MODELING TEMPORAL VOLATILITY OF FARM PRODUCE PRICES IN KENYA

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Abstract
Agriculture is considered a fundamental sector employing over forty percent of the population in Kenya and contributes a large proportion of about 26% of the Gross Domestic Product. To improve investment in this vital sector and ensure secured food production to the increasing population, it is crucial that farmers are aware of the best market opportunities that maximizes consistent income. This work focused on determining the volatility of farm produce prices as a way of establishing opportunities of farming investment. The trends and volatility analysis used average monthly prices of agricultural produce collected and published by the Ministry of Agriculture Livestock and Fisheries (MoALF). It covered the period January 2013 – July 2018. The data extracted was restricted to Maize, Beans, Cowpeas and potato crops. Various ARIMA (p,d,q) time series models were fitted for each respective crop and respective best model was selected based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics. The analysis were done using R software (V3.4.2) and all tests were carried at 5% level of significance.

The analysis identified and fitted unique models for the Irish potato, maize, beans and cowpea to be ARIMA (2,0,2), ARIMA (2,1,0), ARIMA (0,1,1) and ARIMA (1,1,1) respectively. It would be appropriate to use high frequency data, determine the spatial distribution of the prices over the years as well as the effect of co-integrating oil prices the models.

Key words: time series analysis, ARIMA models, price fluctuations, food production, agriculture

1.0 Introduction
Agriculture is among the main priority sectors expected to contribute towards achievement of the Big Four Agenda of the Kenyan Government, Kenya Vision 2030 blue print, and the global Sustainable Development Goals. In developing countries, agriculture contribute about 40% of GDP, while in Kenya it employs over 40% out which over 70% are rural inhabitants derive their livelihoods from agriculture-related activities. The sector remains a vital component in combating poverty and boosting economic growth. According to the Kenya Economic Report 2017 (KIPPRA, 2017), the sector contributed 32.6% to the GDP and 27% of GDP in link to other sectors in 2016.

Effects of farm produce price volatility is very crucial to the rural community especially to those whose livelihoods are only dependent on farming. It affects farmers’ enthusiasm and decision making in investment on agricultural production (Ralph, C. et al, 2006). In liberalized markets such as Kenya (Wangia et al., 2004), the market supply and demand forces determine the optimal prices. Based on the cob-web theory (Ezekiel, 1938), farmers expect that when current produce prices are low it will remain low in the next period. This may dampen their expectation leading to reduced investment in production and therefore scarce quantities produced. Besides, frequent unexpected fluctuation in farm produce prices impact food production since farmers cannot make appropriate production schedules (Munir and Esteban, 2011).

Price fluctuations are as a results of many factors such as yield levels, weather, market cycles, policy developments and changes in related sectors (Trostle, 2008). The Global Market Report (2007) showed extremely high fluctuation of agricultural produce in the commodity markets. This report
attributed these fluctuations to the supply and demand fundamentals contributed by population growth as well as weather condition.

Given the risks and volatility in income due to unexpected fluctuations of the uninsured farm produce prices (Dercon, 2005) coupled with inadequate asset base, the poorest farming community will tend to practice risk-coping behavior by undertaking crop diversification under family and community setup (Dercon, 2005). Being smallholder farmers, this diversification may tend to increase costs of production.

Research studies focusing on coffee have revealed presence of lag in the transmission of price changes in the international market to the domestic markets. Unlike this slow international transmission, prices have notable fluctuations across domestic markets with temporal spillovers over seasons or periods and market interdependence or co-integration (Du et al., 2011). Further, in the domestic market farmers tend to sell their produce at farm-gate prices which is lower than the nearest available market prices (Fafchamps and Hill, 2008). Market liberalization has mainly contributed to lower prices that is visible in the African compared to the other markets (Gilbert and Varangis, 2004).

This work focused on determining the annual temporal trends of farm produce prices among the major crop species in Kenya including the cereals, tubers and legumes categories of agricultural produce in the Kenyan Market.

2.0 Materials and Methods

A longitudinal average monthly data of prices for various food crops collected from major towns across Kenya was downloaded from the National Service Information Service (NAFIS), a website developed by National Agriculture and Livestock Extension Programme (NALEP) under the Ministry of Agriculture, Livestock and Fisheries.

The data was compiled and subset to cover a three-year period between January 2013 and June 2018 and included one crop for each class of crops. The crops selected included maize under cereals, red Irish potato in the roots and tubers and Rose Coco beans and cowpea under the legumes. The crops and/or varieties were selected based on their wide adaptation across the agro-ecological zones in the country whereas two legumes were selected based on the wide range of legumes crops available (Export Processing Zone, 2005).

Data for the different crop categories was analyzed using time-domain financial time series models. All tests of significance were carried out at 5%. R software (Version 3.4.2) was used to analyze and present the data. An Autoregressive Integrated Moving Average (ARIMA) model was identified and fitted based on the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). An ARIMA model can be defined by the equation,

\[ y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j \epsilon_{t-j} + \epsilon_t \]

Where, \( p \) is for the autoregressive and \( q \) for moving average terms.

Jarque-Bera test for variance was then carried out to determine any presence of conditional variance (Engle, 1982) on the fitted models. This technique has been applied on food prices volatility elsewhere (Gilbert and Morgan, 2010).

3.0 Results

3.1 Summary Statistics

To allow for ease of comparison prices were transformed to amount per kilogram. As shown in table 1, the monthly mean prices for the entire period for the different crops ranges were KSh 60 – 93 for beans, cowpea was Ksh 56 – 93, maize KSh 26 - 51 per kilogram, white potato between KSh 17 – 36.
The results indicate very high deviations in prices for cowpeas (10.49) followed by beans (7.18) and maize (5.19) whereas potato had the least deviation of 3.98.

Table 1: Summary statistics for monthly crop produce

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Rose Coco Beans</th>
<th>Cowpeas</th>
<th>Dry Maize</th>
<th>White Irish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>59.89</td>
<td>55.84</td>
<td>26.86</td>
<td>17.41</td>
</tr>
<tr>
<td>Max</td>
<td>93.27</td>
<td>92.82</td>
<td>50.68</td>
<td>35.77</td>
</tr>
<tr>
<td>Median</td>
<td>70.83</td>
<td>72.68</td>
<td>31.45</td>
<td>26.40</td>
</tr>
<tr>
<td>Mean ± 95% CI</td>
<td>72.38 ± 1.959</td>
<td>73.98 ± 2.864</td>
<td>32.76 ± 1.415</td>
<td>25.88 ± 1.086</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.98</td>
<td>1.43</td>
<td>0.71</td>
<td>0.54</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>7.18</td>
<td>10.49</td>
<td>5.19</td>
<td>3.98</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.66</td>
<td>0.04</td>
<td>1.89</td>
<td>-0.06</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.36</td>
<td>-1.15</td>
<td>3.29</td>
<td>-0.06</td>
</tr>
</tbody>
</table>

On normality, the cowpea is negatively skewed whereas the maize is positively skewed indicating that the prices for cowpea tend to be always high while the maize is lower compared to their average price. The beans and potato prices tend to be normally distributed over the years. The results are presented in figure 1 below.
The raw results for the price trends for the four crops are presented in figure 2. The prices groups the crops into two categories. The legumes consistently had almost triple the price of cereals and tubers and roots and generally all the trends had similar directions over the entire period. Interestingly, over the entire period, all the produce prices had season peaks in the middle of the odd years (2013, 2015 and 2017) with the largest peaks occurring in 2017.

3.2 Identifying Time Series models
Unit root test and co-integration test was used to determine stationarity of each price series using Dickey Fuller statistic with the default lag of 3. The results presented in table 2 indicate that all the produce prices did not have significant unit roots at 3-months interval over the period indicating lack of non-stationarity with the highest value observed obtained in cowpea ($ADF = -2.213$, $p$-value $= 0.4888$).

### Table 2: Augmented Dickey-Fuller Test

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Rose Coco Beans</th>
<th>Cowpeas</th>
<th>Dry Maize</th>
<th>White Irish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dickey-Fuller</td>
<td>-2.946</td>
<td>-2.213</td>
<td>-2.951</td>
<td>-3.013</td>
</tr>
<tr>
<td>p-value</td>
<td>0.1936</td>
<td>0.4888</td>
<td>0.1914</td>
<td>0.1664</td>
</tr>
<tr>
<td>Lag</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

The presence of non-stationarity reveals fluctuations of data prices for the different crops within the period. This is consistent with short periods for beans, cowpeas, peas and green gram legumes of about three months. One the other hand, major maize production takes about a year whereas most potato farmers despite having shorter maturity periods experience one rainy season.

We tried to remove the non-stationary in series by differencing at lag 3 and the results plotted as presented in figure 3. A high fluctuation occurred between the second and third year with addition deep highs and lows at the end of the period. AFC and PACF were used to determine the relevant ARIMA models for the series (Pindyk and Rubinfeld, 1991).
3.3 Estimation of ARIMA Model Parameters

The object of this paper was to determine presence of volatility in prices for the different selected crops. To establish this, the mean equation for the different identified models were fitted and the residuals tested for volatility using Auto-Regressive Conditional Heteroscedasticity (ARCH) models presented below. Table 3 shows the parameters of the fitted mean equation models and table 4 are the test results for the ARCH tests.

<table>
<thead>
<tr>
<th>Crops</th>
<th>ARIMA(p,d,q)</th>
<th>Parameters</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irish Potato</td>
<td>ARIMA (2, 0, 2)</td>
<td>0.789, -0.805, -0.160, 0.704</td>
<td>271.56, 259.85</td>
</tr>
<tr>
<td>Maize</td>
<td>ARIMA (2, 1, 0)</td>
<td>0.558, -0.092, -0.150, 0.704</td>
<td>215.34, 211.48</td>
</tr>
</tbody>
</table>
At the 13th JCUA Scientific, Technological and Industrialisation Conference

Beans | ARIMA (0, 1, 1) | - | - | 0.410 | - | 290.83 | 283.10
Cowpea | ARIMA (1, 1, 1) | -0.002 | - | 0.134 | - | 315.38 | 313.44

As shown in the above table, the optimal mean equation models for the different crops are as follows:

Irish potato: \( Y_t = 0.789Y_{t-1} - 0.805Y_{t-2} - 0.16e_{t-1} + 0.704e_{t-1} \)
Maize: \( Y_{dt} = 0.558Y_{t-1} - 0.092Y_{t-2} \)
Beans: \( Y_{dt} = 0.410e_{t-1} \)
Cowpea: \( Y_{dt} = -0.002Y_{t-1} - 0.134e_{t-1} \)

3.4 Determining Presence of Volatility
Test for presence of volatility was determined using Lagrange Multiplier (LM) test recommended by Engle (1982). The test basically randomness of the residuals of after fitting the mean equation (ARIMA) model.

Table 4: Residuals ARCH-LM Volatility Test

<table>
<thead>
<tr>
<th>Irish Potato</th>
<th>Maize</th>
<th>Beans</th>
<th>Cowpea</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (2, 0, 2)</td>
<td>ARIMA (2, 1, 0)</td>
<td>ARIMA (0, 1, 1)</td>
<td>ARIMA (1, 1, 1)</td>
</tr>
<tr>
<td>ARCH-LM statistics,( p )</td>
<td>2.435</td>
<td>1.692</td>
<td>4.514</td>
</tr>
<tr>
<td>Prob. Chi-square (p)</td>
<td>0.9918</td>
<td>0.9982</td>
<td>0.9212</td>
</tr>
</tbody>
</table>

The results reveal no heteroscedasticity in the residuals of the fitted models. The conditional variance became negligible and volatility could not be determined.

4.0 Discussion and conclusions
This study focused on establishing presence of price fluctuations of farm produce as an opportunity for farming opportunity. However, it neither determined the effect of prices of farming input on this viability nor explored the variability of the prices across the different market in the country. The recent idea of warehouse receipting system introduced by the National Cereals and Produce Board may play an important role of stabilizing prices (Coulter and Onumah, 2002).

The study establishes different optimal ARIMA models for the different crops. The models identified are ARIMA (2,0,2) for Irish potato, ARIMA (0,1,1) for bean, ARIMA (2,1,0) for maize and ARIMA (1,1,1) for cowpea.

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References
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