000)	4.3282*** (0.0000)	4.0461*** (0.0000)
Dummy3	4.0746*** (0.0000)	4.2058*** (0.0000)	8.1425*** (0.0000)	4.4292*** (0.0000)	4.1410*** (0.0000)
Dummy4	3.9456*** (0.0000)	3.9134*** (0.0000)	8.2623*** (0.0000)	4.2179*** (0.0000)	3.8894*** (0.0000)
Dummy5	3.8133*** (0.0000)	3.7289*** (0.0000)	8.0708*** (0.0000)	4.0541*** (0.0000)	3.7345*** (0.0000)
Dummy6	3.8625*** (0.0000)	3.7286*** (0.0000)	7.9467*** (0.0000)	4.0730*** (0.0000)	3.7420*** (0.0000)
Dummy7	3.7869*** (0.0000)	3.6634*** (0.0000)	7.9929*** (0.0000)	3.9679*** (0.0001)	3.6738*** (0.0000)
Dummy8	3.7079*** (0.0000)	3.5507*** (0.0000)	7.9089*** (0.0000)	3.9072*** (0.0001)	3.6170*** (0.0000)
Dummy9	3.7391*** (0.0000)	3.6442*** (0.0000)	7.8851*** (0.0000)	3.9455*** (0.0001)	3.6447*** (0.0000)
Dummy10	3.8627*** (0.0000)	3.8358*** (0.0000)	7.8668*** (0.0000)	4.0634*** (0.0000)	3.7671*** (0.0000)
Dummy11	3.9073*** (0.0000)	3.8110*** (0.0000)	8.0082*** (0.0000)	4.1132*** (0.0000)	3.8167*** (0.0000)
Dummy12	4.0732*** (0.0000)	4.0899*** (0.0000)	8.0713*** (0.0000)	4.2902*** (0.0000)	4.0014*** (0.0000)
R 2	0.8341	0.8225	0.8401	0.8358	0.8353
Log Likelihood	38.7098	35.2173	36.6124	33.5634	35.4933
Durbin Watson	1.8701	1.9635	1.8822	1.9064	1.9982
AIC	-0.1725	-0.1285	-0.1335	-0.1077	-0.1068
SIC	0.3101	0.3540	0.3683	0.3748	0.4143
HQC	0.0235	0.0674	0.0703	0.0882	0.1048
Observations	159	159	159	159	159

Figures in parenthesis are the p-values. Note: *** = Significant at 1%, ** = Significant at 5%, * = Significant at 10%

Table 3 Empirical Results from Price and Variance equations

Variables	TGARCH (1, 1)	EGARCH (1, 1)	EGARCH-M (1, 1)	APARCH (1, 1)	ACGARCH (1, 1)
Conditional mean					
Constant	0.1597***	0.1105	0.1015	0.0499	0.0436
	(0.0000)	(0.0006)	(0.03990	(0.0188)	(0.0817)
PPS (t-1)	0.8950***	0.9391	0.9561	0.9687	0.9607
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PPS (t-2)	0.1160***	0.0588	0.0171	0.1377	0.0976
	(0.0017)	(0.3351)	(0.8420)	(0.0039)	(0.0089)
PPS (t-3)	-0.1188**	-0.0914	-0.0942	-0.1593	-0.1296
	(0.0126)	(0.3775)	(0.3709)	(0.0015)	(0.0088)
PPS (t-4)	0.0101	0.0162	0.0108	-0.0411	0.0100
	(0.8432)	(0.9008)	(0.9310)	(0.3847)	(0.8344)
PPS (t-5)	0.1129	0.0371	0.0363	0.1338	0.1060
	(0.1921)	(0.7740)	(0.7673)	(0.0001)	(0.0164)
PPS (t-6)	-0.0616	-0.0628	-0.0546	-0.0486	-0.0679
	(0.5578)	(0.5218)	(0.5805)	(0.1741)	(0.1194)
PPS (t-7)	-0.0535	0.0299	0.0420	-0.0199	-0.0023
	(0.5003)	(0.6531)	(0.4645)	(0.4412)	(0.9454)
Time (t-1)	0.0006***	0.0005	0.0007	0.0001	0.0001
	(0.0003)	(0.0425)	(0.0250)	(0.2460)	(0.2781)
Conditional variance					
Constant	0.0005*	-4.8646***	-5.3685***	0.0000***	0.0000***
	(0.0958)	(0.0022)	(0.0002)	(0.0000)	(0.0000)
R 2	0.9477	0.9484	0.9501	0.9465	0.9469
a	-0.0221***	-0.7494	-0.6953***	0.0167	0.9997***
	(0.0000)	(0.7494)	(0.0001)	(0.3924)	(0.0000)
γ	-0.9152*	0.1345	0.1728	0.1575	-0.0059
	(0.0168)	(0.2852)	(0.2364)	(0.3323)	(0.6022)
b	0.7096***	-0.0237	-0.1036	0.9901	0.0691
	(0.0000)	(0.9324)	(0.6733)	(0.3319)	(0.8422)
Log Likelihood	185.9116	172.7877	176.4109	211.76	211.3183
Durbin Watson	1.8415	1.9322	1.9439	1.9439	1.9265
AIC	-2.1480	-1.9849	-2.0175	-2.4566	-2.4263
SIC	-1.8992	-1.7361	-1.7496	-2.1887	-2.1201
HQC	-2.0469	-1.8839	-1.9087	-2.3478	-2.3020
Observations	161	161	161	161	161

Figures in parenthesis are p-values. Note: *** = Significant at 1%, ** = Significant at 5%, *= Significant at 10%

Table 4 Elasticities of lamb production during the years 2000M1-2013M12

Model	Expected price of lamb (EPPS)		Conditional variance (EPPSV)	
	Short-run	Long-Run	Short-run	Long-Run
EGARCH	0.2184	0.6817	-0.1385	-0.22974

Table 5 Within-sample predictive power of the EGARCH supply model for the conditional mean and variance of real Sheep prices

Equation	Intercept	Slope	R^2	F-statistics
Conditional mean				
	0.0072	0.9966***		0.3846
EGARCH (1 1)	(0.4756)	(0.0000)	0.9476	(0.6814)
Conditional Variance				
	-0.0118**	0.3394***		1251***
EGARCH (1 1)	(0.0108)	(0.0000)	0.0075	(0.0000)

Figures in parenthesis are p-values. Note: *** = Significant at 1%, ** = Significant at 5%, *= Significant at 10%. Source: Author's calculation

Table 6 Diagnostic test for Asymmetry

Variable	Coefficient	Standard. Error	t-Statistic	Probability
Individual Test				
SBT	-0.0107	0.0075	-1.4280	0.1553
NSBT2	0.0110	0.0542	0.2025	0.8398
PSBT2	-0.0045	0.0285	-0.1579	0.8747
Joint Test				
Constant	0.0148	0.0335	-0.4414	0.6595
SBT	-0.0147	0.0088	-1.6652	0.8979
NSBT2	-0.0356	0.0631	-0.5645	0.5732
PSBT2	0.0298	0.0341	0.8750	0.3829

Note: SBT = Sign bias test, NSBT = Negative sign bias test, PSBT = Positive sign bias test.

Figures 1

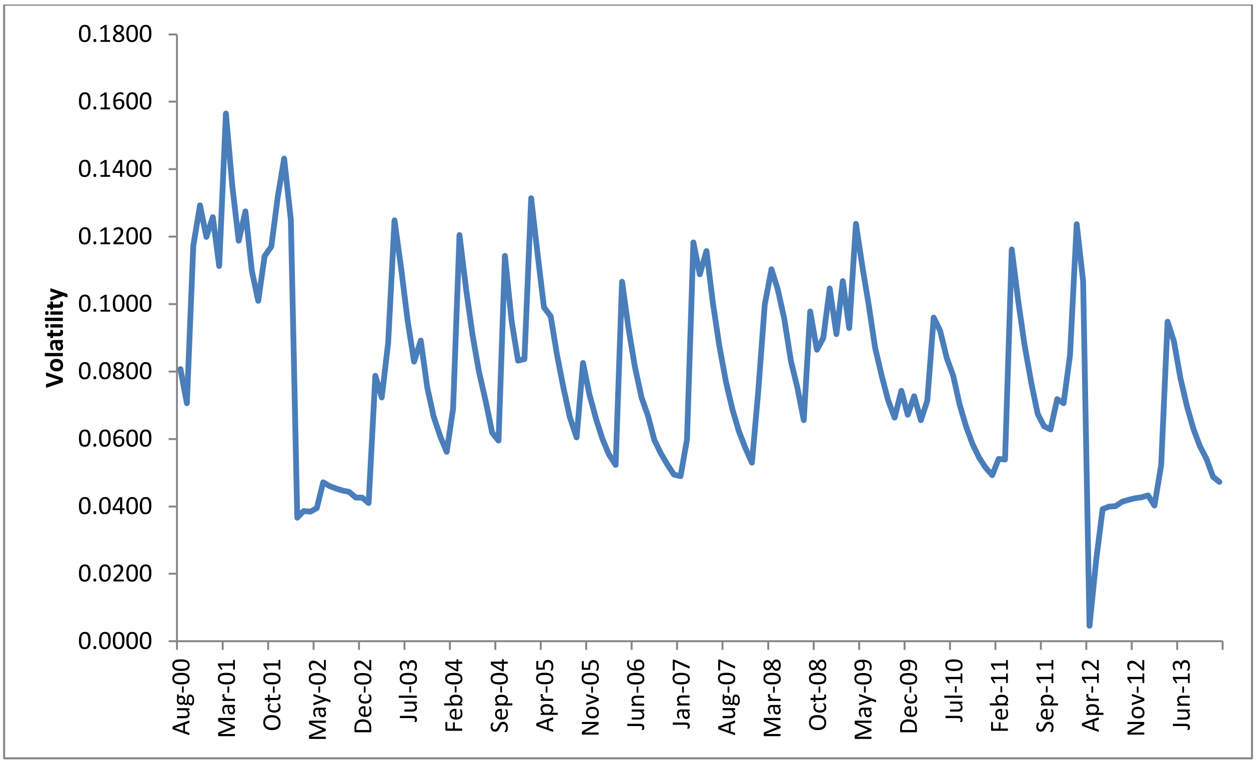

Figure 1 Conditional standard deviation of lamb price. Source: Author calculation

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Appendices Tables

Appendices Table A1 Descriptive statistic of the data

Statistics	PPS	EPPS	PPSV	QSSC	YMAZ
Mean	8.9025	2.0937	0.0855	58373.71	805077.80
Median	8.1700	2.1032	0.0863	59993	701635.00
Maximum	19.1900	2.9310	0.2312	123548	2064457.00
Minimum	3.1600	1.1848	0.0092	9773	196075.00
Std. Dev.	3.8540	0.4102	0.0204	26160.57	426712.60
Skewness	1.1693	-0.1938	1.7023	0.1747	1.1036
Kurtosis	4.1121	3.3677	19.4040	2.1833	3.6849
Jarque-Bera	46.6610	1.9863	1953.0920	5.2935	37.1636
Probability	0.0000	0.3704	0.0000	0.0719	0.0000
Observations	167	167	167	167	167

Note: PPS = Producer price of sheep; EPPS = Expected producer price of sheep; PPSV = Producer price of sheep volatility; QSSC = Quantity supplied of sheep Carcass weight and Ymaz = Yellow maize.

Appendices Table A2 Unit root test

	ADF		KPSS		Elliot-Rothenberg-Stock	
Variables	Test-Stat	Critical value	Test-Stat	Critical value	Test-Stat	Critical value
PPS	-2.7051	-4.0135	5.7103	0.739	-2.8048	-3.4996
QSSC	-1.3307	-4.0204	0.321	0.216	-1.0179	-3.5200
Ymaz	-1.7345	-4.0139	0.7805	0.739	-1.8709	-3.4996

Where PPS = Producer price of sheep; QSSC = Quantity supplied Sheep Carcass weight; Ymaz = Yellow maize.

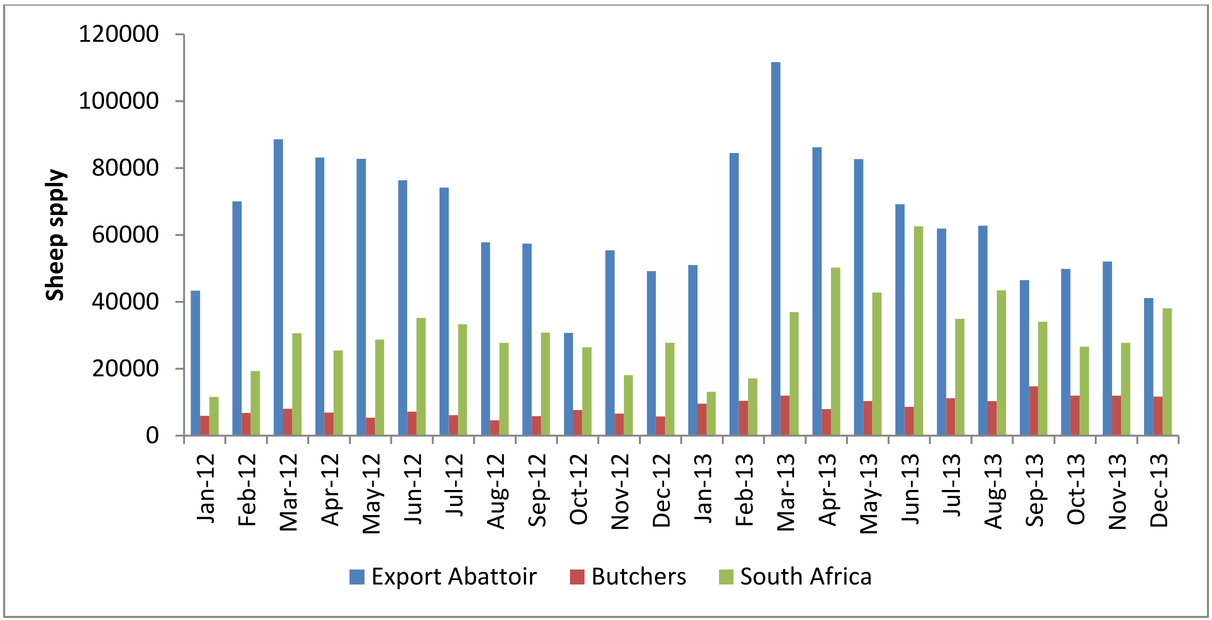
Appendices Table A3 Diagnostic Test for the EAGRCH (1, 1) Supply and Price model

	Price Model		Supply model	
	Serial Correlation Test		Serial Correlation Test	
Lag	Q-Stat	Probability	Q-Stat	Probability
Q1	0.993	0.319	0.014	0.906
Q5	4.106	0.534	2.351	0.799
Q10	14.409	0.155	11.596	0.313
Q15	20.354	0.159	17.411	0.295
Q20	25.568	0.181	26.536	0.149
Q25	25.938	0.411	27.059	0.353
Q30	26.171	0.666	34.385	0.266
Q35	29.764	0.719	39.387	0.280
	ARCH effect-Heteroskedasticity Test			
	$N.R^2$	Probability	$N.R^2$	Probability

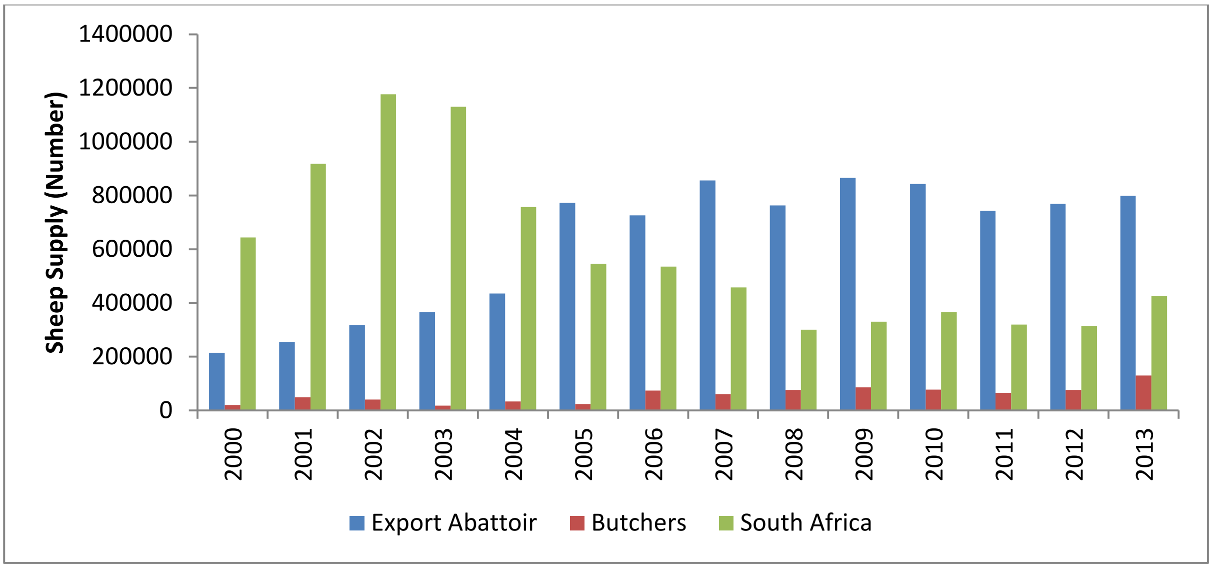
LM	0.153	0.695	0.074	0.517

Note The null hypothesis for the serial correlation test = No serial correlation in the residual. The Lagrange Multiplier LM test is a test of Hoemoskedasticity in the residual, The null hypothesis for the LM test = No Heteroskedasticity!

Appendices Figures



Appendices Figure A1. Monthly sheep supply for both local and export abattoir. South African export is live sales. Source: Meat Board Namibia (2014)



Appendices Figure A2. Annual sheep supply for both local and export abattoir. South African export is live sales. Source: Meat Board Namibia (2014).