The Transmission of World Maize Price to South African Maize Market: A Threshold Cointegration Approach

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Abstract

This paper seeks to provide an explanation for the relationship between domestic maize price in South Africa and world maize prices in order to evaluate co-movement and transmission of world prices to domestic prices in Sub-Sahara African countries. This is done by comparing nested and non-nested models that capture different forms of nonlinearity in the price spread. Adopting a Bayesian approach that allows for comparison of models using Bayes Factor, we found that the relationship between South African price and world price for maize indicates the presence of nonlinearity in price transmission with three regimes that is triggered by the price spread in previous period.

JEL Codes: C5, C11, Q0, Q13, Q18

Keywords: Import Parity, Export Parity, Autarky, Transmission Threshold Cointegration, Bayes Factor

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1 Introduction

World food prices increased dramatically in 2007 and continued to increase until the second quarter of 2008, creating a global food crisis and causing political and economic instability and social unrest in both poor and developed nations. Though the global economic recession led the prices to fall in the later part of 2008, world food prices has continued to increase again since 2010 and is even higher than the 2008 high in 2011 (Figure 1). The increase in food prices has been attributed to droughts in grain-producing nations and rising oil prices with feedback effect on other agricultural inputs such as fertilizers, food transportation, and industrial agriculture (FAO (2006)). There is also the increasing use of agricultural commodities for biofuels around the world including Brazil and China. Other factors that have been highlighted in the literature include climate change and structural changes in trade and agricultural production.

While some of these factors are endogenous to the economies of developing countries, we can argue that some of these factors are beyond their control. For instance, factors such as increased demand for agricultural commodities used for biofuels drive world commodity prices higher and can be said to be beyond the control of many African countries. Understanding the relationship between world food prices and local prices is therefore important for planning and gauging how exposed a country (especially developing economy) is to fluctuations in international food prices. This also plays an important role in understanding the impacts of exogenous price shocks on food security, especially pertaining to food affordability in these nations. The perceived vulnerability of Sub-Saharan African countries to changes in world food prices justifies the need to model the behavior of prices during a shock.

This paper seeks to contribute to the literature and understanding on price transmission between world and South African maize prices in four ways:

1. South Africa is a major player in the maize market in the Southern African region. Changes in South African prices therefore not only affect local food prices, but also the countries to which they export. Despite this, little evidence has been found on how international prices are transmitted to local prices. Previous studies including Minot (2011) and Kirsten (2012) found no long run relationship between South African maize prices and world maize prices based

on the assumption that the two prices should adjust back to equilibrium at all times. However, as evidenced by the trend analysis that shows prices rising in African countries during the global food crisis, (Figure 3 presents a plot of the relationship between South African white maize and world price of yellow Maize) and stated by Minot (2011), there seems to be a relationship between the prices that is not fully captured by econometric methods adopted. This paper evaluates the relationship between South African maize prices and world prices by allowing for the possibility of nonlinearity (threshold model) in the price spread.

2. A Bayesian approach is adopted that allows for comparison between different model specifications that are non-nested, in order to test which model the data supports in capturing the relationship between the prices.

3. An improvement in the understanding of global price changes on local South African prices. This will in turn improve the understanding of the effect of global shocks on food security in terms of food affordability for low income household in South Africa.

4. It is expected that the maize prices in other countries in the region are to some extent affected by prices in South Africa. An understanding of the effect of global price changes on South Africa could therefore also contribute to knowledge of market efficiency and food security within the region.

2 Related Literature

2.1 Price Transmission

The transmission of spatial and vertical price signals has been studied extensively in economics. One of the main arguments in this area is that appropriate level of price transmission has the ability to broadly predict efficient market arbitrage in two markets. It also serves as a signal for a well functioning and efficient market. This premise relates to the concept of the *Law of One Price* (LOP) in a standard competitive market where price relations in two markets are expected to be equal with factors such as exchange rates, trade and public policies, market power, transaction costs, economies of scale and product differentiation considered to be the major cause of price differentials. Thus, effective price transmission between two markets are considered to be the product of a perfectly competitive market.

Given the openness of many countries, price transmission across borders is of interest to gauge market efficiency and competitiveness in different countries. However, of paramount interest, and in line with the global food crisis is the extent to which changes in world food price sends signals to local markets. The study of the effect of changes in price of the same commodity in two locations will help explain how a country will be affected by fluctuations in world food prices. Minot (2011) reviews a framework for measuring the transmission of world prices to domestic markets in line with the import and export parity price. This is based on bounding the domestic price by the world price and transportation cost in the absence of trade barriers assuming efficient output production. Price transmission is therefore defined by the level of transportation cost, trade barriers, lack of market information or uncompetitive markets. Under favorable conditions, we should expect price transmission between world and domestic prices.

Alternative approaches to measuring price transmission through different behavioral rules have stringent data requirements and can be difficult to implement in developing countries.[2] In this paper, we follow the literature based on the premise of the LOP. However, the behavior of the price differences between two countries, as a function of transaction costs, conditional on competitive market conditions and a lack of trade barriers are explicitly modelled.We will elaborate on this method in the next sections.

2.2 Overview of methods used to study market integration

The methods used to analyze spatial price relationships have evolved considerably over time. The objective of this section is therefore to give a brief overview of how market integration studies have developed and to give a review of studies specifically focussed on market integration of staple commodities in Africa.

Early studies such as Cummings (1967), Blyn (1973), Richardson (1978), and Stigler

[2]Conforti (2004) has a review of some of the methods used in the study of price transmission in selected agricultural markets

and Sherwin (1985), used basic static correlation and regression methods to analyse bi-variate price relationships. The problem associated with these methods is its failure to account for spurious relationships and the presence of incidental co-movements in prices in different markets - caused by common effects from exogenous factors. The results obtained with correlation/regression methods can therefore indicate market integration when there is, in fact none. An improvement on these models is the distributed lag as used by Ravallion (1986). This type of model allows the researcher to identify long-run and short run spatial relationships between locations. A key concern is that these models can have inefficient estimators which might lead to incorrect inference testing. Granger causality and cointegration methods builds on the concepts as used by Ravallion (1986), and can be used to establish the existence of a true long-run linear relationship between variables. These methods were popularized, in agricultural economics, by studies such as Ardeni (1989) and Goodwin and Schroeder (1991). Widespread implementation of these methods can be seen in empirical studies such as Lloyd, *et al* (1999), Cudjoe, Bresinger and Diao (2008) and Minot (2011). The Granger causality and cointegration methods are however also not free from criticism, in that, it does not consider the role of transaction cost in the trade and price transmission process, and as a result it excludes the possible existence of non-linear dependencies between prices at different locations. In a response to this, two methods have been proposed to model the effect of transaction cost on price transmission between regions explicitly. The first is the Parity Bound Model (PBM) as applied by Sexton, Kling and Carman (1991), Blauch (1997) and Negassa and Myers (2007). This method uses information on transaction cost in conjunction with prices for a single period to identify price spreads that correspond to prices that are inside or outside the parity bounds. The second is a threshold autoregressive (TAR) and threshold cointergration (TIC) models as applied by Abdulai (2000), Goodwin and Piggott (2001) and Myers (2010). These models incorporate transaction cost by allowing for a different relationship between variables once a certain threshold has been surpassed Van Campenhout (2006).

This study will focus on the TAR and TIC models due to the limitations of the PBM model. These limitations include the model's inability to account for lag price adjustments and the stringent requirement of explicit data on transaction cost. In addition to this, Van Campenhout (2006) also states that threshold models are better able to capture the dynamics of the arbitrage process underlying markets that are connected. TAR models are however not without its shortcomings. Most TAR models assume that transaction cost is constant over time and that the underlying distribution of the threshold term is plagued by non-normality and nuisance parameters. The TAR model can be extended to include a time trend as in Van Campenhout (2006) for a symmetric TAR model while the second issue is not an issue in the Bayesian framework adopted in this paper where the nuisance parameters can be integrated out.[3]

2.3 Review of Spatial Transmission Studies for Sub-Sahara Africa

Table 1 presents a summary of studies done on spatial price transmission by methods adopted in Sub-Saharan African (SSA). Although Table 1 is not an exhaustive list on spatial price transmission studies done for SSA countries, it does paint a picture of the gaps in empirical literature. Even though threshold and regime switching advancements have been applied in some studies, this was done predominantly to investigate inter regional/country trade within the region. The impact of global shocks to local commodity prices have however only been analysed with cointegration/ ECM techniques (see Kilima (2006) and Minot (2011)) with inconclusive evidence in terms of the co-movement of domestic prices and international commodity prices in many cases (Minot (2011)). With prices in South Africa potentially playing a pivotal role in maize price formation in SADC it is imperative to gain an in depth understanding of the effect of global shocks to South African maize prices. This study therefore adds to the literature by modeling price transmission between world prices and South African prices using a nonlinear time series model. The study also adopts a Bayesian framework that provides a relatively simple and direct way to compare the models, including linear versus nonlinear models with big penalty for the nonlinear model.

[3]Accounting for changes in threshold trigger becomes important when there is a structural change in the transaction cost that will make the mean change over a period. In the case of the commodity markets, one major component of the transaction cost is transportation cost with a change in the mean of the series since 2005.

3 Threshold Cointegration Model:

The concept of cointegration as described in the classic papers of Granger (1986) and Engle and Granger (1987) has helped in explaining how nonstationary economic variables interact and move together over time. This concept has been applied to many macro economic series including stock prices and dividends (Campbell and Shiller (1987)); consumption and GDP (Campbell (1987)) and most importantly to explain relationship between commodity prices (Ardeni (1989)). Cointegration of two variables implies that the error term that defines the relationship between the two variables is stationary and the two variables have the tendency to revert to equilibrium when there is a shock. This can be represented as:

$$y_t - \beta x_t = \nu_t \tag{1}$$

where $\nu_t = \rho\nu_{t-1} + \varepsilon_t$ and cointegration exists between y_t and x_t when $\rho < 1$. This ensures that two variables will always revert to equilibrium in the long run.

However, peculiarities in some economic variables such as fixed costs of adjustment and transaction costs as pointed out by Balke and Fomby (1997) has led to the extension of cointegration to series with discontinuous adjustment to a long-run equilibrium.[4] Adjustment and restoration to equilibrium is only triggered when the series move outside of a threshold region and within the threshold the series is allowed to roam freely. Thus, the condition $\rho < 1$ only needs to hold when ν is above a certain threshold (e.g. $|\nu| > \tau$).

Threshold cointegration has helped to explain how series (such as prices) in spatially separated markets move together and respond to shocks with unobservable data on transaction and adjustment costs. Some of these papers include Goodwin and Piggott (2001), Abdulai (2000), Van Campenhout (2006) and Balcombe, Bailey and Brooks (2007). In this paper, we will also apply the concept of cointegration to understand the relationship of commodity prices in different markets within the Bayesian framework. We will argue that our paper is different from previous papers in this area in the following ways:

1. We adopt the Bayesian approach which allows us to compare different possible

[4] McNew, and Fackler (1997) and Barrett (1996) popularized the idea of accounting for transaction cost in modeling market integration and spatial trade

model specifications and forms of threshold. This enable us to choose a model supported by the data as described in Koop and Potter (2000). As economic theory does not dictate what the exact form of the trigger is in the threshold model, coupled with the need to compare linear and nonlinear models that are non-nested, the Bayesian framework we adopt in this paper gives an easy to implement algorithm.

2. We apply the concept of threshold integration to understand the relationship between South African maize price and world maize price. This is useful given the importance of South Africa in the African maize market.

4 Model

Similar to Balke and Fomby (1997), we model the relationship between the price of South African Maize (P_t^s) and world yellow maize price (P_t^w) as:

$$P_t^s = \alpha P_t^w + Z_t \tag{2}$$

where $Z_t = \rho Z_{t-1} + \varepsilon_t$.

As stated earlier, the two variables are said to be cointegrated when $\rho < 1$. However, the presence of transaction cost between the prices can lead to the presence of threshold in the relationship. The nature of the relationship of the transaction cost between the two markets indicates an asymmetric threshold as described in Balke and Fomby (1997). Assuming asymmetric transaction cost seems reasonable and a better generalization given differences in freight costs and tariffs that exists between countries.[5] Given this, we can express Z_t as:

$$Z_t = \begin{cases} \mu^{(1)} + \rho^{(1)}(L)Z_{t-1} + \sigma^{(1)}\varepsilon_t, & \text{if } I_t = 1 \\ \mu^{(2)} + \rho^{(2)}(L)Z_{t-1} + \sigma^{(2)}\varepsilon_t, & \text{if } I_t = 0 \\ \mu^{(3)} + \rho^{(3)}(L)Z_{t-1} + \sigma^{(3)}\varepsilon_t, & \text{if } I_t = 2 \end{cases} \tag{3}$$

where I_t is an indicator variable for the regimes that will be defined later; μ is the

[5]Symmetric transaction cost is a special case of the model we propose here.

constant term that together with $\rho(L)$ are used to measure stationarity and cointegration conditions for the error variable Z_t.[6] We also allow for the possibility of a regime-switching behavior for the error variance with different σ in each regime and $\varepsilon_t \overset{iid}{\sim} N(0,1)$.

Given the specification of the equilibrium error Z_t and using $P_t^s = P_{t-1}^s + \Delta P_t^s$, we can rewrite (2) as a regime switching model of the form:

$$\Delta P_t^s = \begin{cases} \mu^{(1)} + \beta^{(1)} P_{t-1}^s + \alpha^{(1)} P_t^w + \rho^{(1)}(L) Z_{t-1} + \sigma^{(1)} \varepsilon_t, & I_t = 1 \\ \mu^{(2)} + \beta^{(2)} P_{t-1}^s + \alpha^{(2)} P_t^w + \rho^{(2)}(L) Z_{t-1} + \sigma^{(2)} \varepsilon_t, & I_t = 0 \\ \mu^{(3)} + \beta^{(3)} P_{t-1}^s + \alpha^{(3)} P_t^w + \rho^{(3)}(L) Z_{t-1} + \sigma^{(3)} \varepsilon_t, & I_t = 2 \end{cases} \tag{4}$$

I_t can take different forms and represents a defined threshold trigger that can either be an exogenous variable or a function of the lags of the Z_t with a delay parameter d that indicates how long it may take for agents to respond to a shock. Below are the different forms I_t can take:[7]

1. A linear model assuming no threshold effect exists in the relationship between the two prices - setting $I_t = 0$ for the 3 regimes. This will be the preferred model if cointegration between the two series are observed in every period.

2. A three regime model where we set $I_t = 1$ if $A_{t-d} < r_1$, $I_t = 0$ if $r_1 \leq A_{t-d} \leq r_2$ and $I_t = 2$ if $A_{t-d} > r_2$.

   Nested in the three regime model is the case where $\sigma^{(1)} = \sigma^{(2)} = \sigma^{(3)}$ indicating no regime switching behavior for the error variance (Homogenous errors) and/or:

   - $A_{t-d} = \frac{\sum_{d=1}^{p} Z_{t-d}}{d}$
   - $A_{t-d} = \frac{Z_{t-1} - Z_{t-d-1}}{d}, d = 1, ..., p.$

3. A two regime switching model where $\mu^{(2)} = \mu^{(3)}; \beta^{(2)} = \beta^{(3)}; \alpha^{(2)} = \alpha^{(3)}; \rho^{(2)}(L) = \rho^{(3)}(L)$ and $\sigma^{(2)} = \sigma^{(3)}$.

[6] We refer the readers to Balke and Fomby (1997) for an explanation on necessary and sufficient conditions for stationarity in this model

[7] While there are other forms of the model specification that can be explored, we will argue that the specifications highlighted here is sufficient to explain the relationship we want to measure in this paper.

An additional model specification for the two regime case is when $A_{t-d} = |Z_{t-d}|$ for the second regime - $I_t = 0$ and $I_t = 2$. Other forms of this model can also be defined for the case of no regime switching behavior in the error variance and A_{t-d} defined as in the 3 regime case.

4.1 Model Comparison

Bayesian model selection and/or averaging has gained popularity among researchers in recent years as one of the best solution to the model specification problem. Bayesian model selection methods are used to select a model(s) with maximum posterior probabilities conditional on the data. This framework allows us to compare models that are nonnested based on the concept of probability. It also has a number of advantages over the classical tests. For instance, the issue of nuisance parameters that are not identified when comparing a two-regime versus three regime models are not a problem in the Bayesian framework. Also, as shown in Koop and Potter (1999)a), the Bayesian framework is superior to classical approach that has been dominant in the applied literature in evaluating evidence of nonlinearity in economic time series. Koop and Potter (1999)a) argued that the Bayesian Framework's method of integrating with respect to nuisance parameters, built-in protection against over-parameterized model (Occam's razor), the averaging over the entire parameter space and the possibility to combine models in the form of model averaging makes it superior to the classical approach. The ability to average models makes the calculation of features of interest such as impulse responses in the Bayesian framework appealing.

Comparison among these competing models is based upon the posterior probability that a model is supported by the data. By Bayes rule, the posterior probability of model $\mathcal{M}_k$ can be expressed as:

$$p(\mathcal{M}_k|data) = \frac{p(data|\mathcal{M}_k)p(\mathcal{M}_k)}{p(data)} \quad k = 1, \ldots, K, \tag{5}$$

where $p(data|\mathcal{M}_k)$ denotes the *marginal likelihood*, $p(\mathcal{M}_k)$ is the prior probability of Model k and $p(\mathcal{M}_k|data)$ is the posterior probability of $\mathcal{M}_k$. Therefore, models can be compared pairwise based on their *posterior odds ratio* which is defined as:

$$PO_{kj} = \frac{p(\mathcal{M}_k|data)}{p(\mathcal{M}_j|data)} = \frac{p(data|\mathcal{M}_k)p(\mathcal{M}_k)}{p(data|\mathcal{M}_j)p(\mathcal{M}_j)}. \tag{6}$$

In practice, the prior odds ratio $p(\mathcal{M}_k)/p(\mathcal{M}_j)$ is usually set to unity for all the possible models considered so that:

$$PO_{kj} = \frac{p(\mathcal{M}_k|data)}{p(\mathcal{M}_j|data)} = \frac{p(data|\mathcal{M}_k)}{p(data|\mathcal{M}_j)} \equiv BF_{kj}, \tag{7}$$

with the ratio of marginal likelihoods denoted as the *Bayes factor* (BF). This Bayes Factor can be written in likelihood function form as:

$$BF_{kj} = \frac{\int \ell(\theta)b(\theta)d\theta}{\int \ell(\eta)b(\eta)d\eta}, \tag{8}$$

where θ and η are parameters of model k and j respectively.

4.2 Prior Selection and Posterior Distribution

We follow Koop, G. and S. Potter (1999)b) and Koop and Potter (2000) by assuming an independent conjugate prior for the parameters in order to arrive at an analytical solution for the posteriors and marginal likelihoods conditional on the threshold parameters. It is well known that a proper prior is needed in order for us not to wrongly select the restricted model (linear in this case) even if nonlinearity is the right model. Let

$$\{\xi^i\} = \left[\{\mu^i\} \quad \{\beta^i\} \quad \{\alpha^i\} \quad \{\rho^i\}\right]$$

and $\tau = [r_1, r_2, d]'$ denote the parameters for the regimes.

The conditional distribution for ξ is calculated by assuming discrete distribution for the threshold parameters in τ using all possible combination of the values. The only restriction on τ is that they are chosen such that sufficient number of observations are placed in each regime (at least 15 percent of the observation lie in each regime). The procedure in this section hinges on the fact that there are finite number of possible threshold values τ, i.e. $\tau = \tau_1, ..., \tau_{\varpi}$ is the set of possible threshold values so that:

$$p(\xi^i, \frac{1}{\sigma}|Y) = \sum_{k=1}^{\varpi} p(\xi^i, \frac{1}{\sigma^i}|\tau = \tau_k, Y)p(\tau = \tau_k|Y) \tag{9}$$

where $Y = \left(\Delta P^s_{p+1}, \ldots, \Delta P^s_T\right)'$.

Conditional on τ, the regime switching equation breaks down into J normal linear regression models. If we assume normal-gamma priors for $\{\xi^i\}$ and $1/\sigma$, the joint posterior conditional for $\{\xi^i\}$ and $1/\sigma$ will also be normal-gamma.[8] Written concisely in matrix form with $X_t^{(i)} = \mu^{(i)} + \beta^{(i)} P_{t-1}^s + \alpha^{(i)} P_t^w + \rho^{(i)}(L) Z_{t-1}$, and parameters for each regime with a joint prior for ξ^i and $1/\sigma^i$ that is $NG(\underline{\xi^i}, \underline{\mathcal{Q}^i}, \underline{s}^{-2(i)}, \underline{\nu^i})$, we have

$$Y_t^{(i)} = X_t^{(i)} \xi^i + \sigma^i \varepsilon$$

This will give us a posterior conditional probability that is $NG(\overline{\xi}^i, \overline{\mathcal{Q}}^i, \overline{s}^{-2(i)}, \overline{\nu}^i)$ where:

$$\begin{aligned} \overline{\nu}^i &= T^i - p + \underline{\nu}^i, \\ \overline{\mathcal{Q}^i} &= (\underline{\mathcal{Q}}^{i-1} + X^{i'} X^i)^{-1} \\ \overline{\xi}^i &= \overline{\mathcal{Q}^i}(\underline{\mathcal{Q}}^{i-1} \underline{\xi}^i + X^{i'} X^i \widehat{\xi^i}) \end{aligned}$$

and

$$\overline{s}^{i2} = \frac{\underline{\nu}^i \underline{s}^{i2} + SSE^i + (\widehat{\xi^i} - \underline{\xi}^i)' X^{i'} X^i \overline{\mathcal{Q}}^i \underline{\mathcal{Q}}^{i-1} (\widehat{\xi^i} - \underline{\xi}^i)}{\overline{\nu}^i}$$

where $SSE^i = (Y^i - X^i \xi^i)'(Y^i - X^i \xi^i)$ and $\widehat{\xi^i}$ is the OLS estimate of ξ^i.[9]

With this specification, the marginal likelihood conditional on τ will also be of the standard form and a product of the marginal likelihoods for each regime. In order to get the marginal likelihood for the three and two regimes models, we proceed by sequentially averaging the conditional marginal likelihoods over d and r_1 and r_2.

5 Application

We apply the above model to measure the relationship between South African white maize and world yellow maize price as reported by the World Bank. Table 2 presents information on the data used for this study with the sources. South African producer prices for white maize were obtained from the South African Futures Exchange (SAFEX). Monthly prices are calculated by taking the average of the daily prices

[8] Our definition of the normal-gamma distribution follows the notation in Koop, Poirier and Tobias (2007) (pp. 336) where for a given Y k-dimensional random vector and h a scalar random variable, if $Y|h, \mu, \Sigma \sim N(\mu, h^{-1}\Sigma)$ and $h|m, \nu \sim \gamma(m, \nu)$ then $\theta = (Y', h)'$ has a normal-gamma distribution denoted $\theta \sim NG(\mu, \Sigma, m, \nu)$.

[9] Note that the priors can be fixed to be the same for each of the regime

for a specific month. This is done in order for South African prices to be compatible with monthly world prices as reported by the World Bank in its commodity price data bank. World Bank prices are reported in \$/ton and was converted into ZAR/ton by multiplying the reported world price in a specific month, with the prevalent average exchange rate for the associated month. For the sake of consistency the exchange rate used in the above mentioned calculation, is the ZAR/USD average monthly nominal exchange rate as reported by the World Bank.

South Africa is a relatively small maize producer by international standards but the industry plays a key role in the local and regional agricultural and food sector. Maize can serve as an alternative product to some horticultural crops such as potatoes, produced in the mid Eastern regions of South Africa. Specific attention is given to white maize and its associated prices as a result of the prevalence of this commodity in the diet of lower income groups in South Africa. White maize is a staple food for the low income proportion of the population, whereas yellow maize is a key input in livestock and poultry production. Also, a higher percentage of the total area planted to maize in South Africa is white maize - more than 60 % from 2000 to 2010 (Table 3). White and yellow maize prices in South Africa move close together, with white maize trading at a premium of about ZAR200/ton.

The rate at which world prices of yellow maize (the volume of yellow maize traded internationally is much larger than that of white maize and as a result the international focus is on yellow maize) transmits to domestic white maize prices in South Africa are therefore imperative in order to understand the effect of global commodity market shocks on poor consumers in South Africa.

It is expected that the prices of maize in South Africa shift between three regimes as discussed in Meyer *et al.* (2006). These are:

- Import Parity: The import parity price is the world price of a commodity plus transport and tariff costs. The difference between import parity price and the domestic price exceeds transfer costs and the possibility of arbitrage integrates the local and world markets at prevailing international prices. This would trigger imports of the commodity into the South African market. One would expect the market price in South Africa to move with the price on international markets, plus the cost of shipping commodities to South Africa.

- Autarky: If domestic prices are below that which triggers imports, but not low enough to be competitive on international markets, domestic prices will be determined by supply and demand conditions in the local market.

- Export Parity: The export parity price is the price one could get for exporting a good from a given location, given the world price and the cost of delivering it to international markets. The difference between export parity price and the domestic price exceeds transfer costs and the possibility of arbitrage integrates the local and world markets at prevailing international prices. The country can export commodities to the world market.

The South African and world maize price series is plotted in Figure 3. From the figure, there is reason to believe that the two prices move together. However, standard cointegration tests for these two prices shows no evidence of cointegration with no long run and consequently short run adjustments found between the two prices using standard cointegration tests. The figure also shows that when the two prices are close to each other, the correlation seems to be more noticeable than when the differences are larger. This gives an indication of the existence of a form of threshold cointegration. Cointegration is therefore only triggered in certain periods based on the level of price differences and adjustments in the short run when the prices differ.

Univariate time series properties of the prices are presented in Tables 4 to 7. The table shows that South African white maize spot prices are not stationary using the Augmented-Dickey Fuller (ADF) and Phillips-Perron tests. It however has a unit root that is difference stationary. Similar properties for the world yellow price shows the series is nonstationary at the levels but difference stationary using the ADF and the Phillips-Perron tests.

Using the AIC and BIC lag selection method to select the appropriate lags, we selected a maximum lag length of 1 ($p = 1$) for both series are selected. In practical terms, this makes sense since one month lag is sufficient to import or export between South Africa and United States for instance. With this lag length, d also reduces to 1.

5.1 Empirical Results

We first focus on the results of the marginal likelihoods for each of the 11 models estimated. Assuming equal probability for the various models the posterior odds for each model will be the ratio of the posterior model probabilities. The posterior probabilities are presented in Table 8 and shows that the model with three regimes, which allows for heterogenous variance across regimes defined by the lag of the price difference, received the highest posterior model probability. The value of the marginal likelihood relative to the other models indicate that this model and nonlinearity in particular is strongly supported by the data. It should also be noted that the lag of the price spread and not a change in the price spread is what defines the regimes. Second to this model is the two regime heterogeneous model with a price spread lag as the trigger. The result indicate that not only are there regime switches between South African price and world price, but the error variance are heterogenous across regimes with the heterogeneous models outperforming models that are homogeneous. Also, evidence for the model with symmetric price transmission is weak as expected. These results are also robust to prior sensitivity analysis.

The result of the threshold cointegration model is presented in Table 9. The estimate of ρ in the table shows that cointegration does not hold when in regime 2 with ρ not different from 1. However, when the the lag price spread moves outside of the threshold of regime 2, equilibrating price adjustments kicks in and cointegration exists between the two series. Higher prices in South Africa in this period also appear to have a self regulating lower price in the next period with the parameters on the lag of South African maize prices negative.

The long run multiplier between South African maize prices and world maize prices is 0.9780 when prices are in regime 1 and 0.9720 when in regime 3. This shows evidence of price transmission between local and international prices and the influence of South Africa in the maize market. About 98 percent of the variation in world prices is eventually transmitted to the maize price in South Africa when the variation occurs in regime 1 and about 97 percent in regime 3. Though the long run transmission is similar in both regimes, the speed of adjustment differs. The adjustment rate is faster in regime 3, with 0.4602, than in regime 1, with 0.3631.

To interpret the results in terms of import and export parity, Regime 1 correspond to export parity, regime 2 to autarky and regime 3 to import parity. In the autarky regime, no long run relationship exists between the two prices with no price transmission in the absence of trade. The speed of adjustment is higher in the import parity regime given that higher South African prices will result in various countries exporting to South Africa and trigger imports into the market. The speed of adjusting the prices to equilibrium is lower when trading at export parity since the size of South African market is small compared to the world market for maize.

Table 10 presents the critical threshold for the *preferred* model and its associated probabilities for thresholds with probabilities greater than 0.01. It should also be noted that these threshold values are averaged over the sample data period (2000-2010). The model with $r_1 = 27.0102$ and $r_2 = 125.9644$ has the highest posterior probability with 0.5314. Next to this is the cutoff with $r_1 = 30.9085$ and $r_2 = 155.8436$ with probability of 0.0382. While our estimates are averaged over all the possible critical threshold values, there is overwhelming evidence in favor of the critical thresholds of $r_1 = 27.0102$ and $r_2 = 125.9644$. This however has to be interpreted with caution given the spike in oil prices since 2005. The changes in oil prices since 2005 have resulted in higher transportation costs around the world. In order to capture this and measure it's impact on the threshold value, we split the sample into two periods (before and after the oil shock in 2005) - Figure 2.[10] The results shows a difference in the threshold values for the two periods with the after oil price shock threshold for export parity estimated to be around - ZAR 55 and that of import parity at around ZAR152 which is about 22 percent higher than the average for the whole period. The average before the oil spike period is even lower at - ZAR 13.33 for export parity and ZAR75.53 for import parity (about 50 percent lower than the higher oil price period).[11]

The estimated threshold values indicate what the value of the spread should be for the market to be functioning in import or export parity. With the threshold value for export parity at - ZAR 55 post oil shock for example. This implies that to induce trade and for the market to be functioning at export parity, the price of white maize in South Africa must be less than the world price by ZAR55. If this is the case prices would be transmitted between the two markets. That is, transmission occurs at the

[10]As we highlighted earlier, transportation cost is one of the major cause of price differentials across borders. With a shift in the mean of the price of crude oil as is shown in the figure, one will expect that the trigger for the threshold will also change. Here we present a simple way to capture this effect by calculating the threshold before and after the oil price shock.

[11]Oil price has increased by more than 50 % since 2005

export parity level as long as the difference between the South African white maize and world price for yellow maize is less than ZAR55. The threshold value for import parity is ZAR152. This is an indication that SA prices should be at least ZAR152 a ton higher than world prices for the market to function at import parity and for prices to be transmitted, as discussed above. The fact that the import threshold spread is much higher than the export spread might be attributed to the main destinations of imports and exports. White maize imports to South Africa usually originate from Zambia and other regional trading partners while exports are also predominantly to regional countries. Yellow maize, in contrast to this, are usually imported from “deep sea” destinations such as Argentina and Uruguay and Eastern European countries such as Romania, with predominantly regional exports. In practical terms, a big proportion of maize exports are delivered regionally and imports (especially in the case of yellow maize) come mainly from “deep sea” destinations.

We are also interested in how many periods it takes for some portion of the total effect of a shock on the price spread to dissipate in the export and import parity regimes. One of such measures is the deviation half-lives. This is approximated by $ln(0.5)/ln(1+\rho)$. In the the two regimes, this is about half the planting season for corn at around 2.25 months. Thus the half of the total effect of a shock on the price spread that makes the price spread increase in the import parity and export parity regimes will take about 2.25 months to dissipate.

Finally, the results of the short-run error correction component of the preferred model is presented in Table 11. Though the short run adjustment for a change in world price can also be calculated from the results of the threshold cointegration, the short run effect of a change in the price spread is appropriately captured by the ECM model. The results show that a one unit increase in the price spread in the import parity region will result in the reduction of prices in South Africa by 0.1314 in the next period, *ceteris paribus.* Short run effect of a unit change in the price spread in the export parity region is not different from zero - international commodity market for corn does not seem to respond to change in the price spread in the short run. The short run effects of a change in the world price on South African price is 0.3630 in the export parity regime and about 0.4599 in the import parity regime. Market failures/ market distortions (this can hamper the incentives for economic agents to adapt to external shocks quickly) in the local markets of the main trading partners (e.g. Zambia, Kenya, Mozambique and Malawi) of South Africa can be possible reasons for the slow short run adjustments in the results.

6 Summary and Conclusions

The effect of the dramatic commodity price increases in 2007-2008 and again in 2010 has beckoned the question: “How exposed are developing countries in Sub-Sahara Africa to increasing world commodity prices? Previous attempts to quantify this were predominantly based on cointegration techniques, with limited provision for non-linearity that might be prevalent in the model. For example, earlier studies on transmission of world prices to local prices in South Africa using cointegration techniques found no long-run relationship between the series.

In this study we applied the concept of threshold cointegration to understand price transmission. The concept of *threshold cointegration* has become popular in applied economic research. It captures the fact that equilibrium adjustment does not have to occur at every instant in a series and while cointegration may be present, a band may exist such that factors such as transaction costs and adjustment cost may be too high to make equilibrium adjustments justified. We make use of a Bayesian framework that allows for comparison of linear and non-linear models and provides empirical evidence of price transmission between world and South African markets. The results show that threshold effects exist, such that small changes in world prices are not transmitted to domestic markets South African maize markets. Only large long-run deviations in price are transmitted. An example of such a deviation is the spike in oil prices that has increased transport cost. Further results show that global prices take longer to filter through to South African prices, when the market is trading at export parity, compared to import parity. This can possibly be attributed to the export trading partners of South Africa, of which a large portion is in the region and also due to the small size of the South African market, by international standards.

Particular interest was given to maize in South Africa for two reasons. Firstly, due to the central role that maize plays in the diets of the low income groups in South Africa. An improved understanding of how international prices affect local prices, would aid in the understanding of how food security, in terms of food affordability, is affected by global shocks. This could ultimately assist in devising policies that would ensure improved food security. Secondly, South Africa can be regarded as the largest consistent maize producer in the region. Price formation and changes in South Africa are therefore expected to have an impact on local prices of regional trading partners such as Zambia, Malawi and Kenya. This, in turn, ultimately speaks to market efficiency and food security in the whole region. This study therefore also serves as a starting point for future research into whether and to what extent, world prices influence other Sub-Saharan African maize prices via the South African market.

References

Abdulai, A. (2000). Spatial Price Transmission and Assymetry in the Ghanaian Maize Market *Journal of Development Economics*, 63, pp. 327-349.

Ardeni, Pier G. (1989). Does the Law of One Price Really Hold for Commodity Prices? *American Journal of Agricultural Economics.*, 71 (3), pp. 661-669

Balke, N.S. and T.B. Fomby (1997). Threshold Cointegration, *International Economic Review*, 38 (3), 627-645.

Balcombe, K. A. Bailey and J. Brooks (2007). Threshold Effects In Price Transmission: The Case of brazillian Wheat, Maize, and Soya Prices, *American Journal of Agricultural Economics*, 89 (2), 308-323.

Barrett, C.B. (1996). Market Analysis Methods: Are Our Enriched Toolkits Well-Suited to Enlivened Markets?, *American Jornal of Agricultural Economics*, 78 (August), 825-829.

Blauch, B. (1997). Spatial Arbitrage and Testing for Market Integration. *American Journal of Agricultural Economics*, Vol 79(2), pp 477-487.

Blyn, G. (1973). Price series correlations as a measure of market integration. *Indian Journal of Agricultural Economics*, Vol. 28, pp. 477-487.

Campbell, J.Y., (1987). Does Saving Anticipate Declining Labor Income? An Alternative Test of The Permanent Income Hypothesis, *Econometrica*, 55, 1249-1274.

Campbell, J.Y and R.J. Shiller (1987). Cointegration and Tests of Present Value Models, *Journal of Political Economy*, 95, 1062-1088.

Conforti, P. (2004) Price transmission in selected agricultural markets. *FAO Commodity AND Trade Policy Research Working Paper.* No. 7

Cudjoe, G., Bresinger, C. & Diao, X. (2008). Local Impacts of a Global Crisis - Food Price Transmission and Poverty Impacts in Ghana. *IFPRI discussion paper - Development Strategy and Governance Division*. December 2008.

Cummings, R.W. Jr. (1967). *Pricing efficiency in the Indian wheat market*. Impex India, New Delhi.

Engle, R.F. and C.W.J. Granger (1987). Co-integration and Error Correction: Representation, Estimation, and Testing, *Econometrica*, 55, 251-276.

FAO (2006). Food Outlook: Global Market Analysis. *Ecoomic and Social Development Department*, No. 2 December.

Goodwin, B.K and N.E. Piggott (2001). Spatial Market Integration In The Presence of Threshold Effects, *American Journal of Agricultural Economics*, 83 (2), 302-317.

Goodwin, B.K and T.C. Schroeder. (1991). Cointergration tests and spatial price linkages in regional cattle markets. *American Journal of Agricultural Economics*, Vol. 73(2), pp. 452-464

Granger, C.W.J. (1986). Developments in the Study of Cointegrated Economic Variables, *Oxford Bulletin of Economics and Statistics*, 46, 213-228.

Kilima, F.T.M. (2006). Are prices in the world market transmitted to less developed countries? A case study of Sugar, Cotton, Wheat and Rice in Tanzania. *Institute for International Integration Studies.*

Kirsten, Johann F. (2012) The Political Economy of Food Price Policy in South Africa. University of Pretoria Working Paper.

Koop, G., D.J. Poirier and J.L. Tobias (2007). *Bayesian Econometric Methods*, Cambridge, Cambridge University Press.

Koop, G. and S. Potter (1999). Bayes Factors and Nonlinearity: Evidence from Economic Time Series, *Journal Of Econometrics.* 88 (2) pp. 251-281

Koop, G. and S. Potter (1999). Dynamic Asymmetries in U.S. Unemployment, *Journal of Business and Economic Statistics.* 17 (3) pp. 298-312

Koop, G. and S. Potter (2000). Nonlinearity, structural breaks or outliers in economic time series? In William Barnett et al.(ed.), *Nonlinear Econometric Modelling.* Cambridge: Cambridge University Press.

Lloyd, T.A., Morgan, C.W., Rayner, A.J and C Vailant. (1999). The transmission of world agricultural prices in Cote d'Ivoire. *The Journal of Trade and Economic Development*, Vol.8(1), pp. 125-141.

McNew, K., and P. Fackler. (1997). Testing Market Equilibrium: Is Cointegration Informative?, *Journal of Agricultural Resource Economics*, 22 (Dec.), 191-207.

Meyer, F.H., P. Westhoff, J. Binfield and J.F. Kirsten. (2006). Model closure and price formations under switching market regimes. *Agrekon.* Vol. 45(4). pp. 370-380.

Minot, N. (2011) Transmission of world food price changes to markets in Sub-Saharan Africa, *International Food and Policy Research Institute Discussion Paper.* www.ifpri.com.

Myers, R.J. and T.S. Jayne. (2012). Multiple-regime spatial transmission with an application to maize markets in Southern Africa. *American Journal of Agricultural Economics*. Vol.94(1), pp. 174-188.

Myers, R.J. (2010). Evaluating the Efficiency of Inter-Regional Trade and Storage in Malawi Maize Markets. *Report for the World Bank*. October 2010.

Negassa, A and Myers, R.J. (2007). Estimating Policy Effects on Spatial Market Efficiency: An Extension to the Parity Bounds Model. *American Journal of Agricultural Economics*, Vol. 89(2), May 2007, pp. 338-352.

Rashid, S. (2004). Spatial integration of maize markets in post-liberalized Uganda. *International Food and Policy Research Institute*. www.ifpri.com.

Rayner, A.J., Vaillant, C., Lloyd, T. and Morgan, C.W., (1999). World Price Transmission in Cote d'Ivoire, *Journal of International Trade and Economic Development*, Vol. 8, pp. 125-141

Ravallion, M. (1986) . Testing Market Integration. *American Journal of Agricultural Economics*, Vol 68 (1), pp. 102-109.

Richardson, J.D. (1978). Some empirical evidence on commodity arbitrage and the law of one price. *Journal of International Economics*, Vol. 8 (2) May 1978, pp.341-351

Sexton, R.J., Kling, C.L. and H.F. Carman. (1991). Market integration, efficiency of arbitrage and imperfect competition: methodology and application to US celery. *American Journal of Agricultural Economics* , Vol. 73, No. 3 (Aug., 1991), pp. 568-580

Stigler, J.S and Sherwin, R.A (1985). The extent of the market. *Journal of law and economics*, Vol 28, No.3 October 1985, p. 555-585.

Tostau, E and W. Borsen. (2005). Spatial Efficiency in Mozambique's Post Reform Maize Markets. *Agricultural Economics*, 33(2), 205214.

Van Campenhout, B. (2006). Modelling trends in food market integration: Method and an application to Tanzanian maize markets, *Food Policy*, 32 (1), 112-127.

7 Tables and Figures

Table 1: Related Spatial Price Transmission Studies by Country and Method Used

Author(s)	**Study**	**Focus**	**Country**	**Method**
Abdulai, A.(2000)	Spatial price transmission and asymmetry in the Ghanaian maize market.	Asymmetric movements of prices within Ghana.	Ghana	TAR
Kilima, F.T.M. (2006)	Are prices in the world market transmitted to less developed countries?	Determining the effect of global shocks on cotton, sugar, rice and wheat prices.	Tanzania	Cointegration
Minot, N. (2011)	Transmission of world food price changes to markets in Sub-Saharan Africa	Determining the effect of global shocks on food prices in Africa.	Various	VECM / Cointegration
Myers, R and T.S Jayne. (2012)	Multiple-regime spatial transmission with and application to maize markets in Southern Africa	Regime identification based on quantities traded and not on price spreads.	Zambia	TAR/TIC
Myers, R.J. (2010)	Evaluating the efficiency of Inter-Regional Trade and Storage in Malawi Maize Markets	Efficiency of inter-regional trade in Malawi.	Malawi	TAR
Rashid, S. (2004)	Spatial Integration of maize markets in post liberalized Uganda	Efficiency of inter-regional trade in Uganda	Uganda	VECM / Cointegration
Tostau, E and W. Borsen. (2005)	Spatial Efficiency in Mozambiques post reform maize markets	Efficiency of inter regional trade in Mozambique	Mozambique	PBM
Van Campenhout, B. (2007)	Modelling Trends in Food Market Integration: Method and Application to the Tanzanian Maize Market	Efficiency of inter-regional trade in Tanzania.	Tanzania	TAR

Table 2: Data and Sources

Data Series	**Description**	**Unit**	**Time length**	**Source**
South African Maize producer Prices	Monthly SAFEX White Maize Spot Prices (R/ton)	ZAR/ton	Jan 2000 Dec 2010	South African Futures Exchange
International Maize Prices	Monthly World Corn Price (R/ton)	Converted from $/ton to ZAR/ton	Jan 2000 Dec 2010	World Bank Commodity Price Data

Table 3: Area planted maize

Year	White Maize	Yellow Maize
2000	62%	38%
2001	59%	41%
2002	61%	39%
2003	72%	28%
2004	66%	34%
2005	60%	40%
2006	65%	35%
2007	62%	38%
2008	62%	38%
2009	61%	39%
2010	63%	37%

Source: Author's computation using data from SAGIS/CEC Area Planted & Final Production Estimate - Summer Crops Publication (Various Years).

Table 4: Time Series Properties of South African Maize Price

Intercept and Trend Model

Lags	Critical Value (5%)	ADF Test Statistic	PP test statistic	Stationary
3	-3.4452	-2.526599	-2.0678	No
2	-3.445	-2.403898	-1.9744	No
1	-3.4447	-2.313538	-1.8384	No
0	-3.4445	-1.570083	-1.57	No

Conclusion: SA White Maize Price is non-stationary

Table 5: Time Series Properties of First Difference of South African Maize Price

No Intercept and Trend Model

Lags	Critical Value (5%)	ADF Test Statistic	PP test statistic	Stationary
3	-1.9424	-4.76922	-7.9395	Yes
2	-1.9424	-5.29222	-7.9204	Yes
1	-1.9424	-6.60513	-7.9404	Yes
0	-1.9424	-7.92715	-7.9271	Yes

Conclusion: First Difference of SA White Maize is stationary with unit root.

Table 6: Time Series Properties of World Yellow Maize Price

Intercept and Trend Model

Lags	Critical Value (5%)	ADF Test Statistic	PP test statistic	Stationary
3	-3.4452	-2.30753	-2.0251	No
2	-3.445	-1.95322	-1.9384	No
1	-3.4447	-1.98124	-1.8992	No
0	-3.4445	-1.7982	-1.7982	No

Conclusion: World Maize Price is non-stationary

Table 7: Time Series Properties of the First Difference of World Yellow Maize Price

No Intercept and Trend Model

Lags	Critical Value (5%)	ADF Test Statistic	PP test statistic	Stationary
3	-1.9424	-4.93819	-10.306	Yes
2	-1.9424	-5.35253	-10.268	Yes
1	-1.9424	-7.66236	-10.278	Yes
0	-1.9424	-10.2784	-10.278	Yes

Conclusion: First Difference of World Maize Price is stationary with unit root.

Table 8: Classes of Models and Corresponding Marginal Likelihood

Models	*Threshold Trigger*	Marginal Likelihood
Linear	-	1
2THOZ	Z_{t-1}	6.07
2THODZ	ΔZ_{t-1}	37.14
2THOAZ	$\|Z_{t-1}\|$	8.78
2THEZ	Z_{t-1}	4.07E+06
2THEDZ	ΔZ_{t-1}	57.78
2THEAZ	$\|Z_{t-1}\|$	2.56E+06
3THEDZ	ΔZ_{t-1}	1.54E+04
3THEZ	Z_{t-1}	6.47E+7
3THODZ	ΔZ_{t-1}	1.27E+03
3THOZ	Z_{t-1}	18.55

Table 9: Result for the Threshold Cointegration Model

Variables	Regime 1 (out)	Regime 2 (In)	Regime 3 (out)
Constant	28.8007 (20.2178)	-20.4866 (32.0018)	45.9647 (53.5289)
P^s_{t-1}	-0.3631 (0.0634)	-0.5030 (0.1248)	-0.4602 (0.1993)
P^w_t	0.3551 (0.0654)	0.4564 (0.1332)	0.4473 (0.1859)
ρ	0.3560 (0.1286)	1.0768 (0.5238)	0.3657 (0.2192)
σ^2	2473.9 (631.6)	2290.3 (1221.7)	1521.2 (2486.0)

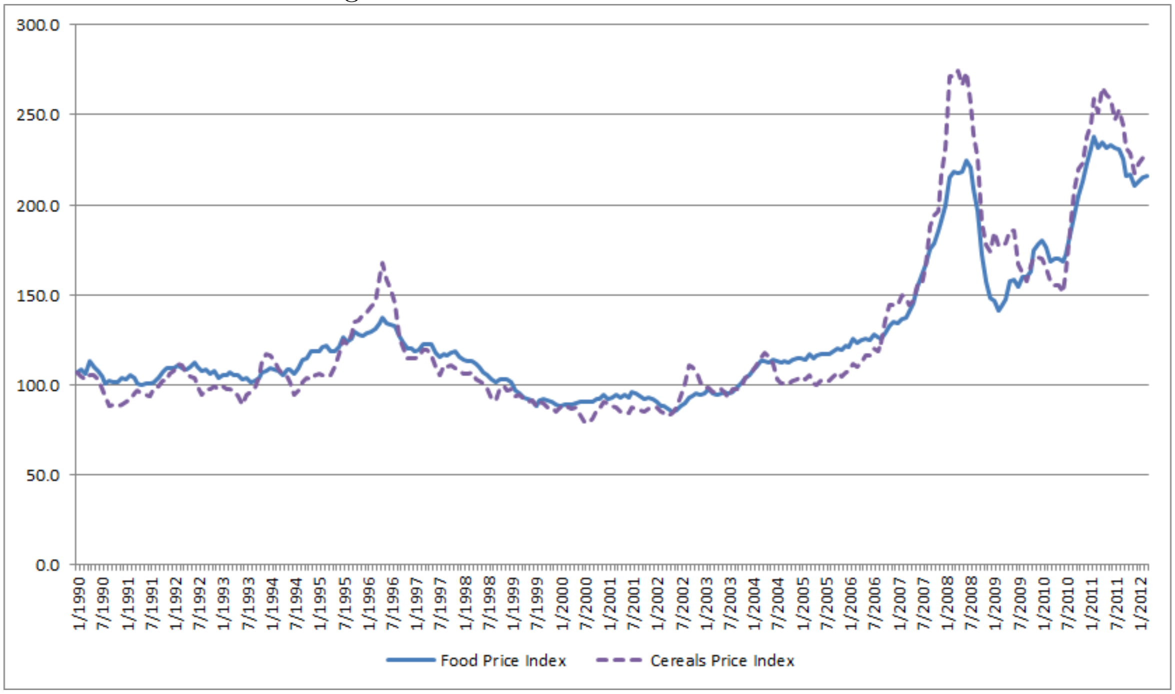
Table 10: Critical Thresholds for the Three Regime Heterogeneous Model with Associated Probability

$r1$	$r2$	$Prob(\tau_i \vert Y)$
27.0102	125.9644	0.5314
30.9085	155.8436	0.0362
19.7415	125.9644	0.0242
30.9085	145.0203	0.0230
-1.1997	125.9644	0.0213
27.0102	155.8436	0.0195
52.0900	155.8436	0.0160
30.9085	151.8962	0.0155
30.9085	140.3110	0.0144
30.9085	147.8235	0.0137

Table 11: Result for the Error Correction Model

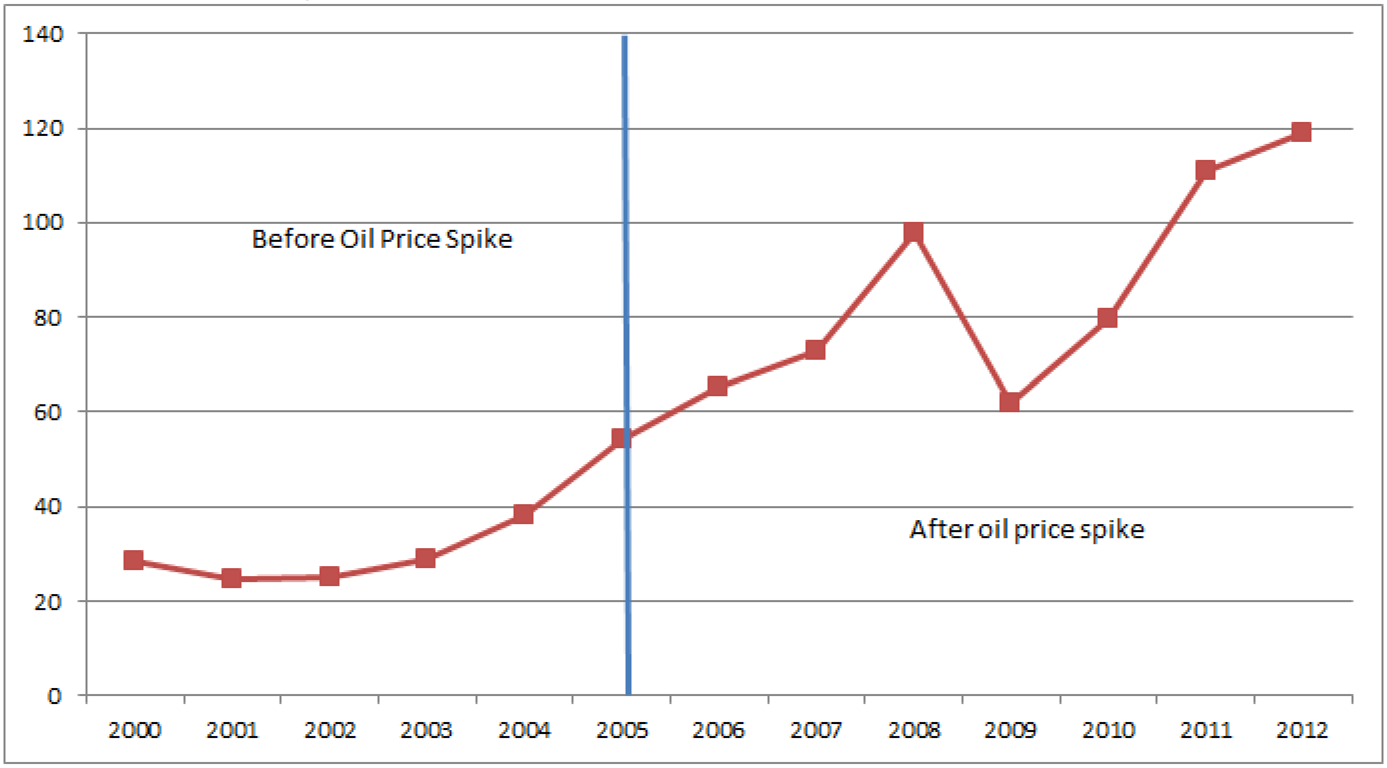
	Regime 1 (out)	Regime 2 (In)	Regime 3 (out)
Constant	21.1001	-14.7196	44.2703
	(11.8561)	(28.8851)	(28.0849)
ΔP^s_{t-1}	-0.0490	0.2565	0.3743
	(0.1117)	(0.0.1186)	(0.1042)
ΔP^w_t	0.3630	0.5602	0.4599
	(0.0629)	(0.11167)	(0.1674)
λ	0.0067	0.0624	-0.1327
	(0.0999)	(0.3121)	(0.0589)
σ^2	2464.1	1780.6	13198.0
	(621.8)	(819.7)	(2141.0)

Figure 1: Food and Cereal Price Index



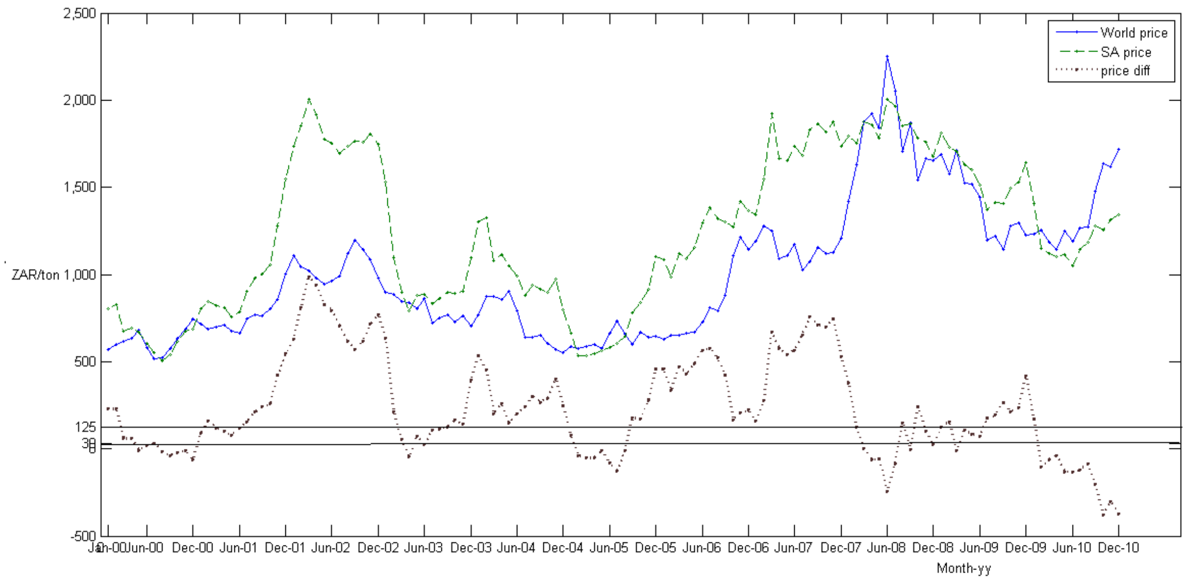
Source: Food and Agriculture Organization of the United Nations

Figure 2: Crude Brent Oil Prices 2000 - 2010



Source: Bloomberg

Figure 3: World and South African Maize Price Series and differences



Source: South African Fututres Exchange and World Bank Commodity Price Data