Maize Supply Response to Climate Variability and Prices in Kenya

Leonard Kipkemoi Kirui
Productive Sector Division
Kenya Institute for Public Policy
Research and Analysis

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Bishops Garden Towers, Bishops Road
PO Box 56445-00200 Nairobi, Kenya
tel: +254 20 2719933/4; fax: +254 20 2719951
email: admin@kippra.or.ke
website: http://www.kippra.org

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Abstract

The study investigates the effect of climate variables and prices on maize supply in Kenya. Autoregressive Conditional Heteroskedastic (ARCH) approach is used to determine the significance of risk due to climate unpredictability and price volatility with the use of monthly climate data and monthly price data from 2009-2012. An error corrected supply response model was used to determine the effect of risk due to price and climate variables on maize supply. The results significantly indicate that price of maize, mean rainfall, and temperatures have unpredictable changes. This means that maize producers and consumers in Kenya would have some difficulty in making decisions on the most important staple crop. The risk due to temperature is found to be stronger than the risk due to rainfall and prices. There is need to establish systems for monitoring stress indexes related to climate and prices, which can be used for forecasting and scenario analysis. This will enable the prioritization of adaptation strategies based on the rank of the risks.

Abbreviations and Acronyms

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARCH-LM	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
FAO	Food and Agriculture Organization of the United Nations
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GoK	Government of Kenya
IPCC	Inter-governmental Panel on Climate Change
NAGARCH	Non-linear Autoregressive Conditional Heteroskedasticity
NCPB	National Cereals and Produce Board
OLS	Ordinary Least Squares

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1. Introduction

1.1 Background

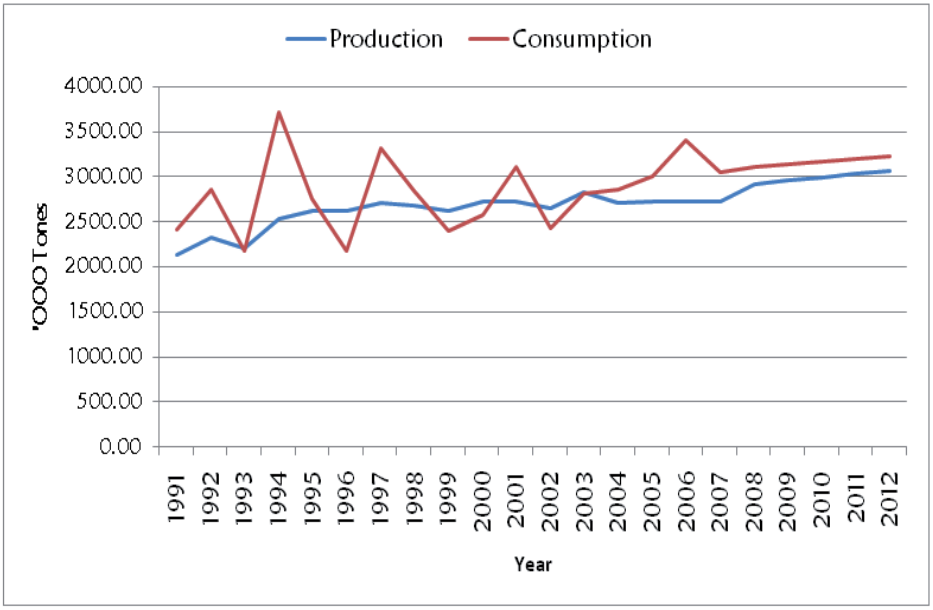
Projected changes in the frequency and severity of climate variability are predicted to have more consequences on agricultural food than changes in projected average mean and temperature (Intergovernmental Panel on Climate Change - IPCC, 2007). At the same time, regional disparities will heighten with time (Parry *et al.*, 2005), as large negative impacts will be felt most in developing regions compared to developed regions because of their large exposure to climate variability and dominance of agriculture in their economies (IPCC, 2007). Climate variability greatly affects agriculture and it is considered to be one of the important sources of agricultural commodity supply and price fluctuations (Gilbert and Morgan, 2010). Price fluctuation is mainly as a result of shocks in production and consumption. Production shocks can occur due to variation in yield or in the area planted, typically owing to weather. Consumption varies due to changes in income, price of substitutes or shift in taste and preference. Demand shocks such as income and policy shocks (Christiaensen, 2009; Gilbert, 2010) also play an important role.

The World Bank (2007) has identified changes in temperature, rainfall, carbon dioxide fertilization and surface water runoff as some of the key climate variables that could severely affect the agricultural sector. Climate variability can lead to destruction of the entire harvest, causing a dramatic decrease in food supply. The food price spike will occur if demand does not keep up with the supply as evidenced in the year 2009, when climate variability in major production regions in Kenya led to a massive crop failure and consequent rise in food prices. This greatly affected both rural and urban households (Nyoro *et al.*, 2007).

Maize is the most widely consumed staple food crop for over 80 per cent of Kenya's population with a per capita consumption of 88 kilogrammes (Ariga, Jayne and Njukia, 2010). Growth in production of maize stands at 2 per cent against the country's population growth rate of 3.4 per cent (KNBS, 2013). This is expected to heighten cases of food insecurity and reliance on imports as was the case in 2009, when the country imported 16.8 million bags of maize (Government of Kenya, 2010). The prices of maize have been a major concern in recent times, because it affects both the producers and the consumers. Producers are mainly affected by climate-related variables in production and since production is mainly dependent on rainfall (Wokabi, 1997), it is subject to climate-related fluctuations. This especially affects poor rural households (Barnett and Mahul, 2007).

The demand for maize in Kenya has outstripped production for several years. In 2,012 production was 40 million bags while the national demand was 44 million bags. In 2008, production was 27 million bags against the national requirement of

Figure 1.1: Maize production and consumption for the period 1991–2012



Source: FAOSTAT (2012)

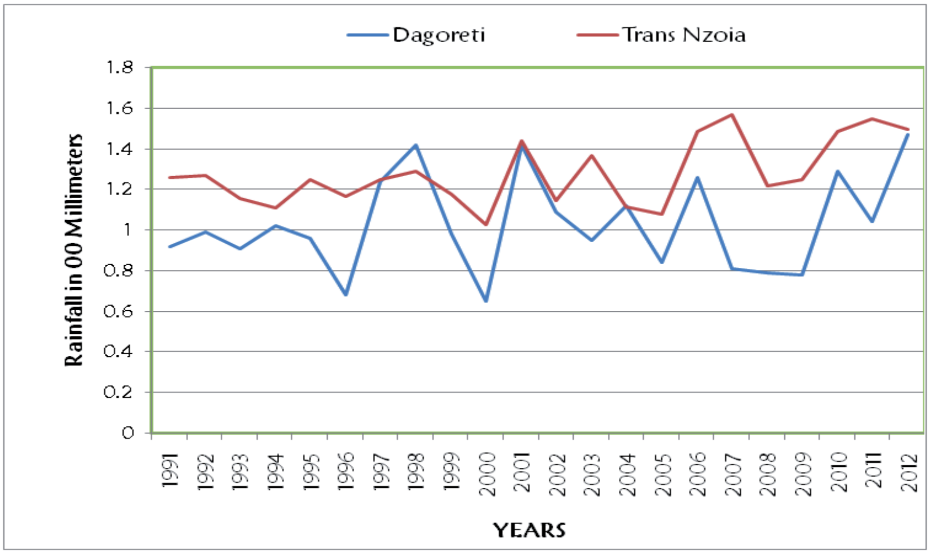
34 million bags, (MoALF, 2013). This widening gap has been bridged by imports particularly from Uganda and Tanzania (Nyoro *et al*., 2007). Continued reliance on imports implies that foreign exchange reserves and resources set aside for development are often diverted to purchase of food. Maize consumption since the year 2004 has always outstripped domestic production. Figure 1.1 compares the production and consumption of maize for the period 1990 to 2012.

In Kenya, weather conditions play a major role in the price formation mechanism of most agricultural commodities. This is because any disturbances in the expected weather conditions or shocks are expected to result in supply disturbances, which are in turn expected to affect maize prices. Weather-related shocks are mainly exogenous shocks and their analysis is very important in achieving stability of maize supply and prices. Figure 1.2 shows the erratic behaviour of rainfall in Dagoretti and Trans Nzoia weather stations for the period 1991-2012.

1.2 Problem Statement

In the recent past, domestic supplies of maize have not been matching the changing demand. This gap has been widening, despite several efforts by both government and non-governmental organizations. The safety nets as well as incentives have been wide but conventionally limited to mainly demand factors

Figure 1.2: Annual average rainfall for the period 1991–2012



within our control. However, the increasing frequency of climate variability has been a major bottleneck in the development and sustainability of the maize sub-sector in Kenya. The maize outputs have been substantially low, leading to unprecedented hunger and malnutrition. This is exuberated by declining producer gross margins and uncontrolled increase in consumer prices. Variation in maize supply has wide implications for a country such as Kenya, which is substantially dependent on agriculture. Maize is commonly grown by rural household, using rain-fed agriculture and a bit of irrigation, hence production has always been affected by rainfall and temperature patterns. Changes in maize prices are driven mainly by the structure of maize production, marketing and consumption, where a number of participants are involved, among them farmers, traders, processors, retailers and individual consumers. The effect of climate variability on trade is important for the maize sector participants because it is critical to their decision on how much to grow, sell, store and consume.

Previous studies have tried to quantify the effect of inconsistent trade policies on domestic prices of maize (Elodie *et al.*, 2013) using the ARCH model. This study intends to take a different dimension though using a related theory on price volatility to look at the effect of climate variability and maize prices on supply. The study seeks to establish the relationships between unpredictable climate variability and maize prices with supply of maize.

1.3 Objectives

The general objective of this study is to examine the response of maize supply to climate variability and unpredictable prices. The specific objectives are to examine the unpredictability of monthly rainfall, temperature and maize prices; and determine the response of maize supply to unpredictable rainfall, temperature and maize prices.

1.4 Research Questions

(i) How unpredictable is the monthly rainfall, temperature and maize prices in Kenya?

(ii) How do maize supplies respond to risk due to rainfall, temperature and maize prices?

1.5 Justification

Maize is a major staple food for over 80 per cent of Kenya's population, with a per capita consumption of 88 kilogrammes per year (Nyameino *et al.*, 2003). It contributes 65 per cent of the total staple food caloric intake and 36 per cent of total food caloric intake (FAO, 2011); therefore, its shortage in supply is, to a large extent, associated with food insecurity. One major challenge in the maize sector is how to effectively deal with climate variability and maize price instability. These are the two major impediments to smallholder productivity growth and food security. This study intends to focus, in particular, on the effect of climate variability and maize price on supply. There is a significant importance linked to the effect of abrupt changes in food supply on access and livelihoods, which is potentially devastating. The long-run food price trends have a varying impact on the poor population compared to the challenge of food supply. In the short-run, price fluctuations are unpredictable over the longer horizon and the vulnerable population gets easily exposed to shocks, especially those emanating from climate variability. Therefore, it is important to understand how unpredictable climate and prices affect the market supply so that policies formulated by the government would conveniently address the food security situation in Kenya as stipulated in the economic pillar of Kenya's development blueprint, Vision 2030.

2. Literature Review

2.1 Theoretical Literature

Agriculture is relatively distinct from other sectors in that there is an extended consideration on the biological processes and climate factors that play an important role in the production process. Although these characteristics seem to be quite obvious, they were not given much attention in the first market models because specific models for agricultural commodities emerged from more general ones that tried to explain the difference between the observed price cycles in the markets from those predicted by Marshall's theory of normal price. This theory postulates that the normal price is the price that the market should tend to settle over a period of time, long enough to bring demand and supply into equilibrium.

There are two models in economic literature from within which price evolution is framed from; these are the model of rational expectations (Muth, 1961) and the cobweb model of adaptive expectations (Cochrane, 1958; Ezekiel, 1938; Nerlove, 1958). The aforementioned model assumes rationality amongst the economic agents in the use of all the accessible information, and that price dynamics result from exogenous factors, mainly weather shocks. Prices evolve in response to endogenous influences according to the Cobweb model statement, where high prices would attract a rise in production leading to lower prices in response to which farmers reduces production of a particular crop in the second season. The lower production in the second season pushes the price up in the third season and so on (Barré, 2011) Price volatility can be tackled in two ways, as proposed by the two approaches. The Cobweb approach suggests price stabilization by government interventions such as production quotas in order to manage the commodity supply in a country (Mitra and Boussard, 2012), while the later proposes spreading of risks amongst economic agents, including insurance schemes, temporal and spatial arbitrage, storage and free-trade policies.

The two approaches were altered later to allow for their shortcomings. The cobweb model developed by Ezekiel (1938) was extended by Nerlove (1958), suggesting that economic agents use current prices and the preceding years' forecasting errors to form their price expectations. Boussard (1996) extended this further to incorporate risk aversion and non-linear trends (Hommes, 1992).

However, Deaton and Laroque (1996) disagreed on whether the Cobweb model could reconcile its predicted negative first order auto-correlation regarding prices in respect to the empirical evidence, which showed positive auto-correlation (Barré, 2011).

The rational expectations model mainly implies that economic agents avoid systematic forecasting errors. This would lead to a steady state of price series, thus disputing empirical findings of non-stationarity of most commodity price series. Barré (2011) accounted for this shortcoming by stating that competitive storage model was developed to explain the prices positive auto-correlations (Muth, 1961), kurtosis and positive skewness (Deaton and Laroque, 1992). The competitive storage model was extended by adding the overshooting hypothesis linking the dynamics of prices in the commodity markets to advances in the monetary policy. It is possible to represent positive auto-correlation, skewness and kurtosis of a given data series with a rational expectations model without competitive storage. There are other main challenges in empirical estimations, which include structural breaks or regime shifts and non-linear components (Deaton and Laroque, 2003).

Apart from the role of expectations, the degree of perishability, and the weather effects on agricultural commodity price variability, Newbery and Stiglitz (1981) mention other demand and supply factors that can either be systematic or non-systematic. As for the demand factors, the income of the consumers, the price of close substitutes or compliments, change in tastes, and the change in technology of derived products stand out. On the other hand, the major source of supply factors is the price of inputs and the technical change in the production of the commodity in question and/or for alternative commodities. Transport costs, tariffs and taxes cause variations in both demand and supply, thus contributing to price volatility in the market. However, these are not specific features of agricultural commodity market models, but refer to traditional variables usually included in a typical market analysis.

2.2 Empirical Literature

The effect of climate variability on agriculture can be found in many research studies such as those generated by Deressa *et al* (2008) for Ethiopia, Akpalu, Hassan and Ringler (2008) for maize in South Africa, and Ringler *et al* (2010) for food security in Sub-Saharan Africa (SSA). These researchers have used different approaches, some of which are reviewed in this study, to empirically evaluate climate variability impacts on the agricultural sector.

Climate variability affects food security through its negative effect on food prices and supply. Since food is a basic necessity, its demand is highly price elastic. A decrease in food surplus may lead to an increase in food prices, therefore affecting food accessibility. Ringler *et al* (2010) in their study on climate change impacts on food security in SSA find that child malnutrition is worsened by climate variability through higher food prices, which is manifested through inadequate supply.

Balanay and Valera (2014) used an error corrected supply response model to determine the producer's behaviour towards price volatility and climate oscillation. The study finds that, among other risks, the risk due to changes in climatic variability is stronger than due to price changes.

Aker (2010) finds that climate variability may have an effect on entry and exit of food traders in response to the profitability of trading. This is because the markets are not well integrated and the spread of agricultural food prices is high in least developed countries and, therefore, shocks due to climate variability may amplify them, hence worsen food supplies (Araujo *et al.*, 2005).

A study conducted in Ghana by Henry and Clement (2013) on the effects of previous price and climatic variables on maize supply applied a lag model using the OLS technique and a quartile regression approach. The findings by the lag model showed that an increase in preceding year's maize price and temperature impacted positively on current year's maize supply. Blanc (2011), on the other hand, estimates the influence of weather and climate on farmers' choice of cropping decisions. His findings indicated that farmers' supply decisions are influenced by weather and climate. The regressions further showed a negative impact of precipitation and varying temperature on the study area allocated to some crops, thus increasing climate risk. Farmers respond by diversifying income sources and crops.

A study on the supply response to price of maize and non-price factors and sensitivity of fertilizer and labour demand to price and non-price factors was conducted in Kenya using the Nerlovian lag adjustment model by Olwande (2008). He incorporated cross-sectional data from 1,187 maize farmers for the year 2003/2004. The own-price elasticity of maize supply was less than unity, which indicated that price support for maize is not an appropriate policy for increasing maize supply. In this particular study by Olwande 92008), he found out that fertilizer use and land sizes were important in maize production. However, market access and educational level of the household head were found not to have much influence on maize supply. The study, however, did not give any emphasis on aspects of uncertainty of supply due to price volatility and climate variability, which is the main concern for this current study.

Studies on price uncertainties have been increasing because of the importance of price formation in commodities' market (Rezitis and Stavropoulos, 2009). The possibility of forecasting prices accurately is very important in policy and business circles (Bernard *et al.*, 2006). However, highly volatile prices are an impediment to agricultural productivity, which tends to intensify inflationary pressure (Kargbo, 2005). Unpredictable prices increase the uncertainty faced by farmers and agricultural enterprises, which in turn affects investment decisions, thus creating serious ramification on productivity and farm income. Based on the reviewed literature, this study considers the ability of climate variability to influence the economic factors of maize prices and supply. The amount of risk that climate variability can create is best studied with the use of empirical models, which have the capability of estimating these risks. One of the approaches that has been used by researchers to study price volatility that is known to induce risk is Autoregressive Conditional Heteroscedasticity.

The generalized version of ARCH or GARCH approach was used in the 1990s to study price uncertainty and volatility in the broiler market. The study provided evidence that price volatility is an imperative risk factor in broiler supply. Rezitis and Stavropoulos (2009) have used different versions of GARCH in their study on Greek pork market. Their study also found that price was an important cost factor in Greek pork supply, and high uncertainty restricted the growth of the Greek pork sector. Based on these examples, ARCH is likewise considered a good approach to take for the estimation of risk associated with volatile factors and the extension of analysis to maize supply response in order to understand supplier's behaviour towards the patterns of volatility in the Kenyan maize market.

2.3 Government Policies and Major Changes in the Maize Sector

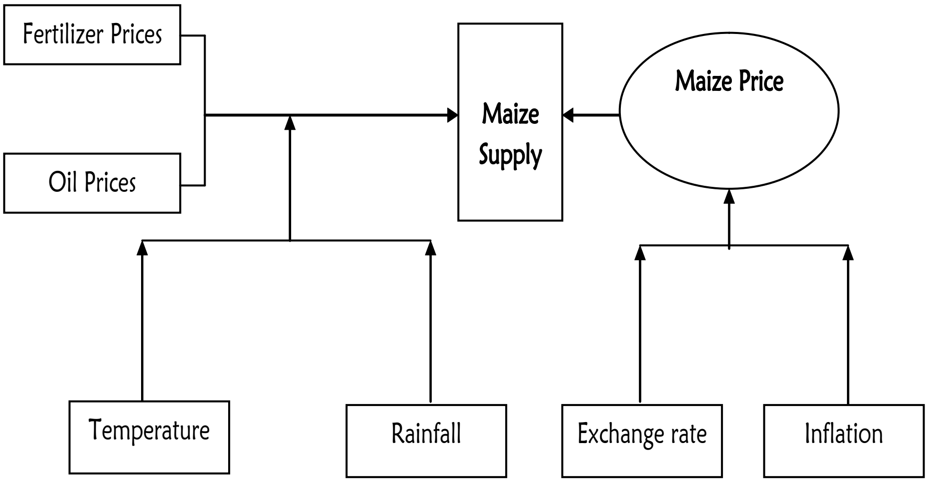
Maize production in Africa is known to be heavily controlled by government, and this phenomenon dates back to colonial times. The maize policy in Kenya during these times reflected the interest of large scale commercial farmers (Hugo *et al*., 2005). In Kenya, the government intervenes in three ways: through non-tariff barriers on maize imports, variable import tariffs on maize imports, and maize procurement at support prices by the National Cereals and Produce Board (NCPB). These particular policies are aimed at stabilizing the maize prices and also act as an incentive for producers to produce more maize. Earlier before 1992, maize was marketed through the NCPB. The Board used to set seasonal and territorial prices. However, in 1992, the government liberalized the maize sector by eliminating restrictions on movement of maize and removed price controls on maize trading, deregulated maize and maize meal prices, and abolished direct subsidies on maize sold to registered maize millers. Private traders were allowed to trade and transport maize across districts without barriers. Prior to the policy change, traders were required to acquire movement permits for varying quantities of the maize they transported. However, NCPB still purchases maize for strategic reserves and stabilization of the market when prices go below the marginal cost (Jayne *et al*., 1997).

In the past two decades, Kenya has shifted from an exporter of maize to an importer as a result of sector reforms since 1992. The factors that have contributed to the country being a net importer of maize include: poor macroeconomic policies; changes in weather patterns; population increasing faster than growth in production; low maize productivity; rising costs of production in relation to neighbouring countries such as Uganda; poor research linkages between researchers, extension workers and the farmers; low private sector investment in research and development; and poor infrastructure development.

2.4 Conceptual Framework

Climate indicators can influence agricultural output through the effect on future prices, which is reflected through direct impact on yields. The factors affecting price dynamics can be classified into short and long term. The short term factors are climatic factors, which are basically idiosyncratic shocks around the long term trend. On the other hand, examples of long term factors are technological change, income levels, population growth, changes in tastes and preference, and other similar trend setting factors. The effect of these short term factors on agricultural commodity prices is dependent on institutional settings such as market structure, national policies on trade, amount of commodity stock at the time of shock, exchange rate, among others. Climate factors can influence commodity prices through the effect on their supply and expectation about the future price dynamics, which can be seen through their consumption decisions.

Figure 2.1: Conceptual framework



Source: Authors' own

3. Methodology

3.1 Analytical Framework

Autoregressive Conditionally Heteroskedastic (ARCH) model is used in this study to estimate climate variability and price uncertainty. This is borrowed from the works of Rezitis and Stavropoulos (2009), where they used the model to generate values and expected variances for supply response analysis in a rational expectation framework. In this study, climate variability is represented by mean monthly rainfall and temperature changes. The supply response model is estimated with an error correction term because of the likelihood of cointegration, which will be tested with Johansen test for cointegration. The supply response model tries to model the behaviour of maize suppliers, mainly producers towards climate and price-related risks. The process of estimating price and climate risks is adopted from the research of Modelina *et al.* (2003) as cited by Balanay and Valera (2014).

It is first important to establish the stationarity of data before conducting an ARCH analysis. To do this, the study has used the Augmented Dickey Fuller (ADF) test to test for stationarity of data in level form and at first difference. The ARCH estimation uses only stationary data, which is characterized to have no unit roots. Once the variables are tested for stationarity with respect to the form in which the data is selected, the next step will be an ARCH-LM test, which determines the presence of ARCH effects or unpredictable behaviour in the pattern. ARCH approach can only be used when the ARCH effects are statistically significant. If, in any case, the ARCH effects are not significant, it will then necessitate the use of autoregressive integrated moving average (ARIMA). The use of ARIMA will mean that the data series has predictable fluctuations. The lag length for the case of ARIMA is determined through Akaike Information Criterion (AIC). However, in the OLS estimation of the supply response, the error correction factor is integrated because of the spatial cointegration where the test is done with the use of Johansen test for cointegration.

The basic framework of analysis for climate variability and price uncertainties is based on the work of Rezitis and Stavropoulos (2009), where they evaluated the Greek meat market for its response to volatility. In this study, a simple autoregressive conditionally heteroskedastic (ARCH) approach is specified, whose functional form is as follows:

$$P_t|\Omega_{t\text{-}1} = c_0 + \sum_{n-1}^{n} P_{t-i} + \varepsilon_{2t-i} \quad \text{...}(1)$$

$$h = b_0 + \sum_{i-1}^{q} b_{1i}\varepsilon^2_{2t-i} + \sum_{i=1}^{p} b_{2i}h_{t-i} \text{ ....} (2)$$

Where $b_o>0, b_{1i} \geq 0$ $i=1,\ldots,q, b_{2i} \geq 0$ $i=1,\ldots,p, \sum b_{1i} + \sum b_{2i} < 1$.

The ARCH (Engle, 1982) makes the conditional variance *ht* to depend on previous period volatility measured as a linear function of past errors ε_{2t}, while leaving the unconditional variance constant. In equation 1, ε_{2t} is a discrete time stochastic error, and Ω_{t-1} is the information set of all past states up to the time *t-1*. In equation 2 (GARCH conditional variance equation), h_t is the conditional variance specified as a linear function of *p* lagged squared residuals, and its own *q* lagged conditional variances. The variance is expected to be positive, and also the coefficients b_o, b_{1i} and b_{2i}. The stationarity of the variance is preserved by the restriction $\Sigma b1i+\Sigma b2i <1$. The predictions of Pt^e and h_t are to be generated by the ARCH/GARCH model, which could be used in estimating the supply response function (Rezitis and Stavropoulos, 2009). The deflated retail prices of maize would be evaluated with equation 1, and the generated errors from equation 1 would be auto regressively analyzed with equation 2. The same criteria are used in analyzing the behaviour of the mean rainfall and temperature, and the predictability of its changes over the months of 2009 to 2012.

3.2 Model Specification

Estimates of equations 1 and 2 are integrated in the supply response functions of maize supply in the country, which have been analyzed through an OLS regression with a weighted error to absorb the effect of cointegrating relationships that would be determined using the Johansen test for cointegration. This modification is necessary for cointegration in order to get robust results. The specification model for the maize supply response is as follows:

$lnSUPPLY = \alpha0 + \alpha1 lnSUPPLY_{t-1} +_{\alpha2} lnMZPRICE_t + \alpha3\ lnRAIN_{t-5} + \alpha4 lnTEMP_t + \alpha5\ lnOILP_t + \alpha6\ lnFERT_{t-1} + \alpha7 lnCPI_{t-1} + \alpha8 lnEXRATE_t + ECM_{t-1} + \varepsilon$

Where;

ln= Natural logarithm of variables;

$SUPPLY_t$ = Maize supply at period *t*;

$MZPRICE_t$= Maize price at period *t*;

$RAIN_{t-5}$= Rainfall at period *t-5*;

$TEMP_t$= Temperature at period *t*;

$OILP_t$= Oil prices at period *t*;

$FERT_{t-1}$= Fertilizer prices at period $t-1$;

CPI_{t-1}= Consumer price index at period t;

$PCGDP_t$= Per capita gross domestic product at period t;

$EXRATE_t$= Exchange rate at period t;

ECM_{t-1}= Error correction mechanism;

ε= Error term; and

α_o-α_8= Parameters estimates.

3.3 Sources of Data

The data sources for this study was mainly FAOSTAT website. Other sources of data include: the Kenya Meteorological Department, Central Bank of Kenya, Kenya National Bureau of Statistics, and World Bank. The data period is from January 2009 to December 2012. Domestic maize prices were deflated using the Kenyan CPI base of 2007, which was extracted from the Kenyan National Bureau of Statistics (KNBS).

4. Results of Empirical Analysis

4.1 Descriptive Statistics

The estimations presented in this section are based on the economic theory presented in section three as well as understanding the economic and production dynamics of the maize sub-sector in Kenya. Table 4.1 presents the mean, median, and standard deviation as well as the minimum and maximum values of the variables used in the estimation.

Table 4.1: Descriptive statistics of normalized variables

Variable	Mean	Median	Maximum	Minimum	Standard deviation	Observations
Supply	10.6371	10.6868	10.9326	10.0352	0.2171	48
Maize prices	3.4905	3.6096	3.9359	2.8565	0.3178	48
Average rainfall	3.9866	4.6405	5.6142	-2.3026	1.5682	48
Average temperature	3.2488	3.2347	3.3911	3.1398	0.0626	48
Oil prices	4.4842	4.4805	4.7461	4.1913	0.1869	48
Fertilizer prices	8.0142	8.0310	8.2161	7.6497	0.1589	48
Consumer price index	4.8241	4.8708	4.9551	4.6529	0.1097	48
Exchange rate	4.4109	4.4018	4.6035	4.3162	0.0664	48

Source: Data analysis

4.2 Stationarity of Variables

Stationary data are very crucial in ARCH and supply response analysis in order to obtain reliable results. The study examined the response of maize supply to climate variability and price unpredictability with selected economic factors from January 2009 to December 2012. The unit root test was performed using ADF test technique. The results indicate that not all the data at normalized form are stationary. Stationary data at normalized form were found at supply, rainfall and temperature data while the rest were non-stationary. The results of the unit root test are presented in Table 4.2.

Table 4.2: Unit root test

Variable	At level	First difference	Inference
Supply	-4.4769	-	I(0)
Maize prices	-1.9874	-3.0834	I(1)
Average rainfall	-4.3424	-	I(0)
Average temperature	-4.1304	-	I(0)
Oil prices	-0.4708	-4.8930	I(1)
Fertilizer prices	-1.1514	-6.2868	I(1)
Consumer price index	-1.535	-7.2159	I(1)
Exchange rate	-1.7606	-4.9479	I(1)

Source: Data Analysis

4.3 Co-integration and ARCH Effects

Cointegration indicates that deviations from the equilibrium are stationary with finite variance, although the series themselves are non-stationary and have an infinite variance (Engle and Granger, 1987). This, at significant level, will yield dubious results in the estimation; therefore, model adjustment has to be done through an error correction factor, specifically in supply response analysis. In order to obtain robust estimates, it is imperative to address the problems associated with cointegration. In this study, Johansen test is used to detect the presence of cointegrating relationships that have obscured the true long term relationship of the factors under study, specifically those involved in the consequent supply response analysis. The results of the Johansen test for cointegration are presented in Table 4.3.

Table 4.3: Co-integrating test results (normalized values)

Hypothesis	Trace statistic	Eigen value	5% critical value	Decision
Ho: r = 0; H1: r > 0	80.3566*	0.4121	79.3415	Indicate two co-integrating equation
Ho: r = 1; H1: r > 1	55.9250*	0.3848	55.2458	
Ho: r = 2; H1: r > 2	33.5782	0.3159	35.0109	
Ho: r = 3; H1: r > 3	16.1138	0.1745	18.3977	
Ho: r = 4; H1: r > 4	7.2931**	0.1466	3.8415	

NB: The trace test was used to test the null hypothesis that the number of cointegrating vectors is less than or equal to k, where k is equal to 0 to 6. ** and * indicates significantly different from zero at 5% and 10% levels respectively.

Source: Data analysis

Table 4.4: ARCH-LM test results for ARCH effects of climate and price variables

Variable	**ARCH-LM statistic**
F-Statistic	
Retail price of maize	12.3993**
Average rainfall	15.0681***
Average temperature	3.4622*
Observed square of residuals	
Retail price of maize	10.113**
Average rainfall	11.5561***
Average temperature	3.3556*

***, **, and * indicate significance at 1%, 5% and 10%, respectively

The ARCH-LM test was used to test the ARCH effect, where its results are shown in Table 4.4. Significant ARCH effects show the presence of unpredictable tendencies of the data series, thus suggesting that the use of ARCH for analyzing climate and price unpredictability is warranted. As shown in Table 4.4, the climate and price parameters have unpredictable propensities in their movement.

4.4 Unpredictability of Climate

Based on the results in Table 4.5 and 4.6, the effect of climate variability increases the uncertainty of climatic behaviour because the range at which rainfall and temperature can change has expanded. The ARCH/GARCH coefficients in the variance equations are significant, which indicates the risk associated with increased uncertainty due to the expanded range of change. Rainfall and temperature are important in maize production. These results show that the climate variables can take extreme levels that are not favourable for maize production. Particularly, rainfall and temperature affects the yields, and thus lowers productivity. The results show that both temperature and rainfall are very random because their current levels are determined by their previous month's level, although temperature is the most significant compared to rainfall, which means that its effects are more detrimental than rainfall.

Table 4.5: Unpredictability of rainfall

Variables	Coefficient	Std. Error	z-Statistic	Probability
Mean equation				
Constant	3.401641	0.699914	4.8601	0.0000
Lagged average rainfall, t-1	0.232222	0.118065	1.9669	0.0492*
Lagged average rainfall, t-2	0.014129	0.071299	0.1982	0.8429
Variance equation				
	Coefficient	Std. Error	z-Statistic	Probability
Constant	0.286266	0.200199	1.4299	0.1527
ARCH(1)	1.247367	0.43486	2.8684	0.0041
ARCH(2)	-0.122971	0.207381	-0.593	0.5532
N	48			
Log likelihood	-60.593			

***, **, and * indicate significance at 1%, 5% and 10%, respectively
Source: Data Analysis

Table 4.6: Unpredictability of temperature

Variables	Coefficient	Std. Error	z-Statistic	Probability
Mean equation				
Constant	1.123787	0.388022	2.8962	0.0038
Lagged average temperature, t-1	1.035759	0.165195	6.2699	0.0000***
Lagged average temperature, t-2	-0.385418	0.224934	-1.7135	0.0866*
Variance Equation				
Constant	0.000461	0.000158	2.9236	0.0035
ARCH(1)	0.092053	0.055051	1.6721	0.0945
GARCH(1)	1.616074	0.068952	23.438	0.0000
GARCH(2)	-0.978592	0.081921	-11.946	0.0000
N	48			
Log likelihood	89.36959			

***, **, and * indicate significance at 1%, 5% and 10% respectively

Source: Data Analysis

4.5 Unpredictability of Prices

The analysis of maize price changes intends to capture the volatility behaviour in the maize price series, which is associated with price risk in the maize market. Suppliers of goods whose prices have significant price risk often find themselves in a situation where planning environment has perplexing conditions. Risky price movements are linked with market uncertainties because of the difficulty in price formation due to the inability of commodities market to develop and compete sustainably. In the analysis of maize price risk with ARCH, the results are presented in two forms. Expected price levels are shown under the mean equation, while the expected price variance (ARCH/GARCH) parameters are exhibited in the variance equation. The significance of expected variances indicate the price uncertainty that is associated with price risks, because the range within which price can vary is widened (Rezitis, 2003).

As indicated in Table 4.7, the results of price estimates through ARCH indicate the presence of price uncertainty, which means that maize prices in Kenya are expected to be unpredictable. This shows that maize producers and consumers in the country are confronted with market risks, which implies that they will have a difficulty in meeting market expectations and making decisions. The price uncertainty is indicated by the significant coefficients of ARCH/GARCH parameters in the variance equation of Table 4., while the parameters under the

Table 4.7: Price volatility of maize prices

Variables	**Coefficient**	**Std. Error**	**z-Statistic**	**Probability**
Mean equation				
Constant	0.152517	0.142959	1.0669	0.286
Lagged retail price of maize, t-1	1.631803	0.120471	13.545	0.0000***
Lagged retail price of maize, t-2	-0.67635	0.115047	-5.8789	0.0000***
Variance equation				
	Coefficient	Std. Error	z-Statistic	Probability
Constant	0.000202	0.000162	1.2478	0.2121
ARCH(1)	-0.146294	0.082811	-1.7666	0.0773
GARCH(1)	1.095331	0.009563	114.54	0.0000
N	48			
Log likelihood	70.08238			

***, **, and * indicate significance at 1%, 5% and 10%, respectively.

Source: Data analysis

mean equation indicate the basis of price expectation among the maize producers and consumers in the country.

4.6 Supply Response Estimates for Maize

The results of estimating the supply response to the risks posed by climate variability and price uncertainty are presented in Table 4.8. The parameters in the supply response for the maize consist of maize supply lagged by one month, maize prices, input prices represented by oil prices and fertilizer prices, lagged by one month, consumer price index lagged by one month, exchange rate and an error correction factor to represent the effect of feedback mechanisms. The climate variability shocks are represented by the monthly average rainfall lagged by five months and the monthly average temperature. The supply of maize in the last one month and the rainfall in the past five months are the most significant factors that could affect the supply response of maize in the country. A one percent increase in the previous month supply of maize will lead to 0.71 per cent increase in supply in the current month. On the other hand, a 1 per cent increase in rainfall recorded in the past five months will lead to a 0.03 per cent increase in the amount of maize supply in the current period. This was significant at 5 per cent level. This is because maize production in Kenya is mainly produced on rain-fed systems, and thus indicates the sensitivity of maize supply to rainfall. Moreover, the shocks induced by temperature variability indicate that 1 per cent increase in the current season temperature will lead to a 1.02 per cent increase in the supply of maize in the country.

Table 4.8: Supply response estimate for maize

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	-0.4430	1.3943	-0.3177	0.7527
Supply (t-1)	0.7192	0.1005	7.1577	0.0000
Maize prices	0.4952	0.2533	1.9547	0.0591
Average rainfall (t-5)	0.0347	0.0111	3.1227	0.0037
Average temperature	1.0183	0.3888	2.6191	0.0132
Oil prices	-1.0152	0.5664	-1.7925	0.0822
Fertilizer prices (t-1)	-0.5846	0.3618	-1.6159	0.1156
Consumer price index (t-1)	-0.0578	0.3803	-0.1520	0.8801
Exchange rate	-1.6850	0.6389	-2.6374	0.0126
Error correction term	-1.0823	0.5726	-1.8899	0.0676

***, **, and * indicate significance at 1%, 5% and 10% respectively; R^2 =0.8159; Durbin Watson =2.0966

Source: Data Analysis

Changes in maize prices have a significant effect on the supply. The results reveal that a 1 per cent increase in the price of maize would lead to 0.49 per cent increase in the supply of maize.

Fertilizer prices and oil prices, as some of the important variable inputs in maize supply, showed a depressing effect on the supply of maize in the country. The results indicate that a one per cent increase in fertilizer prices would lead to a 0.58 per cent decline in the supply of maize. On the other hand, 1 per cent increases in oil prices would result in 1.01 per cent reduction in the supply of maize. This is because fertilizer and oil are important inputs in maize production.

The rate of inflation indicated a negative relationship with maize supply. The results showed that a 1 per cent decrease in the inflation rate would lead to an increase of 0.06 per cent in the supply of maize. This basically means that a reduced inflation rate is favourable for maize supply. This could be attributed to the nature of maize being a normal good, which is widely cultivated and consumed in Kenya. Therefore, a reduced inflation rate would not limit the demand for maize as well as its production activities. On the other hand, an increase on the rate of foreign exchange would affect the supply of maize negatively. A 1 per cent increase in the exchange rate would lead to 1.7 per cent decrease in supply of maize. The results indicate that the elasticity of foreign exchange is negative and significant at 10 per cent level. Therefore, a high rate of foreign exchange discourages importation of maize to the country.

The error correction coefficient was significant at 10 per cent. This indicates that market interdependence and feedback mechanisms are strong, such that true long-run relationships of the parameters in maize supply response model can be obscured by cointegrating patterns of behaviour.

5. Conclusion and Policy Implications

5.1 Conclusion

The study is motivated by the current common scenarios of climate variability and agricultural food price changes in the country, which is also globally acknowledged as the game changers of economic development. It shows the importance of climate change on agricultural supply and how climate variability can play a role in production shifting.

The study provides an insight into understanding the effect of unpredictable climate and prices on maize supply. The results show that climate variability could induce risk on the maize market in Kenya. Variability of rainfall, temperature and price uncertainty causes negative effects on the supply of maize. The ARCH-LM tests also indicate significant risk due to unpredictability of rainfall, temperature and price uncertainty. The risks due to these variables are significant enough to depress maize supply. There are indications of variability in climate events becoming more frequent (RMSI, 2009), which suggests that the average monthly or annual impact might become even greater in the future. It is therefore imperative that policy makers take heed of the severe implications of climate variability, especially for the most vulnerable in society, such as resource-poor small-scale farmers and poorer urban households.

5.2 Policy Implications

There is need to establish systems for monitoring stress indexes related to climate and prices, which can be used for forecasting and scenario analysis. These could lead to more accurate estimations for several periods, which would help the government in planning stabilization schemes for the maize sector. On the other hand, there is need to increase market confidence for the maize producers by establishing efficient storage and post-production systems, and even open trade arrangements in maize trading within and outside the country in order to minimize maize price volatility resulting from climate variability.

Although the government has initiated plans to implement irrigation projects as envisaged in the Vision 2030, there is need to increase investment in water resource development and infrastructure in order to curb against uncertainties brought about by unpredictability of rainfall and temperature. This would help to reduce the effects of reduced maize supply.

Given that the first priority of any farmer is to secure material and economic survival, adapting to climatic risks would be an instinctive livelihood response. As agriculture will remain an important economic activity at the local and national level for some time, it is important that governments put in place institutional and macroeconomic conditions that support and facilitate adaptation. At the very least, in line with the recommendations of the Commission for Africa, climate change should be 'mainstreamed' within development policies, planning and activities of the maize sector.

5.3 Areas for Further Study

One of the limitations of this study was lack of sufficient data at the county level, which restricted the study to a relatively high level of aggregation of maize supply. Further studies are recommended to capture the effect of climate variability and price volatility on maize production at county level.

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