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The Bayesian MS-GARCH model and Value-at-Risk in South African agricultural commodity price markets

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Abstract:

The core objective of this paper is to examine the relationship between the prices of agricultural commodities with the oil price, gas price, coal price and exchange rate (USD/Rand). In addition, the paper tries to fit an appropriate model that best describes the log return price volatility and estimate Value-at-Risk (VaR). The data used in this study are the daily returns of agricultural commodity prices from 02 January 2007 to 31st October 2016. The paper applies the three-state Markov-switching (MS) regression, the standard single-regime GARCH, and the Markov-switching GARCH (MS-GARCH) models. To choose the best fit model, the log-likelihood function, Akaike information criterion (AIC), Bayesian information criterion (BIC) and deviance information criterion (DIC) are employed under different distributions for innovations. The results indicate that the price of agricultural commodities was found to be significantly associated with the price of coal, the price of natural gas, price of oil and exchange rate. Moreover, for most of the agricultural commodities considered in this paper, the MS-GARCH models under the MCMC approach outperformed the standard single regime GARCH models in measuring VaR. In conclusion, this paper provided a practical guide for modelling agricultural commodity prices by MS regression and MS-GARCH processes.

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Keywords. Commodity prices, MS-GARCH model, price volatility, South Africa, Value at risk

1 Introduction

Commodity prices are categorized by periods of sharp fluctuations in prices, and the level of volatility itself changes over time (Pindyck, 2001). In financial time series, modelling volatility is an important component in risk management, portfolio management and pricing equity. High volatilities can increase the risk of assets (Luo, 2015). Interest rises on modelling and analysing the dynamic behaviour of financial quantities observed through time after the ground breaking papers by Engle (1982) and Bollerslev (1986). However, there are changes on fi-

nancial and macroeconomic quantities in their behaviour over a sample periods. Financial crises can cause dramatic fluctuations in the behaviour of many economic time series (Hamilton, 2005). They can also abruptly change the government policy. Markov Switching models have been presented to consist of sudden parameter changes in models. The idea is to add a hidden state variable which shows changing the parameter when the process is in a different state. Caporale et al. (2003) showed that high persistence in GARCH models can be the consequence of a structural break. He showed that one can often decompose an IGARCH process to a MS-GARCH.

Since the seminal application of Hamilton (1989) to US real Gross National Product growth, regime switching models have been widely used in applied research. The model has been applied in various areas in economics and finance such as analysis of business cycles (Hamilton, 1989), low and high volatility regimes in returns (Hamilton and Susmel, 1994), oil and the macroeconomic analysis (Raymond and Rich, 1997), asset and stock market returns modeling (Engel, 1994) and so on.

The main contribution of the present work is to develop an appropriate MS-GARCH model to each of the seven agricultural commodity price return series in South Africa. In particular, the analysis is done through three steps. First, I apply the MS regression model to examine the relationship between the prices of agricultural commodities with oil price, gas price, coal price and exchange rate (USD/Rand). Second, I test the Autoregressive moving average (ARMA), or univariate GARCH models are able to capture all dependencies in return series. Third, MS-GARCH models are fitted in order to account for potential volatility breaks.

In line with the established literature on commodity price volatilities, the results in this work provide supportive evidence for the theory of commodity price volatility. More in detail, employing the Bayesian estimation of the MS-GARCH model by using the Maximum Likelihood (ML) estimator as the starting values to account for potential volatility breaks. This is because MS-GARCH models allow time-varying skewness contrary to the standard univariate GARCH-type models. Moreover, I show that the price of agricultural commodities was found to be significantly associated with the price of coal, price of natural

gas, price of oil and exchange rate.

The remainder of the paper is organized as follows. In Section 2 we discuss the data sources. In Section 3 we briefly discuss the main set-up of the MS regression model and MS-GARCH model. In Section 4 we present the results and Section 5 presents concluding remarks.

2 Literature Review

The price of agricultural commodities in general and food prices in particular has been increasing in recent times (Tadesse et al., 2014). For commodity dependent countries and producers commodity price volatility is their big problem. Nearly one third of the global population is dependent on primary commodities such as copper, cotton and rice. Commodity exports are at least half of their foreign exchange earnings for 95 of the 141 developing countries at the national level (Brown et al., 2008).

Factors such as natural disasters, unfavourable weather conditions, exchange rate volatility and shifts in global demand and supply are the major causes of agricultural commodity price uncertainties. Almost a 30-year high food price volatility is observed in December 2010 (Bellemare et al., 2013). Agricultural commodity price volatility has been exceptionally high during the last decade (FAO and UNCTAD, 2011).

The export and import side of numerous least developed countries, particularly in Sub-Saharan Africa face commodity dependence. This leads to a high degree of primary commodities export. Commodity prices dynamics have changed considerably even though trade patterns with regard to main commodities continued fairly unchanging over the last decades. However, commodities particularly agricultural based have experienced extraordinary price boom since the early-2000s with price hikes in mid 2008 and 2011 (von Arnim et al., 2015).

There has been a substantial uncertainty in global agricultural markets since 2006. The world agricultural commodity prices rose by an average of 70 percent in nominal dollar terms in between September 2006 and February 2008. The highest price increases were witnessed in wheat, maize, rice, and dairy products. Prices fell rapidly in the second half of 2008, but sharp price increases were observed again in 2010 and the level reached at the peak of the price spike of 2008 in 2011. The prices dropped again in 2011 and 2012 and then increased again significantly in early 2013 (Sarris, 2014).

There has been many shocks across the range of commodities in the last 30 years. The financial arrangement and environmental management for commodity dependent countries are highly affected by the commodity price uncertainty. These price uncertainty is also widening existing inequalities. It is known that low commodity prices will cause in lesser income for producers and smaller number of jobs for workers. However, volatile prices also have a undesirable outcome on livelihoods (Brown et al., 2008).

According to the World Bank, IMF and UNCTAD commodity prices have a vital role on economic development and on the occurrence of poverty in low income countries (LICs). LICs, in particular SSA countries are strictly dependent on the export of a single or limited commodities. For most of the SSA countries at least half of incomes are coming from the export of just a limited commodities. Thus, commodity price uncertainty can have a huge influence on the well-being of a country's population (Addison et al. 2016).

Price volatilities can cause negative impact on the economy of poor countries (Rodrik, 1999). Volatile prices touch both producers and consumers. Production and investment risks rise for producers, predominantly when the production cycle is extended. Volatile prices is also affecting the consumption decision of consumers when they have a limited income (Wang, 2014). Moreover, economic crisis can be caused by higher and unpredictable volatility (Acemoglu et al., 2003).

The agricultural production uncertainty, especially in a developing countries, affects investment decisions, decreasing technology acceptance and obstructing the acceptance of upgraded farming systems. The high relationship between production, price, and market risks identifies the requirement of a unified and complete approach to risk management and building resilience of African producers (Antonaci et al., 2014).

For African commodity-exporting countries, the consequence is that it is doubtful that there will be much weakening in economic performance. In addition, commodity-producing Sub-Saharan Africa countries that depend on on internal funds to finance investment expenditure will be outperformed by countries that depend on on external financing (Barrow et al., 2017).

Extremely high levels of price volatility has been the sole characterization of commodity markets (Luo, 2015). As shown in Figure 1, the prices of the seven agricultural commodities has been fluctuating in the last 10 years. In the mid 2008, 2011, 2013, 2014 and 2016 the prices of agricultural commodities were at the peak.

Blattman et al. (2007) considered a panel of 35 commodity dependent countries to investigate the impact of trade volatility originating from excessive commodity price fluctuations. Blattman et al. (2007) argued that commodity prices are volatile and natural resource prices in particular have been the deterrent factor to growth. They also discussed that countries experiencing high volatility in their commodity prices tend to grow slowly when compared to countries experiencing low volatility in their commodity prices.

The South African economies are expected to be quit in 2017 when compared to the uncertainty and volatility that will be brought by commodity prices, global geopolitics, domestic politics, and US monetary and trade policy. Growth domestic product (GDP) could recover to 1.4% in 2017 if commodity prices remain near current

values (Barrow et al., 2017).

3 Data and Methodology

3.1 Data description

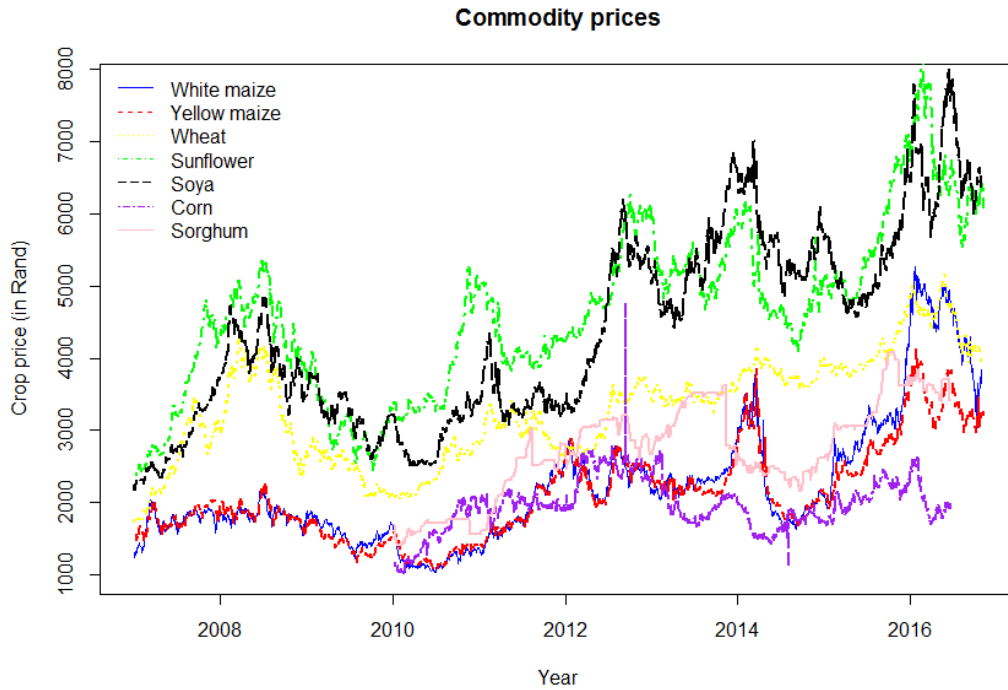
The samples analysed in this paper are the daily returns of South African agricultural commodity prices from

02 January 2007 to 31st October 2016 for yellow maize, white maize, wheat, sunflower and soya, and from 19 May 2010 to 31st October 2016 for corn and sorghum. The data sets consists of the daily returns of agricultural commodity prices. All these data are obtained from the data stream of Johannesburg Stock Exchange (JSE). Figure 1 plot the price of agricultural commodities against time.

Table 1: Variables used in the study

Variable	Explanation
Com_Price	Logarithmic value of prices white maize, yellow maize, wheat, sunflower, soya, corn and sorghum
Oil_Price	Logarithmic value of oil price
Gas_Price	Logarithmic value of gas price
Coal_Price	Logarithmic value of coal price
Exchange_Rate	Logarithmic value of USD/Rand Exchange Rate

Figure 1: South African agricultural commodity prices



In this section we discuss the three different class of models. The first class of models are the constant volatility Markov-switching regression models. The second class of models are the univariate GARCH models such as the linear GARCH and the non-linear GJR models. The last model is the MS-GARCH type models.

3.2 Markov-switching regression models

Consider the classical linear regression model given by

$$y_t = x_t' \beta + \epsilon_t, \quad \epsilon_t \sim \text{i.i.d.} N(0, \sigma^2), \quad t = 1, 2, \dots, T, \quad (3.2.1)$$

where classical assumptions assume that ϵ_t is i.i.d. (independently and identically distributed). In addition, the parameters are assumed to be constant through time. However, this assumption would not be true if some sort

of structural break occurred in the series. In order to overcome this problem, Hamilton (1989) introduced the m-state Markov-switching model which is given as follows

$$y_t = \mathbf{x}_t' \beta_{s_t} + \sigma_{s_t} \epsilon_t, \quad \epsilon_t \sim \text{i.i.d.} N(0, 1) \quad (3.2.2)$$

where β_{s_t} a $k \times 1$ state dependant coefficients, σ_{s_t} is a vector of error standard deviations, \mathbf{x}_t a vector of exogenous regressors and state variable s_t is a random variable that governs all parameters with transition probability, $p(s_t = j | s_{t-1} = i) = p_{ij}$.

3.3 The single-regime GARCH models

Let r_t be the log difference of agricultural commodity price p_t :

$$r_t = \log(p_t) - \log(p_{t-1}) \quad (3.3.1)$$

where p_t is the commodity price at date t .

The simplest univariate GARCH(1,1) model for the agricultural commodity price returns can be specified as follows (see Bollerslev, 1986):

$$\begin{aligned} y_t &= \sigma_t \epsilon_t, & \epsilon_t &\sim N(0, 1), \\ \sigma_t^2 &= \alpha_0 + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2, \end{aligned} \quad (3.3.2)$$

where $\alpha_0 > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ ensures covariance stationarity. The sum $\alpha + \beta$ measures the persistence of a shock to the conditional variance in equation.

3.3.1 The GJR models

Glosten et al. (1993) introduced the nonlinear GJR model in order to model the asymmetric effects of positive and negative shocks to volatility. The GJR(1,1) model can be written as

$$\sigma_t^2 = \alpha_0 + \alpha y_{t-1}^2 + \gamma y_{t-1}^2 I(y_{t-1} < 0) + \beta \sigma_{t-1}^2, \quad (3.3.3)$$

where the γ parameter captures asymmetry and $I(y_{t-1} < 0)$ is an indicator function, which takes the value 1 when $y_{t-1} < 0$ and 0 otherwise.

3.4 The Markov-Switching GARCH model

This model allow to switch between different regimes contrary to the standard GARCH models. In this type of models the asymmetry is time varying. Francq et al. (2001) consider the following switching GARCH(m, n) model, where all coefficients are switching,

$$y_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim N(0, 1), \quad (3.4.1)$$

$$\sigma_t^2 = \gamma_{s_t} + \alpha_{s_t,1} y_{t-1}^2 + \dots + \alpha_{s_t,m} y_{t-m}^2 + \delta_{s_t,1} \sigma_{t-1}^2 + \dots + \delta_{s_t,n} \sigma_{t-n}^2.$$

For the switching GARCH(1, 1) model, the necessary and sufficient conditions ensuring the existence of a strictly stationary solution is:

$$\sum_{k=1}^K \eta_k E(\log(\alpha_k, 1\epsilon_t^2 + \delta_{k,1})) < 0, \quad (3.4.2)$$

which reduces for $k = 1$ to the result given by Nelson (1991) for the standard GARCH(1,1) model. In this paper, I use the terms state and regime interchangeably.

3.5 Estimation

In this paper both ML or MCMC techniques (Bayesian estimation) are employed to estimate the model parameters. Both approaches require the evaluation of the likelihood function. We need to maximize the log likelihood function in order to estimate the model parameters. Let $\mathbf{y} = (y_1, \dots, y_T)'$ be the vector of the log-returns and $\Psi = (\epsilon_1, \theta_1, \dots, \epsilon_k, \theta_k, P)$ be the vector of model parameters. The likelihood function is given as follows

$$\mathcal{L}(\Psi | \mathbf{y}) = \prod_{i=1}^T \log[f(y_t | \Psi, I_{t-1})] \quad (3.5.1)$$

where $f(y_t | \Psi, I_{t-1})$ is the conditional density of y_t given regime i occurs at time t and I_{t-1} denote the information set up to time $t - 1$. Maximizing equation (3.5.1) reveals the ML estimator of $\hat{\Psi}$. The likelihood function is combined with the prior distribution $f(\Psi)$ to build the kernel of the posterior distribution $f(\Psi | \mathbf{y})$ in order to obtain the MCMC estimation (Bayesian estimation).

Note that: in this paper I mainly used the MS-GARCH package developed by Ardia et al. (2016).

3.6 Model selection criteria

Akaike (1974) proposed the most commonly used AIC in order to evaluate models given as follows

$$\text{AIC} = 2k - 2\log \mathcal{L} \quad (3.6.1)$$

where m is the number of parameters in the model and \mathcal{L} is the value of the likelihood function. Similarly, BIC has a similar form

$$\text{BIC} = k\log(T) - 2\log \mathcal{L}, \quad (3.6.2)$$

where T is the sample size. DIC is defined as (see Berg et al., 2004)

$$\text{DIC} = \bar{D} + p_D, \quad (3.6.3)$$

where the measure of the goodness of fit (i.e., deviance) is given by $\bar{D} = E_{\Theta | \mathbf{y}} [D(\Theta)] = E_{\Theta | \mathbf{y}} [-2\ln f(\mathbf{y} | \Theta)]$ and the term which penalizes the complex models is given as $p_D = \bar{D} - D(\Theta)$, Θ is the posterior mean of parameters. Note that: low AIC, BIC and DIC values indicate a better model fit.

3.7 Backtesting Value-at-Risk

“VaR is only as good as its backtest. When someone shows me a VaR number, I don’t ask how it is computed, I ask to see the backtest.” (Brown, 2008, p.20). Value-at-Risk, or VaR at the $(1 - \alpha)$ confidence level ($\text{VaR}_{(1-\alpha)}$) of a portfolio is defined as the minimum amount that is expected to lose in financial markets with a given probability α over a given time horizon k (usually 1-day or 10 days). It is frequently used statistic for determining potential risk of economic losses in financial markets. Let p_t be the price of an agricultural commodity on day t . A k -day VaR on day t is defined by

$$P(P_{t-k} - P_t \leq \text{VaR}(t, k, \alpha)) = 1 - \alpha. \quad (3.7.1)$$

Kupiec (1995) and Christoffersen (1998, 2003) proposed statistical techniques for evaluating VaR.

3.7.1 Unconditional coverage

Let $N = \sum_{t=1}^{\tilde{T}} \tilde{I}_t$ be the number of days over a \tilde{T} period that the portfolio loss was larger than the VaR estimate where the binary loss function (BLF) can be written as:

$$\tilde{I}_{t+1} = \begin{cases} 1 & \text{if } r_{t+1} < \text{VaR}_{t+1|t}^{(1-p)} \\ 0, & \text{if } r_{t+1} \geq \text{VaR}_{t+1|t}^{(1-p)} \end{cases}$$

The number of violations follows a binomial distribution, i.e. $N \sim \text{Bin}(\tilde{T}, p)$. If the VaR model is appropriately specified, then the failure rate of the model equals to the expected ones. This can be stated by the following hypotheses:

$$\begin{aligned} H_0 &: N/\tilde{T} = p \\ H_1 &: N/\tilde{T} \neq p \end{aligned}$$

where p is the failure rate suggested by the confidence interval. To this end, the appropriate likelihood ratio (LR) test statistic for unconditional coverage equals to:

$$\text{LR}_{\text{uc}} = -2 \ln \left[\frac{(1-p)^{\tilde{T}-N} p^N}{(1-\frac{N}{\tilde{T}})^{\tilde{T}-N} (\frac{N}{\tilde{T}})^N} \right] \sim \chi^2(1). \quad (3.7.2)$$

The power of this test is generally poor even though it can reject a model for both high and low failures (Kupiec, 1995).

3.7.2 Conditional coverage

Christoffersen (1998) proposed the conditional coverage (CC) test, designed to test that the entire number of failures equal to the expected one and the VaR violations are independent. The hypotheses can be stated as follows:

$$\begin{aligned} H_0 &: N/\tilde{T} = p \text{ and } \pi_{01} = \pi_{11} = p \\ H_1 &: N/\tilde{T} \neq p \text{ and } \pi_{01} \neq \pi_{11} \neq p. \end{aligned}$$

The appropriate likelihood ratio (LR) is:

$$\text{LR}_{\text{cc}} = -2 \ln \left(\frac{(1-p)^{\tilde{T}-N} p^N}{(1-\pi_{01})^{n_{00}} \pi_{01}^{n_{01}} (1-\pi_{11})^{n_{10}} \pi_{11}^{n_{11}}} \right) \sim \chi^2_2, \quad (3.7.3)$$

where n_{ij} is the number of observations with value i followed by j , for $i, j=0,1$ and

$$\pi_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \quad (3.7.4)$$

are the corresponding probabilities.

3.7.3 Loss functions

The quadratic loss function (QLF) can be written as:

$$\text{QL}_{t+1} = \begin{cases} 1 + (r_{t+1} - \text{VaR}_{t+1|t}^{(1-p)})^2, & \text{if } r_{t+1} < \text{VaR}_{t+1|t}^{(1-p)} \\ 0, & \text{if } r_{t+1} \geq \text{VaR}_{t+1|t}^{(1-p)} \end{cases}$$

This loss function is developed by Lopez (1999) to accommodate the specific concerns of risk managers to measure the accuracy of the VaR forecasts on the basis of the distance between the observed returns and the forecasted VaR values if a violation occurs.

The modified quadratic loss function (MQLF) can be written as:

$$\text{MQL}_{t+1} = \begin{cases} (r_{t+1} - \text{ES}_{t+1|t}^{(1-p)})^2, & \text{if } r_{t+1} < \text{VaR}_{t+1|t}^{(1-p)} \\ 0, & \text{if } r_{t+1} \geq \text{VaR}_{t+1|t}^{(1-p)} \end{cases}$$

The MQLF is proposed by Angelidis and Degiannakis (2006) to overcome the Lopez’s (1999) loss function shortcoming. This method is proposed to determine the difference of the loss with the ES. In this case ES is used instead of VaR as VaR does not provide any idea about the extent of the expected loss.

4 Empirical results

This paper illustrates the different single regime GARCH and MS-GARCH models with normal, Student’s-t, GED and their skewed form innovations.

4.0.4 Descriptive summary of agricultural commodity returns

I estimate the different agricultural commodity price returns using the standard single regime GARCH and MS-GARCH models. This paper compares the agricultural commodity return volatilities of seven agricultural commodities such as white maize, yellow maize, wheat, sunflower, soya, corn and sorghum. The data shows negatively skewed for all commodities except corn. The excess kurtosis statistic which is equal to 13.52, 22.79, 7.196, 15.02, 7.33, 174.39 and 122.41 for white maize, yellow maize, wheat, sunflower, soya, corn and sorghum commodities,

respectively indicate the Leptokurtic characteristics of the return distribution. The Jarque-Bera (JB) test statistic can be calculated as follows: $JB = \frac{n}{6} (S^2 + \frac{1}{4}(K-3)^2)$, where n represents the number of observations, K represents kurtosis and S represents skewness (Jarque & Bera, 1980). The JB statistic with skewness and excess kurtosis are clearly observed for all the daily returns series which

indicate violations of normality assumptions. This implies that we should consider asymmetric distribution for them. Thus, student-t and GED may not be good assumptions. As a result, we fit different GARCH(1,1) models for the marginal using the skewed student-t and skewed GED distributions for innovations.

4.1 Estimation results of Markov-switching models with constant volatility

Estimate the MS and non switching regression model parameters and evaluate the corresponding likelihoods, denoted $\mathcal{L}(\hat{\theta}_{MS})$ and $\mathcal{L}(\hat{\theta}_{Non-switching})$, respectively. The presence of regime switching in the data can be further tested using the standard likelihood ratio (LR) statistic which is given by $\lambda_{LR} =$

$2 \left[\mathcal{L}(\hat{\theta}_{MS}) - \mathcal{L}(\hat{\theta}_{Non-switching}) \right]$, where $\hat{\theta}_{MS}$ is the MLE of parameters in the MS model and $\mathcal{L}(\hat{\theta}_{Non-switching})$ are the MLE for Θ for non-switching model, respectively. Under the null hypothesis, λ_{LR} has an asymptotic χ_k^2 distribution with k degrees of freedom, where k is the number of parameters identified under the null hypothesis. As shown in Table 3, linearity of the λ_{LR} are rejected. Thus, there is a solid confirmation of existence of regime switching, which makes the use of regime switching regression models justified.

$$P_{i,t} = \begin{cases} \beta_0^{(1)} + \beta_{Coal,t}^{(1)} + \beta_{Oil,t}^{(1)} + \beta_{Gas,t}^{(1)} + \beta_{USD/Rand,t}^{(1)} & S_t = 1 \\ \beta_0^{(2)} + \beta_{Coal,t}^{(2)} + \beta_{Oil,t}^{(2)} + \beta_{Gas,t}^{(2)} + \beta_{USD/Rand,t}^{(2)} & S_t = 2 \\ \beta_0^{(3)} + \beta_{Coal,t}^{(3)} + \beta_{Oil,t}^{(3)} + \beta_{Gas,t}^{(3)} + \beta_{USD/Rand,t}^{(3)} & S_t = 3 \end{cases} \quad (4.1.1)$$

The effect of price of coal, price of natural gas, price of oil and exchange rate uncertainty on the price of agricultural commodities are assessed using the two-state and three-state MS regression model. The two-state and three-state MS regression models can be estimated by maximum likelihood estimation (MLE) method. Table 4 shows the estimated parameters with their standard errors reported in parentheses. Almost all the parameters in the table are significant. This result confirms that coal price, natural

gas price, oil price and exchange rate uncertainties do indeed play a vital role in agricultural commodity prices in South Africa. The transition probabilities from regime 1 to regime 1, from regime 2 to regime 2, and from regime 3 to regime 3 are greater than 96% for all commodity prices. This indicates that it is hard to change from regime 1 to regime 2, from regime 2 to regime 3 and from regime 1 to regime 3.

4.2 Bayesian estimation results of GARCH-type volatility models

The hypothesis for the ARCH LM-test is given as follows

Null hypothesis: no ARCH effects

Alternative hypothesis: ARCH effects

As shown in Table 5 the results of the ARCH-LM test are significant and it makes sense to employ an ARCH/GARCH model.

4.2.1 The single regime standard GARCH model estimation results

As we discuss earlier, with skewness and excess kurtosis, all series present clear signs of nonnormality. The

AIC, BIC and DIC values are minimized when we consider an asymmetric conditional density functions such as skewed-t and skewed-GED for innovations. Table 6 shows the selection criteria under the three distributions, namely normal, student-t and GED in the two regime GARCH model. To choose the best fit model, the AIC, BIC and DIC are employed under three distributions.

- GJR(1,1) model performs better for white maize and sorghum under skewed-t innovations
- GARCH(1,1) model performs better for yellow maize, wheat and sunflower under skewed-GED innovations
- GARCH(1,1) model performs better for soya under normal innovations and
- EGARCH(1,1) model performs better for corn under std.

Table 2: Statistical properties of commodity returns, 2007 - 2016 of returns series

Commodities	White maize	Yellow maize	Wheat	Sunflower	Soya	Corn	Sorghum
Mean	2.919e-17	-4.681e-17	2.563e-18	-2.678e-18	1.217e-17	8.761e-18	4.105e-19
Variance	3.995	3.820	1.496	1.728	1.934	12.138	1.791
Skewness	-0.883	-1.356	-0.563	-1.013	-0.365	0.1514	-7.015
Kurtosis	13.52	22.79	7.196	15.02	7.33	174.39	122.41
JB	11658***	40880***	1932.5***	15223***	1976***	1975500***	972110***
Chi-squared	137.7	89.778	93.885	145.82	158.92	673.25	45.63
p-value	2.2e-16	5.451e-14	8.66e-15	2.2e-16	2.2e-16	2.2e-16	4.32e-5

Note: *** denotes the significance at the 1% level.

Table 3: Specification testing for MS models

Variables	White	Yellow	Wheat	Sunflower	Soya	Corn	Sorghum
λ_{LR}	21516**	21027**	22146**	23498**	22789**	1677**	20658**

Note: ** denote the significance at the 1% levels.

The estimated coefficients of the GARCH effects are highly significant for all of the commodities except corn and sorghum. Further in this paper, to examine whether there is high degree of volatility persistence, I compute the quantity $\alpha_1 + \beta_1$ for the seven agricultural commodities. The quantity $\alpha_1 + \beta_1$ are greater than 0.91 for all agricultural commodities except corn, indicating that the existence of

regimes in the conditional volatility dynamics. For example, this measure for wheat equals 0.9907, which implies an expected duration of $1/(1 - 0.9907) = 107.5$ working days for volatility shocks. To explore the feature of volatility in the South African agricultural commodity markets, we estimate the MS-GARCH model and compare its performance with the standard single regime GARCH model.

4.2.2 The regime switching GARCH model estimation results

Table 6 presents the Bayesian estimation results of the two regime MS-GARCH models for the seven agricultural commodities. Most of the regression coefficients in the two-regime MS-GARCH model are statistically significant. Since $E(\epsilon_t^2 | \Delta_t = 1) < E(\epsilon_t^2 | \Delta_t = 2)$, the first component of this table is the low-volatility regime in all cases. All the switching models considered in this paper are stationary since $\alpha_1 + \beta_1 < 1$ and $\alpha_2 + \beta_2 < 1$ in all cases. In addition, $\beta_2 < \beta_1$ indicates that the impact of shocks dies out soon in the high volatility states for the wheat and soya returns. The density gets flatter in state 2 for the white maize, sunflower, and corn price returns since $\nu_2 < \nu_1$.

The transition probabilities, p_{11} and p_{22} are highly significant, indicating that the volatility regime is persistent. For instance, when you enter to a low volatility regime of wheat prices, you tend to remain there with a probability $\hat{p}_{11} = 0.9879$. Applying the standard formula,

the average durations of a low and high volatility regime are:

$$\text{average duration low volatility} = \frac{1}{1 - 0.9879} = 82.65 \text{ days}$$

and

$$\text{average duration high volatility} = \frac{1}{1 - 0.3778} = 1.6 \text{ days,}$$

respectively. Analogous calculations find that the expected durations of low volatility regime are 1, 8, 18, 17, 10 & 6 working days for white maize, yellow maize, sunflower, soya, corn and sorghum, respectively, while the expected durations of the high volatility regime are between 1 and 3 working days. The low volatility regime is very persistent for wheat, sunflower and soya indicating that it is difficult to switch from low volatility state to high volatility state of the market.

4.3 Value-at-Risk estimates: in-Sample

“Risk is like fire: if controlled it will help you, if uncontrolled it will rise up and destroy you.” Theodore Roosevelt

This paper computes the 5% VaR from the single regime GARCH and regime switching GARCH modes over the in-sample risk measures for all dates under MLE and

MCMC methods. Figures 2 and 3 show the 5% and 1% VaR from the different GARCH and MS-GARCH models under the MLE and MCMC for skewed t and skewed GED innovations. They look similar except that the MS-GARCH model often shows bigger spikes than the single regime model when there is a large shift in volatility. This is in agreement with Ardia et al. (2016).

Table 4: Maximum likelihood estimates for selected agricultural commodities

K	Parameter	White maize	Yellow maize	Wheat	Sunflower	Soya	Corn	Sorghum
1	β_{constant}	8.9639** (0.0461)	1.0726** (0.1285)	4.8886** (0.0815)	2.9259** (0.0888)	5.1866** (0.0888)	4.1969** (0.1676)	3.3848** (0.0564)
	β_{Coal}	-0.2314** (0.0046)	0.1166** (0.021)	0.0326* (0.0107)	0.1025** (0.01)	-0.0242** (0.0045)	-0.4841** (0.0026)	-0.2442** (0.0044)
	β_{Oil}	-0.2375** (0.0064)	0.6379** (0.0249)	0.2528** (0.0135)	0.5817** (0.0128)	0.1542** (0.0124)	0.7219** (0.0265)	0.5497** (0.01)
	β_{Gas}	-0.1995** (0.0084)	-0.1331** (0.0135)	0.0929** (0.0077)	-0.0374** (0.0125)	-0.1374** (0.0089)	0.186** (0.018)	-0.1597** (0.011)
	β_{Rand}	0.3188** (0.0117)	1.6405** (0.0345)	0.8991** (0.0169)	1.2254** (0.0253)	1.1582** (0.0164)	0.5684** (0.023)	1.2639** (0.0111)
	Σ	0.054	0.106453	0.059796	0.0985	0.0596	0.0412	0.03379
2	R^2	0.96	0.86	0.81	0.82	0.966	0.953	0.98
	β_{constant}	2.79** 0.046	6.8176** 0.0845	4.8764** 0.0243	8.0797** 0.0621	4.0919** 0.1096	2.0294** 0.3419	3.4216** 0.0948
	β_{Coal}	0.075** (0.0046)	0.0497** (0.0085)	0.0615** (0.0027)	-0.1655** (0.0037)	-0.012 (0.005)	-0.0339 (0.0217)	0.0274** (0.0057)
	β_{Oil}	0.37** (0.0064)	0.0779** (0.0102)	0.2178** (0.0009)	-0.0212** (0.0089)	0.3381** (0.0159)	1.2713** (0.0595)	0.4223** (0.0173)
	β_{Gas}	-0.06** (0.0084)	-0.4195** (0.0101)	-0.0684** (0.0056)	0.0444** (0.0072)	-0.0159* (0.0056)	-1.1741** (0.0396)	-0.2993** (0.0204)
	β_{Rand}	1.416** (0.0117)	0.4387** (0.0199)	0.9638** (0.0094)	0.4151** (0.0139)	1.3006** (0.022)	0.7023** (0.065)	1.2217** (0.0189)
3	Σ	0.049	0.0640786	0.03378	0.0617	0.042768	0.0955	0.0435
	R^2	0.97	0.92	0.9745	0.8394	0.97	0.88	0.9835
	β_{constant}	-0.006 (0.0865)	8.5625** (0.0371)	4.626** (0.1526)		3.7601** (0.053)	8.8215** (0.129)	3.6159** (0.0723)
	β_{Coal}	-0.076* (0.0252)	-0.2071** (0.003)	0.025** (0.006)		-0.2919** (0.005)	-0.1336** (0.004)	-0.2646** (0.006)
	β_{Oil}	0.8395** (0.0254)	-0.1481** (0.0057)	0.2098** (0.0199)		0.554** (0.009)	-0.1477** (0.0171)	0.5051** (0.0109)
	β_{Gas}	-0.4318** 0.0193	-0.1317** 0.0068	-0.1701** 0.01		0.0264* 0.009	0.0359** 0.0104	0.0343* 0.0116
	β_{Rand}	2.137** (0.0208)	0.2463** (0.01)	1.1563** (0.0317)		1.3814** (0.0167)	-0.1369** (0.0249)	1.2358** (0.0159)
	Σ	0.1206	0.047	0.031396		0.0479	0.04385	0.045875
	R^2	0.9449	0.956	0.99		0.9735	0.77	0.93
	P ($S_t = 1 S_{t-1} = 1$)	0.9875	0.992148	0.99534	0.99375	9.93E-01	0.964969	0.9702
	P ($S_t = 2 S_{t-1} = 2$)	0.98178	0.972568	0.9797	0.9951	0.98269	0.969825	0.97988
	P ($S_t = 3 S_{t-1} = 3$)	0.9747	0.98858	0.9856		0.98855	0.984669	0.975476

Note: The standard errors are reported in parentheses. ** and * denote the significance at the 1% and 5% levels, respectively.

Figures 4 and 5 illustrate the exceedances (i.e., true return - predicted VaR) of the in sample forecasts of 5% and 1% VaR resulting from the different GARCH models with skewed-t and skewed GED innovations. As shown in the both figures the differences are negative to a greater extent for the higher significance levels.

4.4 Backtesting Measures

In this paper, Binary loss function (BLF) and Quadratic loss function (QLF) are employed. Moreover, LR_{uc} and LR_{cc} tests of Kupiec (1995) and Christoffersen (1998) respectively are employed for testing the quantile accuracy and independence. Table 7 displays the backtest-

ing measures for the 95 and 99% VaR for different single regime GARCH and MS-GARCH models under the MLE and MCMC approaches. From the table we can see that models with ABLF closest to nominal quantile level $\alpha = 0.05$ and $\alpha = 0.01$ are preferred. The MS-GARCH models result the lowest LR test for conditional coverage statistics for yellow maize, wheat, sunflower, soya and sorghum. A closer look at these models reveals that the ABLF for MS-GARCH models are very close to 5%, which results that MS-GARCH model performs better for yellow maize, wheat, sunflower, soya and sorghum. The complex MS-GARCH and single regime GARCH models performs well for white maize and corn, respectively.

Table 5: MCMC Estimates of standard GARCH models using the complete data

	White	Yellow	Wheat	Sunflower	Soya	Corn	Sorghum
	GJR(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	EGARCH(1,1)	GJR(1,1)
	Skewed-t	Skewed-GED	Skewed-GED	Skewed-GED	Normal	std	Skewed-t
α_0	0.1955* (0.0464)	0.3003* (0.0738)	0.0171 (0.0069)	0.1799 (0.0681)	0.1782 (0.0629)	1.3047* (0.2613)	0.0248* (0.0003)
α_1	0.1441** (0.0223)	0.154** (0.0234)	0.0786** (0.0181)	0.2012** (0.0464)	0.1668** (0.0315)	0.2770** (0.0459)	0.9928** (0.0047)
α_2	0.0325 (0.0208)					-0.0067 (0.0401)	0.0551* (0.0132)
β_1	0.7986** (0.0251)	0.7686** (0.0341)	0.9121** (0.0203)	0.7094** (0.0745)	0.7487** (0.0541)	0.197 (0.1567)	0.0002 (0.0002)
ν	8.5900** (0.6414)	1.3100** (0.0318)	6.3500** (0.2481)	1.1900** (0.0494)	7.8000** (1.14)	0.8681** (0.0303)	2.1000** (0.0005)
ξ_1	0.9499** (0.0285)	0.9586** (0.0194)	0.9723** (0.0243)	1.009** (0.0172)			2.1200** (0.0102)
$\alpha_1 + \beta_1$	0.9427	0.9226	0.9907	0.9106	0.9155	0.474	0.993
Diagnostic							
AIC	9849	9618	7418	7730	8224	6831	-371
BIC	9884	9653	7447	7759	8247	6858	-339
DIC	9847	9615	7417	7730	8227	6831	-378

Note: The standard errors are reported in parentheses. AIC, BIC and DIC are the Akaike, Bayesian and deviance information criterion, respectively. ** and * denote the significance at the 1% and 5% levels, respectively.

5 Discussion

In this paper, I estimate different single regime and two regime GRACH models with different kinds of distributions of the innovations, normal distribution, Student-t distribution, GED and their skewed extensions. As shown in Tables 5 and 6, the AIC and DIC values of MS-GARCH models are slightly smaller than their counterparts of the standard single regime GARCH models. This evidence shows that the MS-GARCH models fit the data much better than the standard single regime GARCH models. In line with the findings of Edwards and Susmel (2003), the ARCH coefficients (i.e., $\alpha_2^{(1)}$ and $\alpha_2^{(2)}$) are insignificant except the coefficient of sunflower in regime 1, indicating that the use of regime switching ARCH model be likely to cause the ARCH effect to be disappeared.

For the 95% VaR, the MS-GARCH with MCMC estimate performs best among all the models for yellow maize, sunflower, soya, and sorghum with skewed-t, skewed-GED, std, and skewed-GED innovations, respectively. The complex MS-GARCH with ML estimate performs best for white maize with skewed-t innovations. The MS-GARCH model with ML estimate with skewed-t innovations is optimal model for wheat; while the single regime GARCH with ML estimate and GED innovations outperforms the

rest of the models for corn.

For the 99% VaR, the MS-GARCH with ML estimates perform reasonably well when compared to other candidate models for white maize, yellow maize, wheat, sunflower and soya. The MS-GARCH model with MCMC estimates performs slightly well for sorghum and GARCH with ML estimate performs well for corn. For 95% VaR, the MS-GARCH with MCMC estimates perform better than those with the ML estimates. However, for 99% VaR, the MS-GARCH with ML estimates dominates those with the MCMC estimates.

As shown in Table 7, there are differences between the models based on symmetric and skewed innovations. The models with the skewed innovations performs better than those with the symmetric innovations except corn in terms of modeling volatility and VaR. With the exception of corn, the standard single regime GARCH models with MCMC estimate exhibit much more persistence. This highlights the importance of applying the two regime MS-GARCH models in modeling volatility and VaR.

The expected duration for white maize in regime 1 and sunflower and corn in regime 2 is 1, indicating that these regimes essentially captures some isolated outliers (Haas & Paolella, 2012).

6 Conclusions

One of the main aim of this paper has been to examine the factors contributing to fluctuation of agricultural commodity prices in South Africa. The empirical results based on the MS regression model can be concluded as follows:

- the price of agricultural commodities was found to

be significantly associated with the price of coal, price of natural gas, price of oil and exchange rate.

- for all agricultural commodities except sunflower, $k = 3$ had and higher log-likelihood vales and lower AIC and BIC values. Thus, the three-state MS regression model outperformed the two-state MS regression model.

Table 6: MCMC estimates of the two regime MS-GARCH models using the complete data

	White	Yellow	Wheat	Sunflower	Soya	Corn	Sorghum
	MS-GARCH(1,1)	MS-GJR(1,1)	MS-GJR(1,1)	MS-GJR(1,1)	MS-GJR(1,1)	MS-GJR(1,1)	MS-GARCH(1,1)
	Skewed-t	Skewed-t	Skewed-GED	Skewed-t	std	std	Skewed-t
$\alpha_0^{(1)}$	0.5281* (0.0984)	0.3502* (0.0612)	0.0066 (0.0026)	0.154* (0.0286)	0.1183** (0.0085)	0.4168* (0.0535)	0.0013* (0.0001)
$\alpha_1^{(1)}$	0.1249 (0.0329)	0.1589* (0.0196)	0.0317* (0.0056)	0.1404 (0.0245)	0.0952** (0.0042)	0.1054* (0.031)	0.0001** (0.000001)
$\alpha_2^{(1)}$			0.0031 (0.0034)	0.1186* (0.0235)	0.0047 (0.0058)	0.0191 (0.0212)	
β_1	0.6785** (0.0565)	0.0173 (0.0141)	0.9565** (0.0081)	0.6537** (0.0377)	0.8472** (0.0049)	0.7399** (0.0281)	0.5704** (0.0445)
ν_1	3.2356** (0.0373)	0.7349** (0.0243)	1.485** (0.0113)	15.43** (0.0192)	10** (0.0069)	2.12** (0.0586)	0.7039** (0.0059)
ξ_1	1.1249** (0.0611)	0.9214** (0.0325)	0.9958** (0.0067)	1.0607** (0.0243)			4.8068** (0.0306)
$\alpha_0^{(2)}$	0.1403* (0.0252)	0.8656* (0.1271)	0.1005** (0.0034)	0.6326** (0.0229)	0.0022 (0.0012)	0.5248** (0.0371)	4.4188** (0.0229)
$\alpha_1^{(2)}$	0.1825* (0.0185)	0.0539 (0.0279)	0.0967** (0.0074)	0.0093 (0.0075)	0.9948** (0.004)	0.1726 (0.0589)	0.1699 (0.0182)
$\alpha_2^{(2)}$			0.0412 (0.0082)	0.0123 (0.0098)	0.0047 (0.0057)	0.0769 (0.0443)	
β_2	0.8064** (0.0183)	0.0694 (0.0156)	0.8567** (0.0031)	0.9596** (0.0101)	0.0024 (0.0029)	0.0683 (0.0731)	0.8062 (0.0308)
ν_2	1.1761** (0.0557)	2.1542** (0.0337)	2.0869** (0.0087)	2.2212** (0.0351)	14.35** (0.0085)	0.7139** (0.0126)	1.1258** (0.0162)
ξ_2	0.9129** (0.0269)	0.9879** (0.0339)	0.0602** (0.0047)	0.5598** (0.0233)			1.8353** (0.0613)
p_{11}	0.1189** (0.0692)	0.8697** (0.033)	0.9879** (0.0039)	0.9457** (0.0089)	0.9411** (0.0035)	0.9028** (0.0236)	0.7853** (0.0064)
p_{22}	0.6312** (0.0454)	0.5411** (0.0453)	0.3778** (0.0094)	0.3135* (0.0363)	0.5234** (0.0078)	0.1573 (0.0498)	0.5313** (0.0673)
$(1 - p_{11})^{-1}$	1	8	83	18	17	10	5
$(1 - p_{22})^{-1}$	3	2	2	1	2	1	2
$E(\epsilon_t^2 \Delta_t = 1)$	1.639	1.8987	0.8021	1.0183	1.4642	1.6949	0.055
$E(\epsilon_t^2 \Delta_t = 2)$	3.551	4.9212	13.3671	5.6481	1.9969	2.6985	13.583
Diagnostic							
AIC	9846	9608	7409	7662	8188	6752	-1617
BIC	9915	9689	7491	7744	8258	6817	-1552
DIC	9832	9593	7394	7654	8172	6745	-2709

Note: The standard errors are reported in parentheses. AIC, BIC and DIC are the Akaike, Bayesian and deviance information criterion, respectively. ***, ** and * denote the significance at the 1%, 5% and 10% levels, respectively.

This paper applies a Bayesian estimation of regime switching GARCH model to examine the volatile nature of the seven major South African agricultural commodity prices. The models were evaluated using the daily South African agricultural commodity price data from the JSE. The key findings based on the standard single regime and two regime GARCH models can be summarized as follows:

- GJR(1,1) with skewed-t innovation performs best for white maize and sorghum, while GARCH(1,1) with skewed-GED innovation performs better for yellow maize, wheat, and sunflower. The symmetric GARCH(1,1) models with normal and std innovations outperform the other for soya and corn, respectively, since the original distribution is not excessively skewed.
- MS-GARCH(1,1) with skewed-t and skewed-GED innovation performs best for white maize and

sorghum, respectively, while MS-GJR(1,1) with skewed-t, skewed-GED, skewed-t, std and std innovation performs better for yellow maize, wheat, sunflower, soya and corn, respectively.

The second aim of this paper was to investigate various GARCH models that can be used to calculate VaR estimates. These VaR estimates were compared using four different backtesting approaches: ABLF, AQLF, LR_{uc} and LR_{cc}.

- The MS-GARCH(1,1) models with std innovation seem to outperform those with a GED error distribution since agricultural commodity markets are characterized by fat tails. The MS-GJR(1,1) with std (i.e., soya and corn) and skewed-t (i.e., yellow maize and sunflower) innovation with MCMC estimate is optimal for the VaR models. The MS-GARCH(1,1) with skewed-t (i.e., white maize and sorghum) inno-

Table 7: Results of the unconditional coverage, independence and conditional coverage tests for 1% and 95% VaR estimation: In-Sample

	Models	Methods	White maize	Yellow maize	Wheat	Sunflower	Soya	Corn	Sorghum
			95% VaR						
ML	GARCH	ABLF	0.0525	0.0484	0.0468	0.0464	0.0452	0.0496	0.0670
		AQLF	0.3705	0.4195	0.1267	0.2123	0.1419	2.018	1.1251
		LRuc	0.303	0.031	0.031	1.047	0.132	0.038	13.638
		LRcc	2.363	0.775	2.75	2.724	1.082	1.231	31.129
	MS-EGARCH	ABLF	0.0472	0.0488	0.0488	0.0452	0.0480	0.0490	0.0707
		AQLF	0.3456	0.4243	0.1400	0.2083	0.1504	2.092	1.1462
		LRuc	0.424	0.073	0.415	0.546	1.047	0.006	9.458
		LRcc	0.639	0.896	1.65	4.286	1.823	1.305	27.825
	Complex MS-EGARCH	ABLF	0.0517	0.0488	0.0448	0.0415	0.0460	0.0341	0.0428
		AQLF	0.3687	0.4268	0.1350	0.2123	0.1458	1.7516	0.9221
		LRuc	0.22	0.031	1.252	3.581	0.695	9.654	1.56
		LRcc	0.524	0.775	3.05	3.724	4.623	1.689	8.062
MCMC	MS-EGARCH	ABLF	0.0456	0.0517	0.0452	0.0476	0.0493	0.0453	0.0446
		AQLF	0.3504	0.4393	0.1318	0.2250	0.1631	2.110	0.9518
		LRuc	0.862	0.22	1.047	0.08	0.007	0.892	0.798
		LRcc	1.008	0.524	1.288	0.275	2.573	1.022	4.441
	EGARCH	ABLF	0.0541	0.0521	0.0379	0.0419	0.045	0.0341	0.0105
		AQLF	0.3708	0.4807	0.1205	0.2125	0.1515	1.7516	0.5974
		LRuc	1.0265	0.3138	7.7579	3.2207	1.2519	11.3301	87.213
		LRcc	2.9254	1.8865	8.5891	3.8633	2.1088	11.7253	NA
			99% VaR						
ML	EGARCH	ABLF	0.0114	0.0073	0.0094	0.0118	0.0098	0.0087	0.0583
		AQLF	0.1482	0.2098	0.0429	0.0931	0.0459	1.3783	1.0075
		LRuc	0.7591	1.388	0.0139	1.1279	0.0072	0.3	183.03
		LRcc	NA	NA	NA	1.9416	1.3631	NA	198.7
	MS-EGARCH	ABLF	0.011	0.0077	0.0094	0.0069	0.0069	0.0087	0.0149
		AQLF	0.1477	0.1181	0.0331	0.0755	0.0247	1.3991	0.6567
		LRuc	0.46	0.554	0.0139	1.9616	1.9616	0.3	4.2081
		LRcc	NA	NA	NA	NA	4.467	NA	NA
	Complex MS-EGARCH	ABLF	0.0118	0.0086	0.0106	0.0118	0.0102	0.005	0.0087
		AQLF	0.1607	0.2215	0.0482	0.1032	0.0522	1.3108	0.5221
		LRuc	1.1279	0.2835	0.2332	1.1279	0.0813	5.0917	0.0833
		LRcc	NA	NA	NA	1.9416	NA	NA	NA
MCMC	MS-EGARCH	ABLF	0.013	0.0102	0.0138	0.0118	0.0138	0.0248	0.0051
		AQLF	0.1591	0.2277	0.0544	0.0925	0.0534	3.7002	0.4351
		LRuc	2.6311	0.0813	3.9437	1.1279	3.9437	1.3542	0.0455
		LRcc	NA	NA	NA	1.9416	4.3782	NA	NA
	EGARCH	ABLF	0.0118	0.0081	0.0126	0.0114	0.0098	0.4668	0.0043
		AQLF	0.161	0.2642	0.0562	0.099	0.0481	6.3253	0.401
		LRuc	1.1279	0.554	2.066	0.7591	0.0072	5.0917	297.41
		LRcc	NA	NA	NA	1.6667	1.3631	NA	314.68

vation under the MCMC estimate performs better than others.

- The single regime GARCH model with symmetric innovation outperforms the two regime GARCH models for corn.

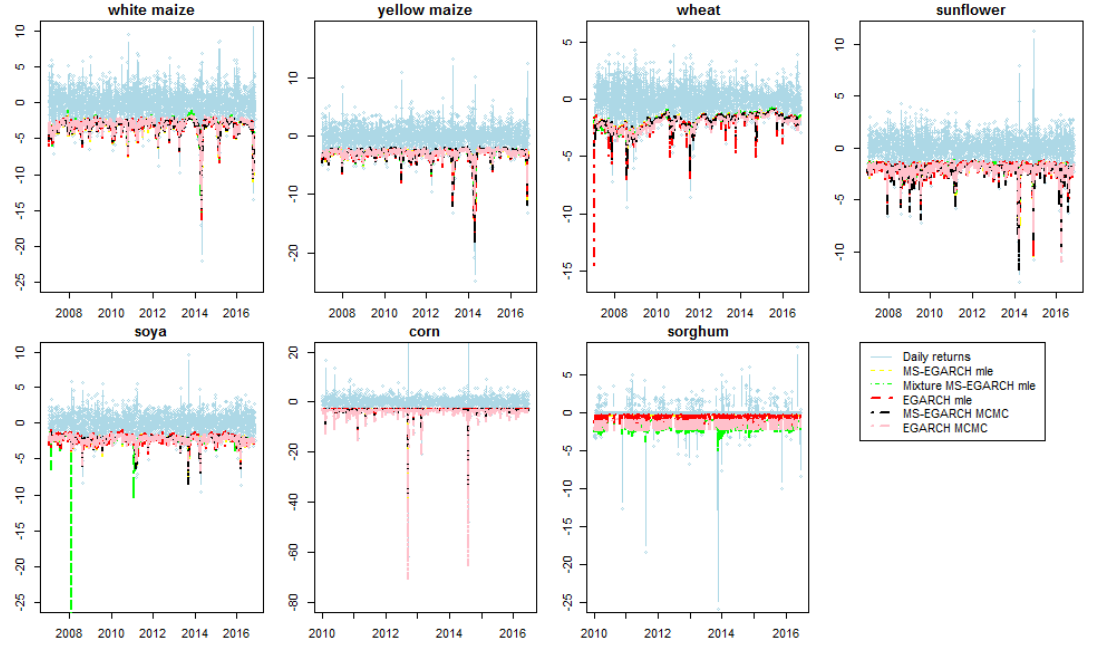
Finally, the overall conclusion is that MS-GARCH models under the MCMC approaches perform well for most of the agricultural commodity markets considered in this paper. Moreover, this paper provided a practical guide for examining volatility and VaR through applying dif-

ferent GARCH processes. The comparison between the single regime and two regime GARCH processes gives an overview of their performances and features. This paper can also be a good reference when facing modelling agricultural commodity price problems.

Conflict of Interests

The author declares that there is no conflict of interest.

(a) 99% VaR



(b) 99% VaR

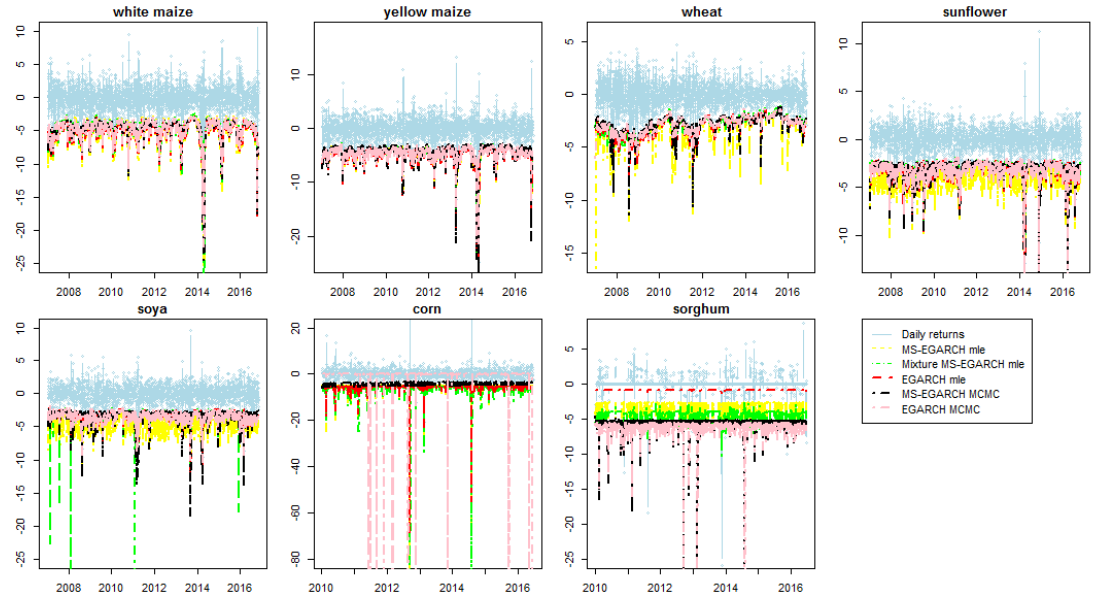
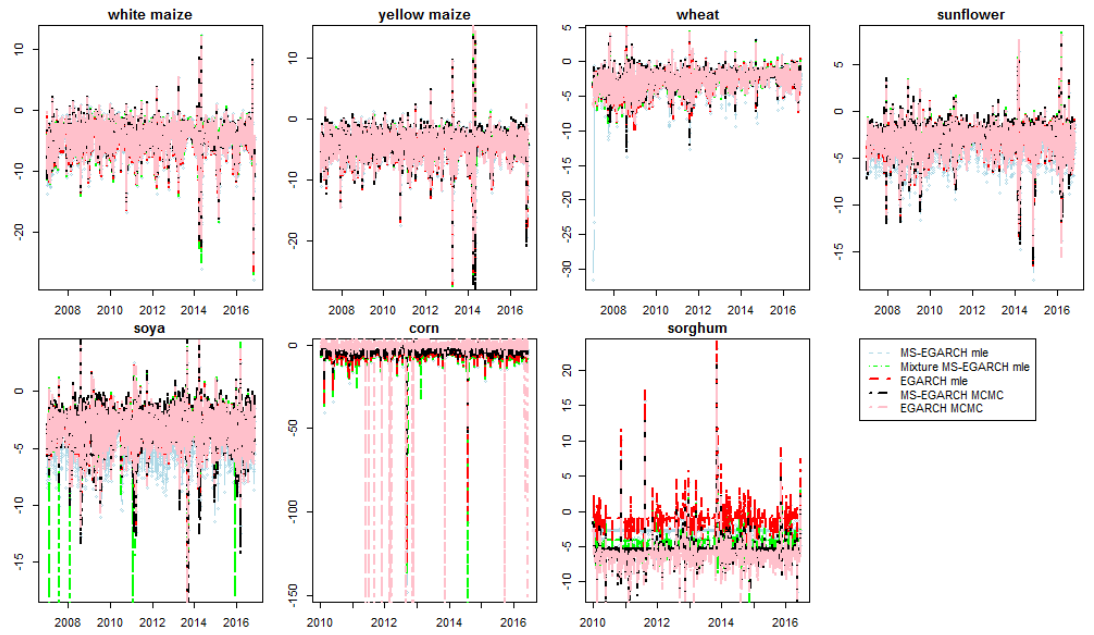


Figure 2: In sample VaR at the 99% risk level for the single and regime-switching GARCH models.

(a) 99% VaR



(b) 95% VaR

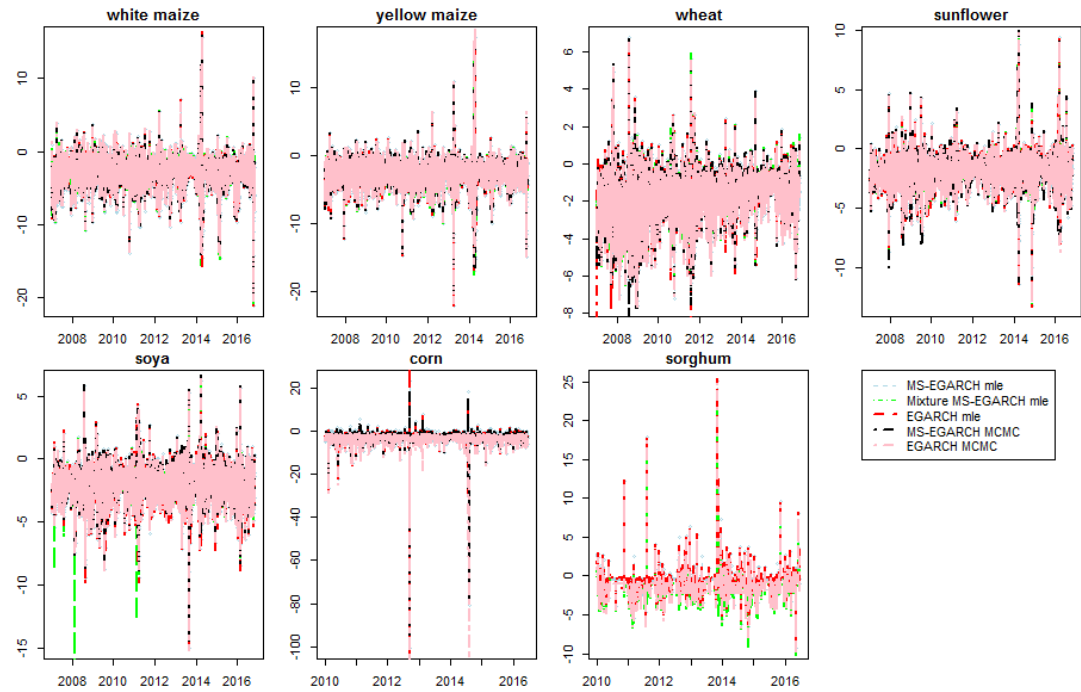


Figure 3: In sample VaR for the single and regime-switching GARCH models: difference between daily returns and VaR

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