Adoption of Genetically Modified Crops in South Africa:
Effects on wholesale maize prices

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235 - Adoption of Genetically Modified Crops in South Africa: Effects on wholesale maize prices

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Abstract

The ability of genetically modified (GM) crops to increase yields and reduce use of pesticides is well established. Based on food security needs and the central role of agriculture, Africa may stand to benefit from green biotechnology given the low agricultural productivity and the looming food crises in most urban areas. However, the adoption of GM crops in Africa has been slow and limited to a handful of countries. The primary objective of this paper is to evaluate the impact of GM maize adoption in South Africa by looking at wholesale spot prices. We are apply a threshold autoregressive model to time series data on price of maize and GM adoption rates in South Africa to address the following questions: (1) Does the adoption of GM maize excite the growth rate of price of maize in South Africa; (2) Does the error variance of the maize price growth rate exhibit regime-switching behavior to impact the volatility? The results shows evidence that the adoption of GM maize influences the dynamics of the maize price growth rate in South Africa. Further, there is strong evidence that the error variance exhibits regime-switching behavior with the posterior mean for the error variance in the first regime about twice as large as that of the second regime. The paper closes with some conclusions and summary of key points.

[1] The authors are listed alphabetically, and not as a reflection of senior authorship.

1. Introduction

The ability of genetically modified[1] (GM) crops to increase yields and reduce the use of pesticides is well established (National Academies, 2012; Brookes and Barfoot, 2012; Benbrook, 2012). According to the recently published report on the "Global status of commercialized biotech/GM crops", developing countries are, for the first time in history, growing more GM crops than industrialized countries as measured by total area planted (Clive, 2012). For a technology that represents the efficiency frontier in food and fiber production, this key milestone positions GMO crops as a new tool for improving food security and alleviating poverty in developing countries.

Based on food security needs and the central role of agriculture to economic development, Africa may stand to benefit from green biotechnology given the low agricultural productivity especially among smallholder farmers and the looming food crises in most urban areas. Yet, despite scientific consensus about the safety of GM crops, public skepticism about this technology continues to grow. In most African countries, public polices and regulations on GM crops are increasingly shaped by public opinion, civic organization and pressure groups. Empirical evidence from African countries that have commercialized GM crops is crucial for an informed dialogue on the economic, environmental and public health implication of GM crops adoption in Africa.

This paper evaluates the effects of GM maize adoption in South Africa. To put the analysis into context, we first explore the key trends on green biotechnology adoption in Africa. This is followed by a brief discussion of the structure, conduct and economic performance of maize production in South Africa. Against this background we chronicle the adoption of GM crops in South Africa with a focus on the maize. The quantitative part of the paper starts with the econometric model, followed by a description of the data, and a discussion of the results. The model applies the Threshold Autoregressive (TAR) methodology to the growth rate of wholesale maize prices in South Africa by evaluating if GM maize adoption rates excite grain price series. The paper closes with some conclusions and summary of key points.

2. Adoption of GM crops in Africa

As of 2012, GM crops were being grown in 20 developing countries and 8 industrial countries conferring beneficial traits such as herbicide tolerance, insect resistance and nutritional enhancement (Clive, 2012). Ironically, in the same year when developing countries take the lead in GM crop adoption, three European countries – German, Sweden

[1] Genetically modified crops are those that have had specific changes introduced into their DNA by genetic engineering techniques or modern biotechnology to carry one or more beneficial new traits. The terms genetically modified crops, biotechnology and genetically engineered crops are used interchangeably in this paper. 'Green biotechnology' refers to application of this technology on agriculture as opposed to 'blue biotechnology' that refers to medicinal and pharmaceutical applications.

and Poland – discontinued planting GM crops. This anomaly in technology adoption trends perhaps confirms Paarlberg's (2008) thesis that without tangible consumer benefits, citizens in rich countries consider GM foods as unnecessary. Developing countries, on the other hand, are increasingly looking at GM crops to sustainably feed their ever growing populations. Indeed, many tropical crops crucial to the livelihoods smallholder farmers, such as cassava, bananas and papaya, are currently being decimated by diseases for which resistance imparted into GM varieties represents the only protection against devastating crop losses (GMO Compass, 2006).

African agriculture is characterized by low productivity. While in Asia cereal yield grew by about 2.3 percent per year in the past two decades, cereal yield in Sub-Saharan Africa has been practically stagnant. Furthermore, over the last four decades, less than 40 percent of the gains in cereal production in Africa came from increased yields (FAO, 2011). The rest of the increased production resulted from expanding cultivated land. Africa's low agricultural productivity has been attributed to a host of factors related to the range and intensity of biophysical constraints to plant growth, large agro-ecological variation, the absence of policies that encourage crop improvement, very low and declining soil fertility, and the underdeveloped state of seed sectors in most countries (DeVries & Toenniessen, 2001). Increased productivity in these agrarian systems, achievable through green biotechnology bears great potential to reducing poverty and improving food security.

Despite the potential advantages, adoption of GM crops in Africa has been slow. At present only four African countries – Burkina Faso, Egypt, Sudan and South Africa – have fully commercialized GM crops. Table 1 shows the area planted to GM crops in Africa during the 2012 cropping year.

Table 1: GM crop adoption in Africa (Hectares planted in 2012)

Country/Crop	**Cotton**	**Soybean**	**Maize**	**Total**
Burkina Faso	300,000	0	0	300,000
Egypt	0	0	1,000	1,000
South Africa	15,000	382,000	1,873,000	2,300,000
Sudan	200,000	0	0	200,000
Total	515,000	382,000	1,874,000	2,801,000

Source: Compiled from Clive (2012)

Yet Table 1 does not tell the full story of GM adoption in Africa. Most African countries are at various stages of creating the enabling environment for GM crop commercialization. Of note, five countries (Cameroon, Kenya, Malawi, Nigeria and Uganda) are currently conducting field trials of biotech crops, the final step before full approval for commercialization. One level lower on the adoption ladder are countries that have put in place the requisite policy and regulatory frameworks. Most African countries have signed and ratified the Convention on Biological Diversity as well as the Cartagena Protocol on

Biosafety (Nang'anyo, 2006). That said, there is growing public opposition to GM crops in Africa that is best described as a fear of the unknown, with little or no scientific merit. For example, in November 2012 the Kenyan government banned all imports of GM foods citing public health concerns.

3. Maize Production and Consumption in South Africa

South Africa is a net exporter of maize, producing about 50% of the maize grain output in Southern Africa. In the 2011/12 cropping season, South Africa produced about 66.4 million tonnes of white maize and 5.4 million tonnes of yellow maize at an average yield of 3.9t/ha and 4.7t/ha respectively (Grains SA, 2013). Figure 1 below shows the total production area planted and average yields for maize in South Africa from 1990 to present. Note that with the possible exception of drought years in 1991/92, 1994/95 and 2006/07 increased production was primarily due to rising yields while area under cultivation has declined.

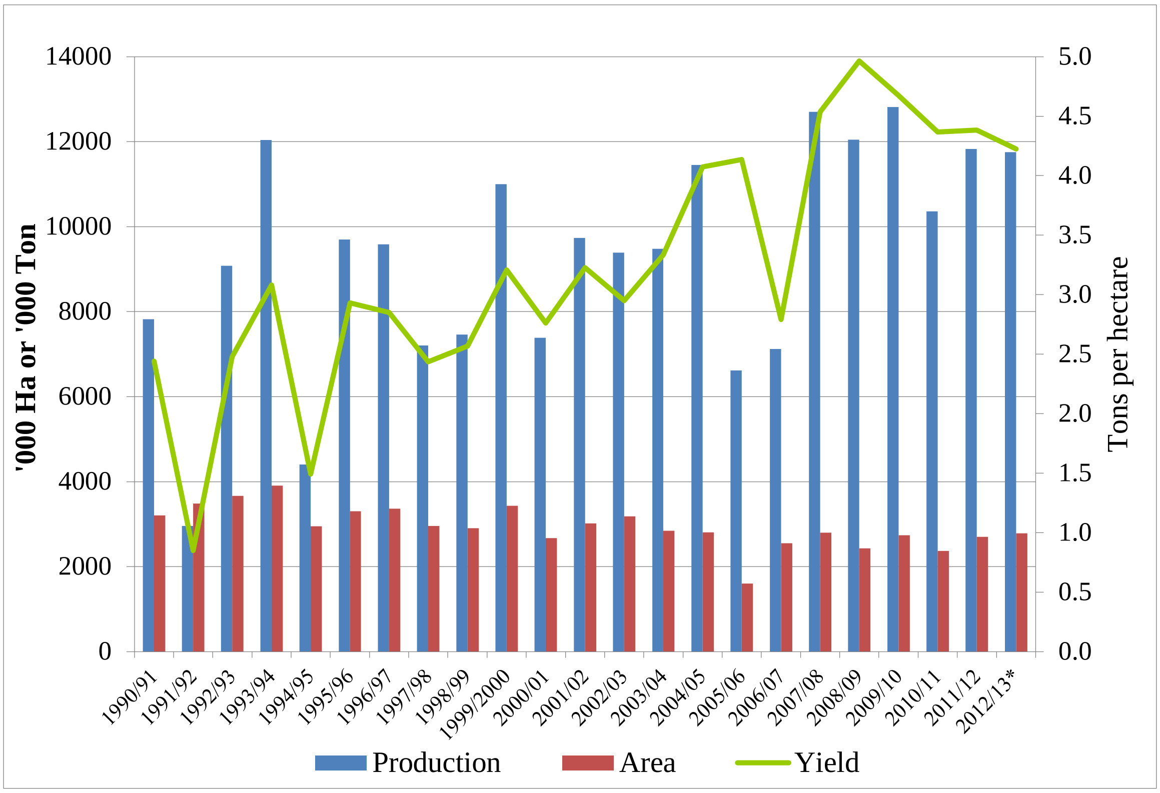

Figure 1: Maize production in South Africa (Data source – Grains SA, 2013)

Maize production in South Africa is dominated by commercial growers who produce more than 90% of the country's maize crop (Gouse et al, 2009). While maize is grown in all nine provinces of the country the bulk of the production is in the Freesate, Mpumalanga and North West provinces. Nearly all of South Africa maize production is rain fed. Although the cropping calendar varies by location and year, the bulk of the planting takes place in November and harvesting starts in April.

In this paper, we seek to measure the impact of GM maize adoption in South Africa by looking at the dynamics of prices over the period of adoption. White maize is one of the major staple foods in South Africa (particularly for low income households) with the gains from adoption of GM maize expected to be seen in low prices or reduction in the growth rate of the price. Also, high volatility in prices is undesirable to both farmers and final consumers. We also seek to measure if GM maize adoption has any impact on volatility in South Africa.

4. GM Maize adoption in South Africa

South Africa was the first African nation to commercialize GM crops with the planting of Bt cotton in 1997. This was followed closely by the commercialization of Bt maize (Monsanto 810) in 1998 and herbicide tolerant (HT) cotton and soybean in 2000. South Africa established a Government committee, SAGENE to draft biosafety guidelines as early as 1978 and field-tested its first biotech crop, Bt cotton, in 1990 that was first commercialized in 1997. Bt cotton was followed by Bt maize (MON 810) commercialized in 1998, herbicide tolerant (HT)[1] cotton and soybeans in 2000, the dual Bt in cotton (Bollgard II) in 2002, and another insect resistant maize (Bt11) in 2003.

GM crop adoption in South Africa was rapid especially among commercial farmers. In the 2011/12 growing season, an estimated 2.3 million hectares of land in South Africa was planted to GM crops up slightly from 2.2 million hectares in the previous year. Leading this high adoption are maize farmers who plated 1.873 of 2.6 million hectares under maize. (Clive, 2013) The adoption rate for GM maize by area planted was approximately 72% shared equally between white and yellow maize. Based on 2009/2010 figures GM yellow maize adoption consisted of the following events (number in parenthesis representing % for yellow maize): Bt (26%), herbicide tolerant (15%), and stacked Bt/Herbicide tolerant (20%). Similar figures for white maize are as follows: Bt (60%), herbicide tolerant (5%) and stacked Bt/herbicide tolerant (8%) (Clive, 2013).

This paper uses adoption rates data for GM maize from 1999/00 to 2011/12 growing seasons as presented in Table 2. Most data sources on the adoption of GM maize in South Africa are incomplete and inconsistent. The primary data are derived from self-reported seed sales by private companies that are extrapolated into total area planted using either recommended or average seeding rates. Three data sources were used to derive adoption rates for GM maize in South Africa as given in Table 2. Total areas of GM maize and GM white maize from 2001/02 until 2011/12 were either sourced directly or derived from ISAAA reports. Adoption rates for GM maize prior to 2001 were sourced from Gouse et al (2009). Data on total area planted to maize and the percentage planted to white maize was sourced from Grain SA database (Grain SA, 2013).

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[1] Herbicide-tolerant crops are genetically modified to withstand the application of specific herbicides that will kill or stunt weed growth, while leaving the crop unharmed.

Table 2: Adoption rates for GM maize in South Africa

Year	Total (Thousand Hectares)	Proportion White Maize of Total	GMO adoption rate (% of land planted		
			White Maize	Yellow Maize	All maize
1999/00	3429.40	0.61	0.00	0.23	0.09
2000/01	2673.90	0.58	0.00	5.00	2.21
2001/02	2636.17	0.57	0.40	14.08	6.30
2002/03	2950.71	0.68	3.00	18.51	8.00
2003/04	2940.16	0.61	8.00	17.28	11.60
2004/05	3216.69	0.57	8.00	19.07	12.75
2005/06	1531.41	0.63	29.00	31.11	29.78
2006/07	2641.95	0.61	44.00	50.67	46.63
2007/08	2848.02	0.59	62.00	48.44	56.43
2008/09	2829.88	0.56	56.00	58.60	57.14
2009/10	2510.92	0.61	79.00	68.19	74.79
2010/11	2599.70	0.58	75.00	70.21	73.01
2011/12	2600.00	0.57	71.99	71.97	72.04

Source: Complied from various sources

4. Preliminary findings of GM maize impact in South Africa

Empirical evidence from several studies suggests that the economic benefits of GM crop adoption in South Africa have been positive. Brookes and Barfoot (2012) estimate that the farm level economic gains to biotech crop adoption in South Africa from inception in 1998 to 2010 was US$809 million of which US$133 million is attributed to 2010 alone. The rapid adoption of GM crops in South Africa can also be taken as *prema facie* evidence of economic benefits to farmers. Farmers spend more on improved seeds when their characteristics give them greater benefits in terms of higher profits, lower costs or greater convenience.

While much of this benefit has gone commercial farmers who grow the bulk of GM crops in South Africa, smallholder farmers have also participated. A study of smallholder farmers growing GM crops in Mpumalanga, KwaZulu-Natal, Eastern Cape, and Limpopo Provinces in South Africa shows significant gains in productivity (Gouse, 2005). For example, over six-season period from 2002 to 2008, Bt maize seed yielded 12% more grain on average than conventional maize. According to the same study, GM maize performance per unit of land was even more impressive, yielded 22% more than conventional maize in 2005/06 season. The same study concludes that GM maize had enabled significant cost savings on pesticides that offset the higher seed cost. Overall, the net benefit of Bt maize for commercial farmers was on average US $24 per hectare on dryland conditions in the North West Province, US $47 per hectare dryland in Mpumalanga, US $85 per hectare under irrigation in Mpumalanga, and US $149 per hectare under irrigation in the Northern Cape (Gouse, 2005).

In highlighting the benefit of GM crop adoption, it is important to point out four key caveats. First, the benefits of GM crops are not restricted to yield maximization. In fact, the most commonly used GM traits, Bt and herbicide tolerance, are primarily cost saving technologies for farmers. Second, while the net environmental benefits of biotechnology are still contested, there is strong evidence to suggest positive externalities from Bt crops resulting from overall decreases in pests. For example, in China, Bt cotton has lowered bollworm populations to a level where producers of non-Bt cotton and other crops also susceptible to bollworm benefited (Pray et al, 2001). Third, we have to be mindful of the dynamic nature of benefit to GM crops. Specifically, recent studies show diminishing efficacy of both Bt and herbicide tolerate crops as widespread use of the biotechnologies have spurred an increase in "superweeds" and hard-to-kill insects that are resistant to Bt toxins (Benbrook, 2012). Last and perhaps most importantly in the case of South Africa, there is no evidence to suggest that benefits to farmers will translate to lower prices for the consumer. Thus, making the leap from increase production efficiency to improved food security through lower prices may be a *non sequitur* argument. The modern agribusiness value chain often dampens price transmission between wholesale level agricultural commodity prices and retail prices of value added food products.

6. Econometric Model

The Box–Jenkins method of expressing any covariance stationary time series as an autoregressive moving average to find the best fit of the series, based on present and past innovations, has been widely used in the literature to study many important macroeconomic variables. In this section we present a model that is in the spirit of the Box-Jenkins method to capture the impact of an outside shock on the dynamics of a series. Specifically, we employ the threshold autoregressive (TAR) model that is a class of nonlinear time series model, to understand the dynamics of the growth rate of the wholesale spot price of maize in South Africa. While the simple and popular Box-Jenkins method has been applied numerous times, the nonlinear TAR models have gained popularity in recent years because the dynamics of a series might change over a period due to changes in the series itself or by exogenous factors.

The model we use in this paper follows the earlier Bayesian treatment of TAR models similar to Potter (1995), Geweke and Terui (1993) and Chen and Lee (1995). However, in contrast the Self-Exciting Threshold Autoregressive (SETAR) model by Potter (1995) and many similar extensions of the TAR that have been useful in empirical work, we use a model with a threshold trigger outside of itself. Specifically, consider a TAR model for a time series y_t for $t = p+1,\ldots,T$ and $t = 1,\ldots,p,$ initial conditions, represented as:

$$y_t = \beta_0^{(r)} + \sum_{k=1}^{p_r} \beta_k^{(r)} y_{t-k} + \varepsilon_t^{(r)} \quad \textit{for } \tau_{r-1} \le z_{t-d} \prec \tau_r \quad \ldots\ldots (1)$$

Where $r = 1,\ldots,R$ are the R possible regimes and d is a positive integer commonly referred to as the delay parameter or threshold lag of the model. The innovation $\{\varepsilon_t^{(r)}\}$ is a sequence of independent and identically distributed (i.i.d) normal random variates - $\varepsilon_t^{(r)} \overset{iid}{\sim} N(0, h_r^{-1})$. The

τ_s are real numbers that partitions the space of the threshold trigger variable z_{t-d} into R regimes. This model, as Chen and Lee (1995) puts it, is a piecewise linear model in the space of z_{t-d} , but not a piecewise linear model in time.

For the purpose of this study, consider a case where $r = 2$ such that:

$$y_t = \begin{cases} \beta_0^1 + \beta_1^1 y_{t-1} + \cdots + \beta_p^1 y_{t-p} + \sqrt{h_1^{-1}}\varepsilon_t \; if \quad z_{t-d} \le \tau \\ \beta_0^2 + \beta_1^2 y_{t-1} + \cdots + \beta_p^2 y_{t-p} + \sqrt{h_2^{-1}}\varepsilon_t \; if \quad z_{t-d} > \tau \end{cases} \quad \text{….. (2)}$$

If we assume that the error variance does not exhibit regime-switching and $h_1^{-1} = h_2^{-1} = h^{-1}$, then we can simplify the above equation by using the notation $\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$ to stack all the parameters of the AR model where $\beta_r = \begin{bmatrix} \beta_0^r & \beta_1^r & \cdots & \beta_p^r \end{bmatrix}'$, $r = 1,2$. Given this, we can write the TAR as: $y = X\beta + \varepsilon,$ Where X is the $(T-p)\times 2(p+1)$ matrix with the row *t* given by $\lfloor D_t \quad D_t y_{t-1} \quad \ldots \quad D_t y_{t-p} \quad (1-D_t) \quad (1-D_t)y_{t-1} \quad \ldots \quad (1-D_t)y_{t-p} \rfloor$, where D_t is a dummy variable - $D_t = \begin{cases} 1 & if, z_{t-d} \le \tau \\ 0 & if, z_{t-d} > \tau \end{cases}; y = \begin{bmatrix} y_{p+1} \\ \vdots \\ y_T \end{bmatrix}; \quad \varepsilon = \begin{bmatrix} \varepsilon_{p+1} \\ \vdots \\ \varepsilon_T \end{bmatrix}$.

When the $\tau's$ are known, the estimation of the parameters can proceed as a normal linear regression model. For example, Tong and Lim (1980) and Tong (1993) apply least squares conditional on *d* and *r* chosen using the AIC. In this paper, we treat τ and *d* as unknown parameters determined within the model and also allow the error variance to exhibit regime-switching behavior. Our TAR model (conditional on *d* and *r*) with switching error variance will therefore be:

$$y^r = X^r \beta_r + \varepsilon^r,$$

where the matrix X^r contains an intercept and *p* lags of the dependent variable for observations in the *r*th regime; y^r contain all the observations on the dependent variable in the *r*th regime.

7. Prior Selection and Posterior Distribution

We follow Koop, et al (2007) by using a normal-gamma prior for β_r and h_r of the form $NG(\underline{\beta}_r, \underline{Q}_r, \underline{s}_r^{-2}, \underline{\nu}_r)$ in each regime. We also assume that the delay parameter (*d*) has a non-informative prior over $1,\ldots,p$ such that each value of *d* have equal probability of been chosen. That is $\Pr(d = i) = \frac{1}{p}$ for all $i = 1,\ldots,p$.

The conditional distribution for β_r and h_r is calculated by assuming discrete distribution for the threshold parameters in τ and *d*. The only restriction is that they are chosen such that sufficient number of observations is placed in each regime (typically we want at least 15 percent of the observation lie in each regime so that the result is not biased by small sample in a particular regime). The procedure in this section hinges on the fact that there are finite numbers of possible threshold values τ , i.e. $\tau = \tau_1,\ldots,\tau_{\varpi}$ is the set of possible threshold.

Posterior Conditional Distribution of $p(\beta_r, h_r \mid y^r, \tau, d)$:

One of the benefits of using the Normal-Gamma prior is that the posterior is a closed form solution. Using Bayes' theorem and the properties of the normal-gamma density, the joint posterior distributions for β_r and h_r^{-1} (conditional on τ and d) is also normal-gamma parameterized as $NG(\overline{\beta}_r, \overline{Q}_r, \overline{s}_r^{-2}, \overline{\nu}_r)$, where:

$$\overline{\nu}_r = T_r + \underline{\nu}_r$$

$$\overline{Q}_r = \left(\underline{Q}_r^{-1} + X^{r\prime} X^r\right)^{-1}$$

$$\overline{\beta}_r = \overline{Q}_r\left(\underline{Q}_r^{-1}\underline{\beta}_r + X^{r\prime} X^r \hat{\beta}_r\right),$$

and

$$\overline{s}_r^{-2} = \frac{\underline{\nu}_r \underline{s}_r^2 + SSE_r\left(\hat{\beta}_r - \underline{\beta}_r\right)' X^{r\prime} X^r \overline{Q}_r \underline{Q}_r^{-1}\left(\hat{\beta}_r - \underline{\beta}_r\right)}{\overline{\nu}_r}$$

T_r is the number of observations in the rth regime; $SSE_r = (y - X\hat{\beta}_r)^{-1}(y - X\hat{\beta}_r)$ and $\hat{\beta}_r$ is the OLS estimate of β_r using data from regime r.

Posterior Conditional Distribution of $p(\tau, d \mid y,)$:

We can use the Bayes' theorem to simplify the joint distribution of τ and d such that the posterior conditional distribution of τ and d is:

$$p(\tau, d \mid y) \propto p(y \mid \tau, d)\, p(\tau, d)$$

By calculating the marginal likelihoods $\left(p(y \mid \tau, d)\right)$ for the normal linear regression model for every possible value of τ and d, we can build up the posterior $p(\tau, d \mid y)$. Thus, for a given value of τ and d, the standard marginal likelihood is:

$$p(y \mid \tau, d) = \iint L(\beta, h \mid \tau, d)\, p(\beta, h \mid \tau, d)\, d\beta dh$$

Given the above, the assumptions of our model imply that

$$p(y \mid \tau, d) = p(y^1 \mid \tau, d)\, p(y^2 \mid \tau, d)$$

Where the relevant formula for the marginal likelihood in each regime will be:

$$p(y^r \mid \tau, d) = \frac{\Gamma\left(\frac{\overline{\nu}_j}{2}\right)\left(\underline{\nu}_j \underline{s}_j^2\right)^{\frac{\underline{\nu}_j}{2}}}{\Gamma\left(\frac{\underline{\nu}_j}{2}\right)\pi^{\frac{T_j}{2}}}\left(\frac{\left|\overline{Q}_j\right|}{\left|\underline{Q}_j\right|}\right)^{\frac{1}{2}}\left(\overline{\nu}_j \overline{s}_j^2\right)^{-\frac{\overline{\nu}_j}{2}}$$

8. Model Application and Data Description

We apply the above model to measure the relationship between the price of South African white maize and the adoption of GM maize. South African maize producer prices for white maize were obtained from the South African Futures Exchange (SAFEX) for the period 2000 to April 2012. The Monthly prices are calculated by averaging daily prices for a given month. The South African white maize spot prices are non-stationary based on the Augmented-Dickey Fuller (ADF) and Phillips-Perron tests (the series also has a unit root that is difference stationary). However, the growth rate in price of maize that we are interested in for this study is stationary and allows for application of the TAR model. Standard Box-Jenkins estimation can be applied to understand the dynamics of prices and allow for forecasting. The data for the same period on GM maize adoption as captured by percentage of area planted was already described in section 4 and presented in Table 2. Figure 2 shows a graph of the series of white maize prices and adoption rate of white Maize in South Africa between January 2000 and April 2012. The graph shows the adoption rate and the price level trending together between 2005 and up to late 2009.

Relating this to our model, we let the GM area planted for white maize be the threshold trigger (z_{t-d}) and the growth rate of the price of white maize be y_t. We assume that GM maize adoption rates affect wholesale spot market prices at harvest time (assumption would be different for futures prices) and therefore we include lags to allow for the period between planting and harvesting periods. One way to measure the influence of GM maize on welfare in South Africa is by looking at the dynamics of the growth rate of prices in the country and evaluate if it is excited by the GM maize adoption rate in the country.

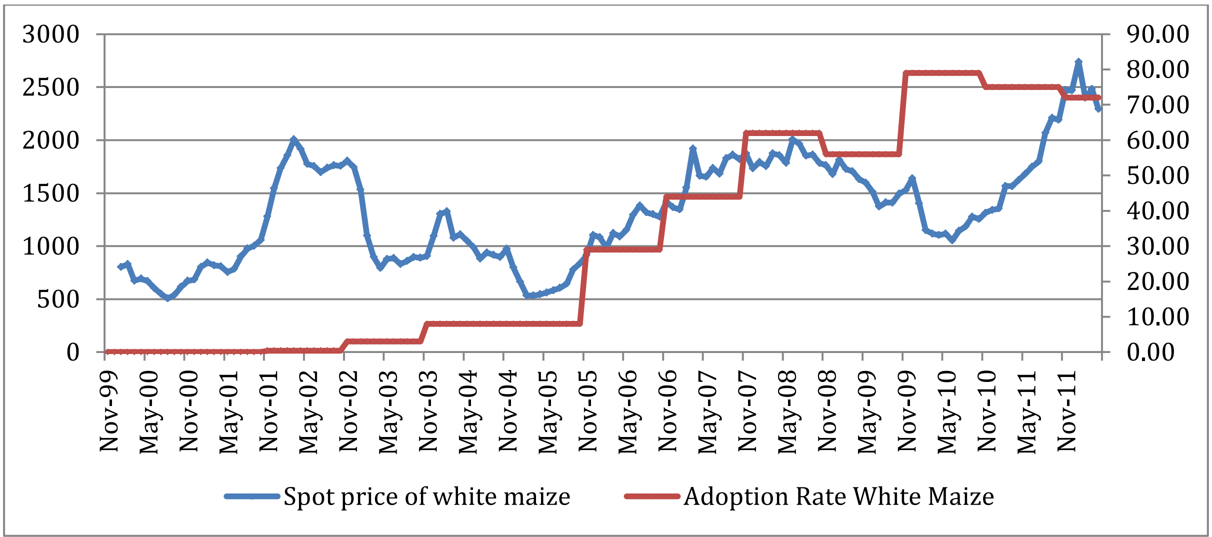

Figure 2: Spot price (R) and GMO adoption rate (%) for white maize in South Africa

9. Results

We fit our TAR model with an outside threshold trigger using the posterior distribution highlighted earlier. Conditional on the delay parameter and threshold parameter our posterior for β_r and h_r has a convenient form and means and standard deviations can be calculated using analytical formulas highlighted in the model section. We perform posterior inference for every possible combination of τ and d.

We are primarily interested in applying the threshold autoregressive model to time series data on price of maize in South Africa to address the following questions: (1) Does the adoption of GM maize excite the growth rate of price of maize in South Africa; (2) Does the error variance of the maize price growth rate exhibit regime-switching behavior to impact volatility?

We begin to address these questions by estimating a simple model with one lag. Our definition of the delay parameter (d) implies that it is bounded at the top by the lag length. This makes sense because the influence of the threshold trigger d periods ago can only be important if that period of the series influences the series itself. This model estimates an AR (1) model with two regimes triggered by the adoption rate of GMO. The posterior properties of β_r and h_r shows differences in the dynamics of the series in the two regime. Parameter estimates and diagnostic statistics are reported in Table 3. The autoregressive coefficient of price growth is estimated at 0.40 (s.d. 0.1060) for the first regime and -0.1462 (0.1969) for the second regime. There is strong evidence that the first regime AR parameter indicated moderate persistence of shocks. The properties of maize price growth rate are characterized as a function of only its own past (depending only on its one period lagged value) while the second regime shows that there is little evidence that the properties are not characterized as a function of its one period lagged value.

Table 3: Posterior results for the TAR model with switches in error variance

Model A with p=1 (Model Marginal Likelihood = 90.04)						
Regime 1				Regime 2		
Parameter	Mean	Std. Dev.		Parameter	Mean	Std. Dev.
β_{10}	0.2981	1.1210		β_{20}	0.8199	0.9547
β_{11}	0.4511	0.1099		β_{21}	-0.0156	0.1279
σ_1^2	87.6264	14.4223		σ_2^2	49.2063	9.9395

The results show evidence that the adoption of GM maize influences the dynamics of the maize price growth rate in South Africa. Another important aspect of the result is the volatility of the price growth rate. Table 3 also shows that there is strong evidence that the error variance exhibits regime-switching behavior. The posterior mean for the error variance in the first regime (87.6264) is about twice as large as that of the second regime (49.2063). That is, before the threshold trigger, growth rate in prices was more volatile than after implying that adoption of GM food has helped reduce risk too. Lastly, the posterior for the thresholds (τ) is presented in Figure 3. Appreciable posterior is found for a number of possible thresholds with the mode of the posterior roughly at about 44% adoption rate corresponding to 2006 planting season. [1] Interestingly, almost none of the posterior distribution is allocated to the adoption rates after the mode.

[1] The initial buzz of GM adoption seems to have excited the price growth rate with some posterior probability support from the data found at about 8% adoption rate. There is also an appreciable percentage of the posterior at around the 29% adoption rate, which is also part of 2006 harvest season.

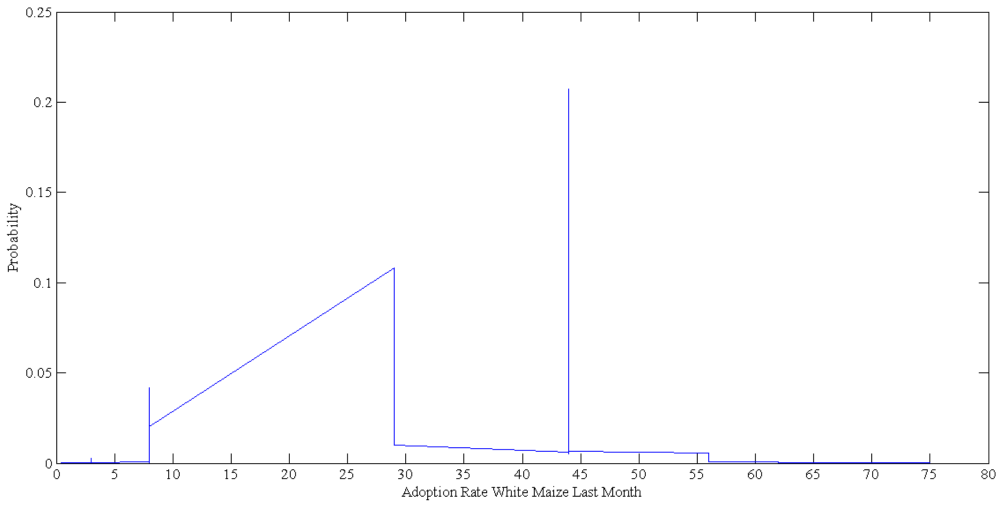

Figure 3: Posterior distribution of the threshold parameter tau.

The above result tells us that there is some evidence that the adoption of GM maize triggered the regime switch observed. However, there is reason to believe that it may take longer than one period to induce the regime switch. That is, the annual average adoption rate over a period is what will actually induce the regime switch and not necessarily last month's adoption rate. In the spirit of this, we compare models with different delay parameter using the Bayes Factor to choose the model that is supported by the data.[1] We use the average rate of adoption as the trigger such that the threshold trigger is average adoption rate of GM over the last *d* months:

$$z_{t-d} = \frac{\sum_{d=1}^{p} z^{*}_{t-d}}{d}$$

Where z^* is the area planted to GM maize for that period.

Figure 4 plots the posterior of *d*. Given that values of *d* imply different threshold triggers, there is no point plotting the posterior of the threshold parameter τ. From the figure, the posterior allocates most of the probability to $d = 6$. This indicates that what triggers a regime shift is the sustained adoption rate averaged over 6 months which is about the average growing season length. Table 4 (Model B) presents the autoregressive parameter estimates for this model. The results of the switches in the error variance and that the properties of maize price growth rate are characterized by its one period lagged value in the first regime is still consistent. However, the result also shows that for the second regime, volatility is lower (12.74) and the properties of maize price growth rate are characterized by its second, eighth and ninth period lags.

[1] The Bayes Factor can be written in likelihood function form as:

$$BF_{kj} = \frac{p(y \mid \tau, k)}{p(y \mid \tau, j)} = \frac{\iint L(\beta, h \mid \tau, k)\, p(\beta, h \mid \tau, k)\, d\beta dh}{\iint L(\beta, h \mid \tau, j)\, p(\beta, h \mid \tau, j)\, d\beta dh}$$

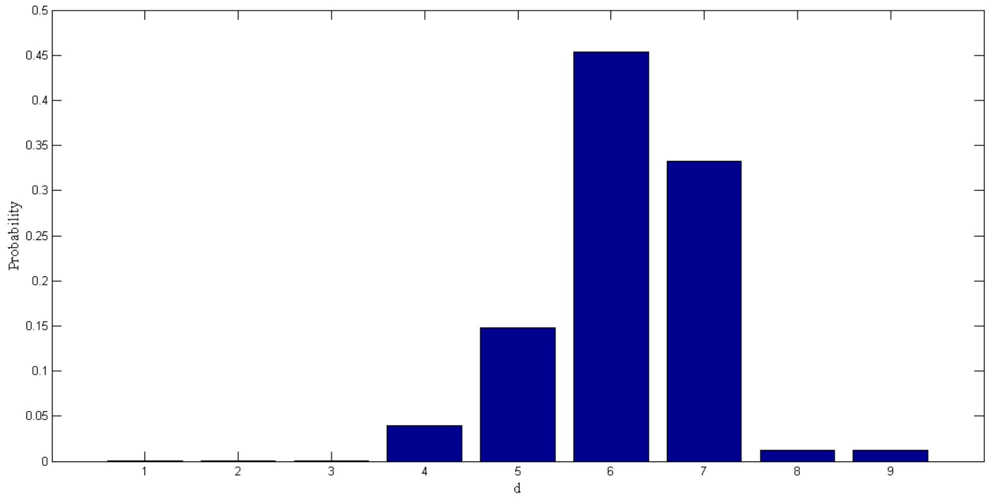

Figure 4: Posterior Distribution of Delay Parameter

Table 4: Posterior results for the TAR model with switches in error variance

Model B with p=9. Model Marginal Likelihood = 221340						
Regime 1				Regime 2		
Parameter	Mean	Std. Dev.		Parameter	Mean	Std. Dev.
β_{10}	0.1392	0.9159		β_{20}	4.5262	1.238
β_{11}	0.3389	0.0926		β_{21}	-0.2972	0.1931
β_{12}	0.0042	0.0985		β_{22}	0.0025	0.1581
β_{13}	0.023	0.0998		β_{23}	0.1272	0.1317
β_{14}	0.0493	0.1011		β_{24}	0.1766	0.1161
β_{15}	-0.1047	0.1012		β_{25}	0.0513	0.1152
β_{16}	-0.0303	0.102		β_{26}	-0.0223	0.1183
β_{17}	0.0805	0.1014		β_{27}	0.1034	0.113
β_{18}	-0.0065	0.0978		β_{28}	-0.2242	0.1153
β_{19}	0.0114	0.0929		β_{29}	0.3013	0.1143
σ_1^2	76.8629	10.2339		σ_2^2	12.7347	5.0789

10. Summary and Conclusions:

GM crops have been extensively tested and found to be as safe as conventional crops. They are being adopted worldwide because of their benefits to farmers and society. Despite the potential advantages, adoption of GM crops in Africa has been slow. South Africa represents the vanguard of GM crop adoption in Africa with full commercialization of GM cotton, soybean and maize. Given the polarized public views on the potential role of GM crops in alleviating food security and possible environmental effect, other African nations (and the rest of the world) are closely monitoring South Africa as a case study. This paper informs the public debate and policy dialogue by examining the empirical evidence on the effects of GM maize adoption in South Africa.

In this paper we evaluated the impact of GM crop adoption on wholesale maize prices in South Africa. A threshold autoregressive model was applied to time series data on wholesale price and GM adoption rates of maize in South Africa for the period between January 2000 and April 2012. Our results show that the adoption of GM maize in South Africa has had an impact on the dynamics of wholesale maize price growth rate in the country. Our analysis shows a regime switch in the 2006/07 growing season when adoption rates for GM white maize reached 44% of the area planted. Further, the analysis shows strong evidence that the error variance exhibits regime-switching behavior with the posterior mean for the error variance in the first regime about twice as large as that of the second regime. Simply put, the growth rate in prices was stabilized by GM adoption thereby reducing price risk. We speculate that the increased stability comes from increased integration with key exporters such as USA, Brazil and Argentina that have also adopted GM maize.

We are careful not to make further inference on consumer welfare. Assuming perfectly competitive markets, we expect these beneficial price effects to be transmitted to consumers in the long-run. However, in the South African context, the welfare gains on consumers are non sequitur for two reasons. First, South Africa has a highly industrialized food processing system wherein food commodities often represent a small percentage of the value added final consumer product. Second, there have been many instances of anti-competitive behavior within the country's grains and milling industries that could delay or prevent symmetric transmission of price signals from wholesale through retail levels. For other African nations seeking to draw lessons from the South African example, we conclude that adoption of GM maize has had a stabilizing effect on wholesale prices *ceteris paribus*.

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