Measuring the Price Volatility of Certain Field Crops in South Africa using the ARCH/GARCH Approach

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Abstract

The conditional volatility in the daily spot prices of the crops traded on the South African Futures Exchange (yellow maize, white maize, wheat, sunflower seed and soybeans) is determined. The volatility in the prices of white maize, yellow maize and sunflower seed have been found to vary over time, suggesting the use of the GARCH approach in these cases. Using the GARCH approach, the conditional standard deviation is the measure of volatility, and distinguishes between the predictable and unpredictable elements in the price process. This leaves only the stochastic component and is hence a more accurate measure of the actual risk associated with the price of the crop. The volatility in the prices of wheat and soybeans was found to be constant over time; hence the standard error of the ARIMA process was used as the measure of volatility in the prices of these two crops. When comparing the medians of the conditional standard deviations in the prices of white maize, yellow maize and sunflower seed to the constant volatilities of wheat and soybeans, the price of white maize was found to be the most volatile, followed by yellow maize, sunflower seed, soybeans, and wheat respectively. These results suggest that the more risk-averse farmers will more likely produce wheat, sunflower seed and to a lesser extent soybeans, while maize producers are expected to utilise forward pricing methods, especially put options, at a high level to manage the higher volatility.

Keywords: Price volatility; field crops; SAFEX; time series analysis, ARCH/GARCH

1. Introduction

Price variability is an important component of profit variability and therefore it is very important to quantify price variability of agricultural products. The differences between the variability in the prices among commodities are

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important for private investment decisions in farming and farm product marketing (Heifner & Kinoshita, 1994). Another reason for the importance of measuring price volatility – especially in South Africa, which is an economy in transition (and sometimes classified as developing) – is the fact that negative price shocks have a greater negative impact on the economic growth of developing economies (Dehn, 2000), and hence on one of the components of the Triple Bottom Line. The Triple Bottom Line considers not only the economic value that a firm creates, but also its impact on society and on the environment (O'Carroll, 2004), and it is designed to promote sustainable development (Anon, 2002, as cited by O'Carroll, 2004). It is thus clear that the volatility in the prices of these crops influences the Triple Bottom Line, and hence sustainable development in South Africa.

The accurate measurement of the stochastic component in the prices may contribute to the decision maker being able to make more informed decisions when choosing one crop over another. It may also contribute to policy decisions regarding the possible implementation of commodity price stabilisation programmes. However, when policy decisions are based on overestimated or inaccurately measured risk, the implementation of policies with the aim to reduce volatility may be at costs greater than the benefits associated with such policy changes. Hence, such policy changes may ultimately lead to results opposite from those initially proposed when it comes to economic growth. This emphasises the importance of an accurate measure of price volatility.

According to Moledina, Roe and Shane (2003) is it "reasonable to expect that producers can distinguish regular features in a price process such as seasonal fluctuations and the ex-ante knowledge of the conditional distribution of commodity prices. On the basis of this information, producers generate probabilistic assessments of predictable and unpredictable elements in a price process". Moledina *et al.* (2003) propose that the predictable and seasonal components of the price process should not be considered part of price volatility. Once the predictable components have been removed, only the stochastic or unpredictable component remains. According to Moledina *et al.* (2003) the stochastic or unpredictable component of the price process is the appropriate measure of volatility. Empirical evidence presented by Just and Pope (2002) furthermore questions the assumption that volatility is deterministic. Campbell *et al.* (1997), quoted in Just and Pope (2002), state that "…however, [it is] both logically inconsistent and statistically inefficient to use volatility measures that are based on the assumption of constant volatility over some period when the resulting series move through time". Thus it is important that the techniques used to quantify volatility account for both the predictable and unpredictable components of the price process and that they allow for changes in volatility over time.

A number of different methods have been used to measure volatility, including the standard deviation of prices, the coefficient of variation, and the Black-Scholes-Merton model. Other methods evaluated by Offutt and Blandford (1986) include the percentage range, the average percentage change, the moving average, and the Coppock index. The unconditional standard deviation and the coefficient of variation assume that past realisations of price and volatility have no influence on current or future realisations. Therefore the unconditional standard deviation does not distinguish between the known and unknown components of price series, leading to the overestimation of the degree of uncertainty. The Black-Scholes-Merton model assumes that the variance of the price is constant or that the price varies in a deterministic fashion. Thus, the Black-Scholes-Merton model is unable to account for periods of changing volatility. The methods used by Offutt and Blandford (1986) centralise around the fact that they do not take into account either the predictable and unpredictable components in the price process, or all the information available to quantify the volatility.

From the brief review of alternative methods to quantify price volatility it is clear that the above-mentioned methods are not suited to quantifying volatility accurately. One method that accounts for both the predictable and unpredictable components in the price process, and hence meets the requirements as stated by Moledina *et al*. (2003) and Just and Pope (2002), is the Autoregressive Conditional Heteroscedasticity (ARCH) or Generalised Autoregressive Conditional Heteroscedasticity (GARCH)[5] approach.

The ARCH/GARCH approach is used in recent studies by Jooste, Alemu, Botha and Van Schalkwyk (2003) to determine volatility in the price of beef in South Africa; by Moledina *et al*. (2003) to determine the volatility of commodity prices in international markets; and by Ghebrechristos (2004) to determine volatility in the South African exchange rate. The focus of the ARCH/GARCH models is the assumption of homoscedasticity – instead of considering heteroscedasticity as a problem to be solved, ARCH and GARCH models treat it as a variance to be modelled. This results not only in the correction of the deficiencies of least squares, but also the computation of a prediction for the

[5] When constructing econometric models it is assumed that the variance of the error term is constant (i.e. homoscedastic or time invariant). To test whether this assumption holds, the ARCH method can be used. If it is found that the homoscedasticity assumption is violated, the GARCH process instead of the Autoregressive Integrated Moving Average (ARIMA) model should be used to determine price volatility (e.g. risk and uncertainty). The choice of model is discussed later in the paper and henceforth the term ARCH/GARCH is used.

variance of each error term (Engle, 2001). The limitation of the ARCH method lies in the fact that a relatively long lag in the conditional variance is often called for, and to avoid problems with negative variance parameter estimates, a fixed lag structure is typically imposed (Bollerslev, 1986). This led Bollerslev (1986) to propose the GARCH approach to extend the ARCH class of models to allow for both a longer memory, and a more flexible lag structure.

The GARCH approach essentially generalises the purely autoregressive ARCH model to an autoregressive moving average model. The weights on past squared residuals are assumed to decline geometrically at a rate to be estimated from the data (Engle, 2004). Engle (2004) goes on to state that the GARCH forecast variance is a weighted average of three different variance forecasts: i.e. one is a constant variance that corresponds to the long-run average, the second is the forecast that was made in the previous period, and the third is the new information that was not available when the previous forecast was made. The weights on these three forecasts determine how rapidly the variance changes with new information and how rapidly it reverts to its long-run mean. It is for these reasons that the GARCH approach makes better use than other methods of the information on volatility contained in the time series.

The aim of this study is to measure and compare the conditional[6] volatilities in the prices of the crops (yellow maize, white maize, wheat, sunflower seed and soybeans) traded on the South African Futures Exchange (SAFEX) using the ARCH or GARCH approach, depending on which of the two approaches is relevant statistically.

2. Data and Methodology

2.1 Data

Daily SAFEX price data on crops included in the study was obtained from Grain SA (2006). Only price data from trading days are used, ending 28 February 2006. Yellow maize, white maize and wheat prices date back to 5 November 1997, while sunflower seed prices are from 7 January 2000 and soybean prices from 15 April 2002.

2.2 Methodology

[6] The conditional volatility (conditional standard deviation) is the one-step-ahead standard deviation (σ_t) for each observation in the sample. The observation at period *t* is the forecast *t* made using information available in *t*-1.

The basic framework that was followed to quantify the volatility in the prices of white maize, yellow maize, wheat, sunflower seed and soybeans is presented as a flowchart in Figure 1. Recall that price volatility in this study is considered to be only the stochastic or unpredictable component in the price of the crop under consideration.

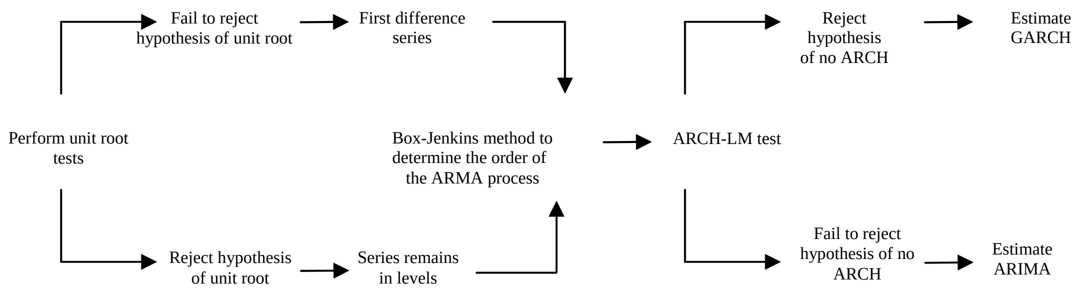

Figure 1 – Flowchart of methodology to compute conditional volatility
Source – Moledina *et al.* (2003)

Moledina *et al.* (2003) suggest that, before testing for stationarity of the time series using the unit root test, the predictable components (such as the effects of inflation[7], trend and seasonality) of the price process should not be considered part of price volatility. These components should be removed, leaving only the unpredictable or stochastic component for further analysis. The effect of inflation is removed by deflating the nominal prices with the consumer price index (CPI)[8], while the seasonal effect can be removed using seasonal dummy variables (Richardson, 2004; Moledina *et al.*, 2003).

The use of seasonal dummy variables tests for the presence of seasonality in the price of the specific crop. The production of an agricultural commodity is highly dependent on growing seasons. (In South Africa, for example, maize is planted in summer [November – January] and harvested during winter [May – July].) The dependence on growing seasons causes seasonal variations in supply and demand for the specific commodity, and since prices are mainly influenced by supply and demand, seasonal fluctuations in prices are also common. Seasonal fluctuation in maize prices may be characterised by lower prices at harvest (May – July in South Africa) compared to prices during other

[7] Most researchers deflate nominal price data in order to remove the effect of inflation from the price process. Moledina *et al.* (2003), however, quantified price volatility using both nominal and real prices and found very little difference between results. There is thus some evidence that it is not really necessary to deflate price data when quantifying price volatility. Since the aim is to remove all the known components from the price process to quantify the true stochastic component, the effect of inflation, although it seems to be relatively small, is removed by deflating the nominal prices.
[8] Since there is no daily CPI available, the best method to eliminate the effect of inflation from daily prices is to use the monthly CPI. Note, however, that the monthly CPI is the average over the whole month and it is thus applicable to each day during the specific month.

months. Eleven seasonal dummy variables were included for the twelve months in a year. The reason for including only eleven dummy variables when there are actually twelve months in a year (twelve categories) is to avoid falling into the dummy variable trap, which is a situation of perfect collinearity (Gujarati, 2003). The twelfth month is used as the base category to which the effects of the different months are compared. The month chosen as the base category does not influence the overall explanatory power of the estimated model, and therefore the month to be used as the base category is chosen arbitrarily.

Table 1 represents the base category and the dummy variables found to be significant to deseasonalise the prices of the crops traded on SAFEX. These regressions were performed using Simetar (Richardson, 2004), while all the other statistical tests were performed using EViews (Lilien *et al*., 1998).

Table 1 – Identification of the base category dummy variables and significant dummy variables to deseasonalise the prices of the crops traded on SAFEX

Crop	Month used as the base category to deseasonalise price data[1]	Months with significantly different prices from the base category
Yellow maize	December	March to October
White maize	January	February to November
Wheat	January	February
Sunflower seed	January	February to July, November and December
Soybeans	January	March to May

[1] Residuals of regressions of real prices of the crops on seasonal dummy variables, with the specified month used as the base category, are used as the dependent variables (deseasonalised prices) in further analyses.

Table 1 shows that December was used as the base dummy variable for yellow maize. The regression output indicates that the prices from March to October were significantly different from the prices in December. Recall that maize in South Africa is harvested during the winter months (May – July), which implies that the supply during that period is greater than in December, and therefore prices are expected to be lower. This seasonal behaviour is evident in the fact that prices from March to October differ significantly from those in December.

The identified models in Table 1 are used to calculate the deseasonalised price data for further analysis. Once the prices have been deseasonalised, the next step is to test for the presence of unit root, since most empirical work based on time series data assumes that the underlying time series is stationary (Gujarati, 2003).

– **Testing for the presence of unit root (non-stationarity)**

The Augmented Dickey Fuller (ADF) test was applied to test for the presence of unit root (Dickey & Fuller, 1981) and to determine the number of times the series needs to be differenced to make it stationary. Once the presence of unit root is confirmed the data needs to be differenced to make it stationary. The ADF test is then applied on the differenced data sets to test whether differencing the data made it stationary. This process is to be repeated until it yields a stationary series that can be used in further analyses. The number of times the series needs to be differenced indicates its order of integration and hence the value of d in the ARIMA(p,d,q) process.

The deseasonalised prices of all the crops in this study are trended[9], suggesting that ADF regressions, including intercepts and trends, are relevant to test for unit root in the prices of all the crops. The results of the ADF tests are presented in Table 2.

Table 2 – ADF test results to determine the number of times the series needs to be differenced to make it stationary

Crop	ADF statistic[1]		Critical value (95%)
	Levels[2]	First difference	
Yellow maize	-1.890538	-43.20602	-1.9395
White maize	-1.711698	-43.43721	-1.9395
Wheat	-1.892562	-43.62074	-1.9395
Sunflower seed	-1.385453	-32.30924	-3.4152
Soybeans	-1.675828	-30.57528	-1.9397

1 Absolute value of the ADF statistic needs to be higher than the absolute value of the critical value to reject the null hypothesis of unit root (non-stationarity).
2 Levels refer to the original series (before it was differenced).

From Table 2 it is evident that the original data series was non-stationary, but that it became stationary once it was first differenced. All of these series

[9] Recall, all prices were deflated in order to remove inflation from the price process. Trends in time series price data, however, may be caused by a number of factors of which inflation is only one. The presence of significant trends in the deflated and deseasonalised data thus implies that there is some other factor(s) causing the trends in the data, which have to be removed due to the assumption that time series data is stationary (Gujarati, 2003).

needed to be differenced once to generate a stationary series, which suggests that all the series are integrated of the order one. Hence, the value of d is 1 for all the crops. Next the Box-Jenkins methodology was used to determine the values of p and q in the ARIMA(p,d,q) process.

– **Application of Box-Jenkins methodology**

Once the level of integration of the different time series was confirmed and the time series were differenced accordingly, the Box-Jenkins methodology together with the Akaike (AIC) and Schwartz (SBC) information criteria were used to select the values of p and q in the ARIMA(p,d,q) process (Box & Jenkins, 1976). The ARIMA process is represented by the following equation (Box & Jenkins, 1976):

$$y_t = \alpha_0 + \sum_{p}^{p\max} \phi_p y_{(t-p)} + \sum_{q}^{q\max} \theta_q \varepsilon_{(t-q)} + \sum_{n}^{n\max} \eta_n D_t \quad (1)$$

Based on equation 1, forty-nine combinations of (AR 0-6) by (MA 0-6) were computed. Theoretically the point where the highest value of either AIC or SBC lies is seen to determine the values of p and q (Pesaran & Pesaran, 1997). In simple terms, an ARIMA(p,d,q) process indicates that the intercept needs to be lagged p times, the series is to be differenced d times to yield a stationary series, and the error term is to be lagged q times to generate the desired results. Note, however, that the highest AIC or SBC value is only a guideline, and the components in the GARCH model also need to be significant.

The values of p and q for the respective crops are presented in Table 3.

Table 3 – Values of p and q in the ARIMA(p,d,q) process determined using the Box-Jenkins methodology

	Values of p, d, and q in the ARIMA(p,d,q) process determined using the Box-Jenkins methodology together with the Akaike information criterion		
	p	d	q
Yellow maize	1	1	2
White maize	1	1	0
Wheat	3	1	2
Sunflower seed	1	1	0
Soybeans	0	1	1

Keep in mind that the values of d were already determined in the previous step, and were found to be 1 for all crops. The values of p, d and q in the ARIMA(p,d,q) process in the case of yellow maize indicated that ARIMA(1,1,2) is the best fit and can be interpreted as follows: the intercept needs to be lagged once, the series is to be differenced once to generate a stationary series, and the error term needs to be lagged twice to generate the desired results. The same method of interpretation can be used for all the crops. The next step is to test whether or not the volatility is time varying through the identification of significant ARCH effect.

– **Test for the presence of ARCH effect**

The rejection of the null hypothesis of no ARCH effect indicates the fact that the series varies over time and suggests that the GARCH approach should be used instead. The Box-Jenkins approach is based on the assumption that the residuals are homoskedastic, or remain constant over time. Since the standard error of equation 1 is used as a measure of volatility, the homoskedastic assumption has the implication that uncertainty or volatility remains constant over time. The robustness of this assumption was tested by fitting ARCH equations.

The presence of ARCH effect (whether or not volatility varies over time) has to be tested in the conditional variance of:

$$h^2 = Var(u_t / \Omega_{t-1}) \quad (2)$$

$$h^2 = \rho_o + \rho_1 u^2{}_{t-1} + \rho_2 u^2{}_{t-2} +,,, \rho_q u^2{}_{t-q} \quad (3)$$

where u_t^2 is the squared residual in period t, and ρ_o, ρ_1, ρ_2, ρ_q are the parameters to be estimated.

When fitting ARCH equations, Lagrange Multiplier (LM) and F-tests were used to test the null hypothesis of no ARCH effect. Probability values lower than 0.05 indicate that the null hypothesis is rejected at 5 percent level of significance, indicating that the volatility varies over time. The results for the ARCH-LM tests are presented in Table 4.

Table 4 – ARCH-LM test results

Crop	F-statistic	Probability
Yellow maize (ARCH1)	3.3345	0.0001*
White maize (ARCH2)	2.1133	0.0019*
Wheat	0.0009	0.9755
Sunflower seed (ARCH2)	3.7602	0.0000*
Soybeans	0.0278	0.8675

*Reject null hypothesis of no ARCH effect at 1 percent level of significance, indicating time-varying volatility

As can be seen in Table 4, the test for the presence of ARCH effect confirmed the presence of ARCH(1)[10] in the case of yellow maize, and ARCH(2) for both white maize and sunflower seed. The confirmation of the presence of ARCH effect in these cases indicates that the volatility in the prices of these crops is time varying, and hence it is suggested that the GARCH approach be used instead.

In the case of wheat and soybeans no ARCH effect was detected and hence there was no need to apply the GARCH approach. The measure of volatility in the prices of wheat and soybeans is hence the standard error of the ARIMA process, which is 0.01190 and 0.01657 respectively.

– **Applying the GARCH approach**

The rejection of the hypothesis of no ARCH effect leads to the application of the GARCH approach. The univariate GARCH(1,1) model is presented as:

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{(t-1)}^2 + \gamma_2 \sigma_{(t-1)}^2 \qquad (4)$$

where σ_t^2 is the variance of ε_t conditional upon information up to period *t*.

When using the GARCH approach the conditional standard deviation is the measure of volatility, and is given by the square root of each of the fitted values of σ_t^2 (equation 4). Unlike the volatility in the absence of ARCH effect (where it remains constant for the entire period and can hence be presented by a single value), the conditional standard deviation varies over time. The fact that it varies over time makes it impossible to present the conditional volatility as a single value over a period, hence it is presented graphically instead.

[10] The value of *p* in the ARCH(*p*) model represents the number of autoregressive terms in the model. In this case, *p* is equal to 1, which implies that only one autoregressive term is included in the specified model.

The discussion of the above methodology concludes this section. In the next section the results of the quantification of the stochastic components in the prices of yellow maize, white maize, wheat, sunflower seed and soybeans are presented.

3. Price Volatility in the Yellow Maize, White Maize, Wheat, Sunflower and Soybean Industries

3.1 Results from GARCH approach to quantify time-varying volatility

Recall that in the cases of wheat and soybeans no ARCH effect was detected and hence there was no need to apply the GARCH approach. The measure of volatility in the prices of wheat and soybeans is therefore the standard error of the ARIMA process, which is 0.01190 and 0.01657 respectively. The GARCH approach was significant for the other crops and hence the conditional standard deviations for yellow maize, white maize, and sunflower seed are presented in Figures 2 to 4 respectively. The presence of discrete spikes and the secular increase of such spikes are two conditions for the presence of price volatility. The scales of the graphs presented in Figures 2 to 4 are the same to allow for easy comparison of the different graphs.

The frequency of the spikes exceeding the two standard deviation boundaries in both Figure 2 and Figure 3 clearly increased substantially since the latter part of 2001. This is an indication that the volatility in the prices of both yellow and white maize increased since that period.

There is also some evidence of periodical up- and downswings in the conditional standard deviations, i.e. the conditional standard deviations increase substantially from around the fourth of May each year. Once the deviation reaches a maximum it drops substantially to a much lower level, with this lower level being more or less the same over the entire period under consideration. The trend of up- and downswings repeats itself up to around mid-2005. The large changes that follow even larger changes and the small changes that follow even smaller changes is a phenomenon that is referred to as leptokurtic behaviour.

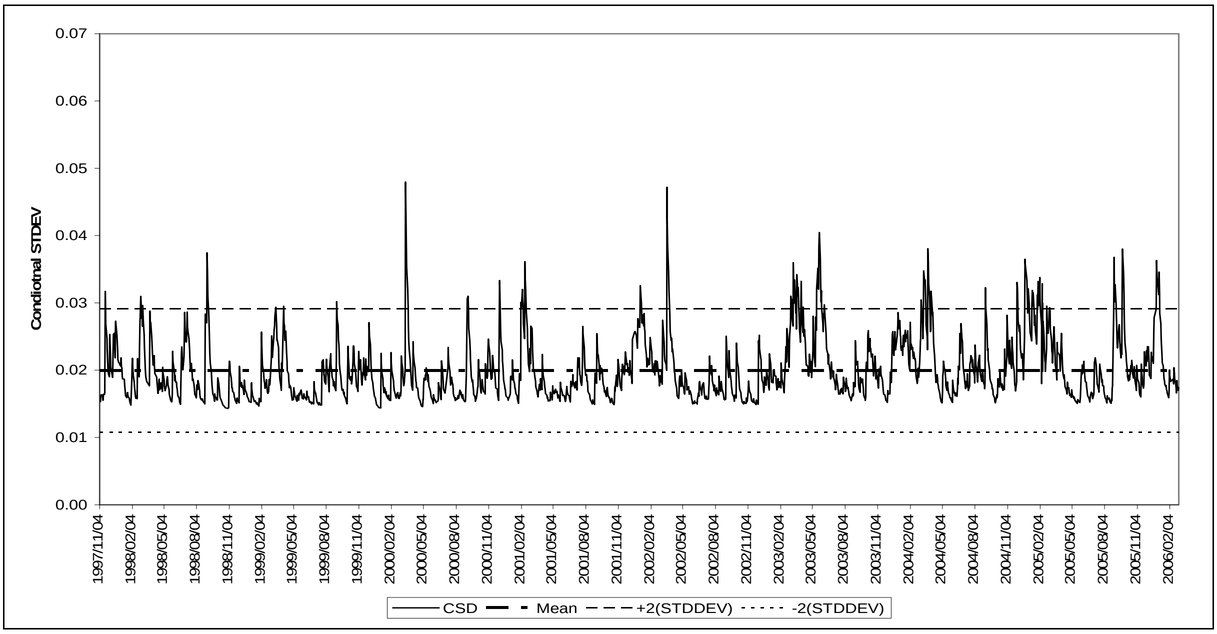

Figure 2 – Conditional standard deviation as a measure of volatility in the price of yellow maize

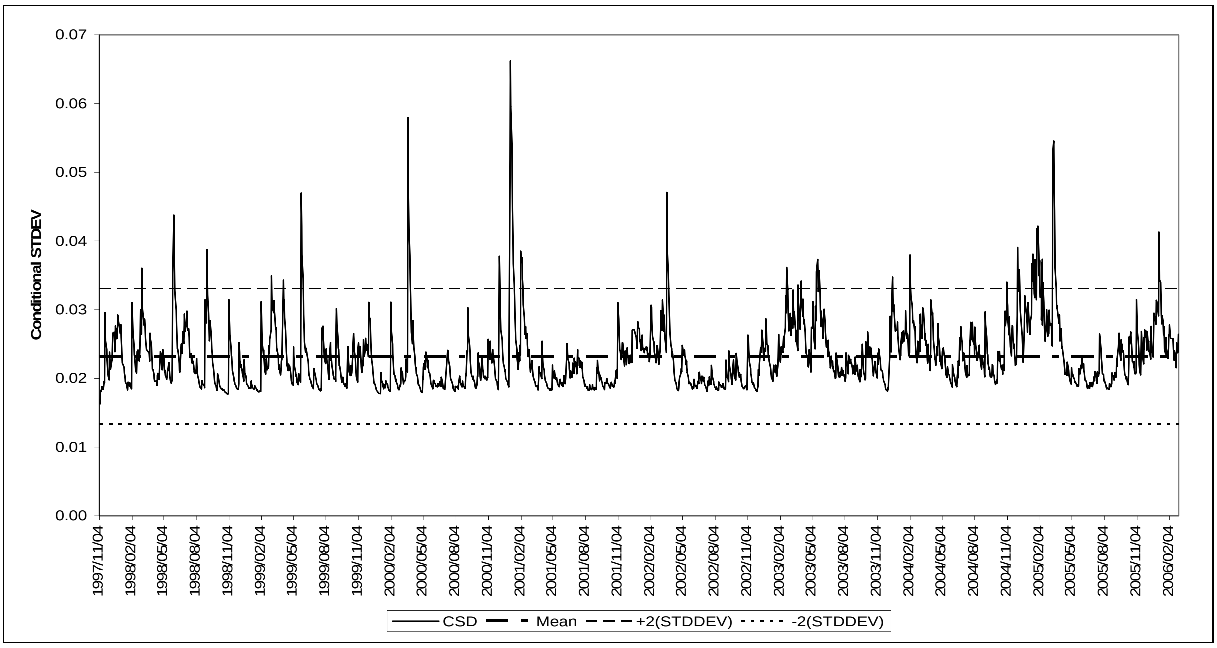

Figure 3 – Conditional standard deviation as a measure of volatility in the price of white maize

The frequency of the spikes exceeding the two standard deviation boundaries for sunflower seed in Figure 4 is relatively high – however, there is some indication that the frequency declines toward the later part of the series. The period between May 2003 and February 2005 is characterised by spikes that are much taller than spikes in other periods, indicating a period of higher volatility.

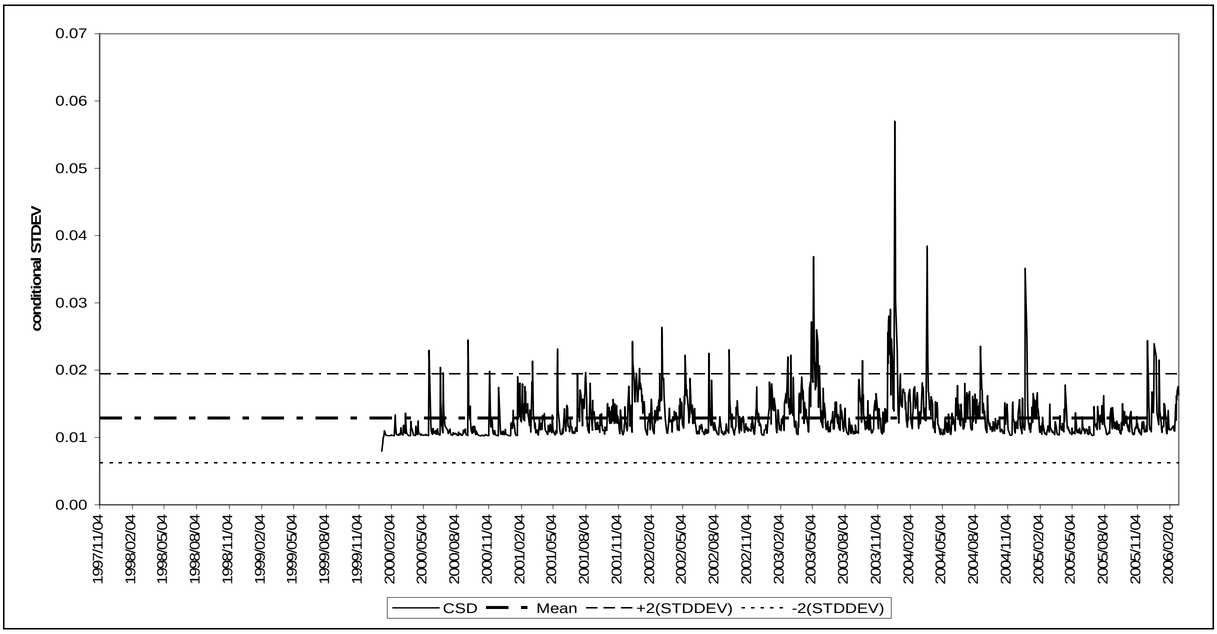

Figure 4 – Conditional standard deviation as a measure of volatility in the price of sunflower seed

3.2 Implications for decision-making

Highly leptokurtic behaviour was found in the conditional standard deviation graphs of white maize, yellow maize, and sunflower seed. There is some evidence that the volatility remains relatively constant for a few months immediately following harvest before increasing substantially as the following year's harvest approaches. The presence of leptokurtic behaviour has some implications for traders. It indicates the need for traders to use different marketing/hedging strategies during the different parts of the year in order to take account of the different levels of risk to which they are exposed.

The frequency with which the spikes of yellow maize exceed the two standard deviation boundaries indicates that the volatility associated with the price of yellow maize is more inconsistent compared to the volatilities associated with the prices of white maize and sunflower seed, especially in recent years. Keep in mind that the volatility in the prices of wheat and soybeans remains constant over time.

When comparing the medians of the conditional standard deviations of white maize (0.02197), yellow maize (0.01860), and sunflower seed (0.01183) over the whole time series ("long-run volatility") to the constant volatilities in the prices of wheat (0.01190) and soybeans (0.01657), the prices of white and yellow maize were found to be the most volatile, followed by soybeans, wheat and sunflower seed respectively. The medians of the conditional standard deviations of the crops with varying volatility for each of the years 1998 to

2005 ("short-run volatility"), and the constant volatilities of wheat and soybeans, are presented in Figure 5. The medians of the conditional standard deviations of yellow maize, white maize and sunflower seed vary substantially. These varying medians indicate that there is more risk associated with the prices of these three crops compared to the prices of wheat and soybeans with constant volatilities.

It is of interest that the "long-run volatility" measures indicate that the price risk associated with sunflower seed is the lowest of all the crops, while "short-run volatility" measures show varying volatility and hence higher risk associated with the price of sunflower seed with respect to the prices of wheat and soybeans. This is again proof that that a wrong decision could have been made if a risk-averse producer based his production decisions on the "long-run" measure of price risk, which assumes that the risk remains constant over time. For example, the decision to produce sunflower seed in this case, due to the seemingly lower risk associated with the price of sunflower seed, may have exposed the producer to more risk than necessary.

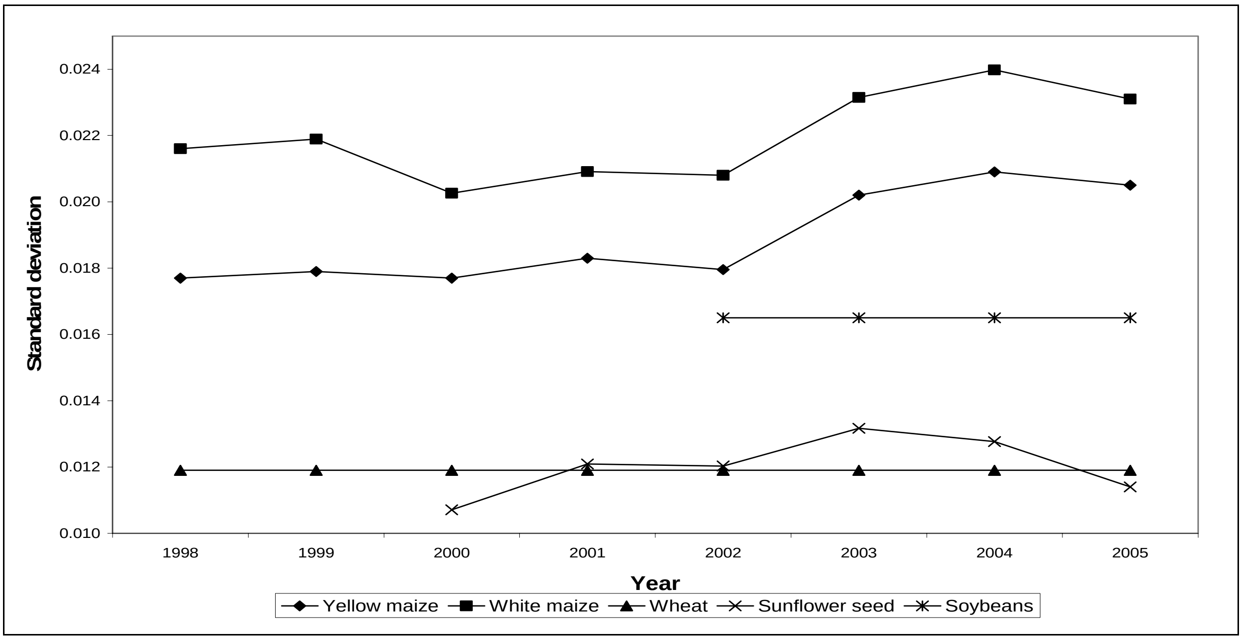

Figure 5 – Medians of conditional standard deviation over time in the prices of white maize, yellow maize, and sunflower seed; Standard error of ARIMA processes of the prices of wheat and soybeans

4. Conclusion

The aim of this study was to quantify the true stochastic components in the prices of white maize, yellow maize, wheat, sunflower seed and soybeans as accurately as possible by eliminating some of the known components (such as the trend and seasonal effect) in the price process, and to compare the risk associated with the prices of these crops in order to assist decision makers to make well-informed decisions regarding the choice of which of these crops to produce, given their personal risk attitudes.

The risk associated with the prices of white maize, yellow maize and sunflower seed was found to be higher than the risk associated with the prices of wheat and soybeans. A producer who is more risk averse is thus more likely to include wheat and soybeans in the crop mix due to a lower and more consistent level of volatility when compared to the other three crops. However, care should be taken not to be misled by using "long-run" measures of volatility that assume in essence that the volatility remains constant over time. When decisions are based on long-run measures of volatility, the short-run changes in volatility may lead to the producer being exposed to more risk than is necessary with regard to personal risk preference.

The significant changes in the medians of the conditional standard deviations of the prices of white and yellow maize, and the high frequency of spikes in the conditional standard deviations that exceed the two standard deviation boundaries, suggest that maize producers are exposed to a substantially larger amount of price risk compared to the producers of other crops. The higher exposure to risk indicates the existence of opportunities to lose some money, but also to make some money. The volatility is, however, difficult to predict, which suggests that maize producers should use price risk management tools such as forward pricing methods, or more specifically put options, to hedge against the risk that the price may fall. The put options will allow them to continue to benefit from positive price movements while guaranteeing them a floor price.

Grain traders need to take note of the leptokurtic behaviour in the volatility in the prices of especially white and yellow maize. The leptokurtic behaviour indicates that volatilities change as the harvest time approaches, and hence the need to adjust marketing/hedging strategies as the harvest time approaches. The leptokurtic behaviour also affects the cost of commodity stabilisation programmes (Moledina *et al*., 2003) and should be kept in mind whenever policymakers propose such programmes as a method to reduce the volatility in the prices of commodities.

Based on the results of this study, the level of volatility in the prices of only white maize, yellow maize and sunflower seed changed over time. Since the objective of the study was only to quantify and compare the volatility in the prices of the crops under consideration, further research on the factors influencing the level of volatility, and the factors influencing a change in the level of volatility, is a clear extension of this study. Factors that may influence the level, or the change in the level, of price volatility include, amongst others, supply and demand, weather conditions, changes in trading volumes, terms of trade shocks, and exchange rates. More knowledge on the factors causing an increase in price volatility may allow the possible implementation of policies to reduce the volatility. Ultimately such research may therefore have a positive influence on sustainable development in South Africa.

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