Egerton University

Tegemeo Institute of Agricultural Policy and Development

Working Paper No. 22
May 2006

SEASONAL ANALYSIS OF SELECTED FRESH FRUIT AND VEGETABLE PRICES AT WHOLESALE LEVEL IN KEY URBAN MARKETS OF KENYA

Mary Mathenge and David Tschirley

Tegemeo Institute Of Agricultural Policy and Development, Egerton University.
P.O Box 20498 Nairobi.
Tel: (020) 2717818
Email: egerton@tegemeo.org and/or tschirle@msu.edu

Support for this research has been provided by the Tegemeo Agricultural Monitoring and Policy Analysis Project (TAMPA) between Tegemeo Insitute/Egerton University and the

Department of Agricultural Economics at Michigan State University. Financial support for this project is provided by the Kenya Mission of the United States Agency for International Development. Additional support is also provided by MSU through resources from the Food Security III Cooperative Agreement.

TABLE OF CONTENTS

LIST OF TABLES

A. Background

Agricultural commodities typically show a strong seasonal pattern in production, with supplies which come off the farm during one or perhaps two distinct periods of the year having to meet relatively stable demand over the course of the entire year. This seasonal pattern in production can give rise to strong seasonal patterns in price movements, with low prices during and shortly after the harvest, rising to peaks just prior to the next harvest. Understanding this price seasonality, the typical timing and levels of seasonal highs and lows, and the reliability of each, is a key task for anyone wishing to understand the market for an agricultural commodity.

In this Technical Note we present the results of seasonal analysis for seven fresh fruit and vegetable crops in Nairobi, Mombasa, and Kisumu. We chose ripe bananas, kales, dry onions, tomatoes, cabbages, oranges, and potatoes due to their importance in urban consumer diets. Nairobi, Mombasa, and Kisumu were chosen to provide a cross section of the most important urban consumer markets in the country. The next section presents the data and methods which we used, while section C presents and discusses results.

B. Data and Methods[1]

Data for this analysis come from the Market Information Branch of the Ministry of Agriculture. For over 10 years this unit has collected daily prices on about 40 products in over 15 markets in Kenya. We chose to use wholesale prices, as they provide the best overall indicator of market conditions for these seven commodities. The period of analysis is 1994-2003.

Cleaning

Prior to analysis, data cleaning proceeded in six steps:

1. First we merged all yearly files together into a single SPSS data file with variables for year, month, day, market, crop, collection unit, and price.

2. Prices of most crops were consistently collected based on a single unit (e.g., bananas in a "large bunch", or tomatoes in a "medium crate"). For crops with different units, we only maintained the most common unit and excluded the rest of the cases. This resulted in the exclusion of only about 50 cases out of more than 26,000.

3. We followed a two-step procedure to identify and eliminate outliers. First we plotted the daily data over the entire time period for each commodity in each market – 21 graphs in all. Such plotting immediately reveals prices which differ from surrounding prices by large factors. For example, the graph below shows a plot of uncleaned prices for dry onions in Mombasa. One can clearly

[1] Goetz and Weber (1986) provide excellent background to the methods used in this report.

see prices which are wildly higher or lower than their surrounding prices. Such extreme values are easily classified as outliers, and were replaced with the mean of the two immediately surround values.[2] This procedure resulted in the replacement of about 300 values out of more than 26,000.

4. In the second cleaning step we plotted the prices from this first round of cleaning, and noted that there were continuing instances of single day prices which differed dramatically from their surrounding values. We therefore decided to identify cases where the price was ≥ 50% above both the previous and following price and where the price was ≤ 1/2 of both the previous and following price, and to replace these prices also with the mean of the surrounding prices. This procedure resulted in the replacement of about 270 cases, or about 1% of the data base.

5. Finally, about 35 cases had missing values for the price variable. These were also filled with the mean of the surrounding prices.

6. Every replaced or filled value was flagged for documentation purposes and the file resulting cleaned file was saved for use in the analysis.[3]

These procedures resulted in a relatively clean data set for analytical purposes. By computing monthly averages of the daily data, any remaining recording or data entry errors for the daily data were largely eliminated.

Calculation of Seasonal Indices

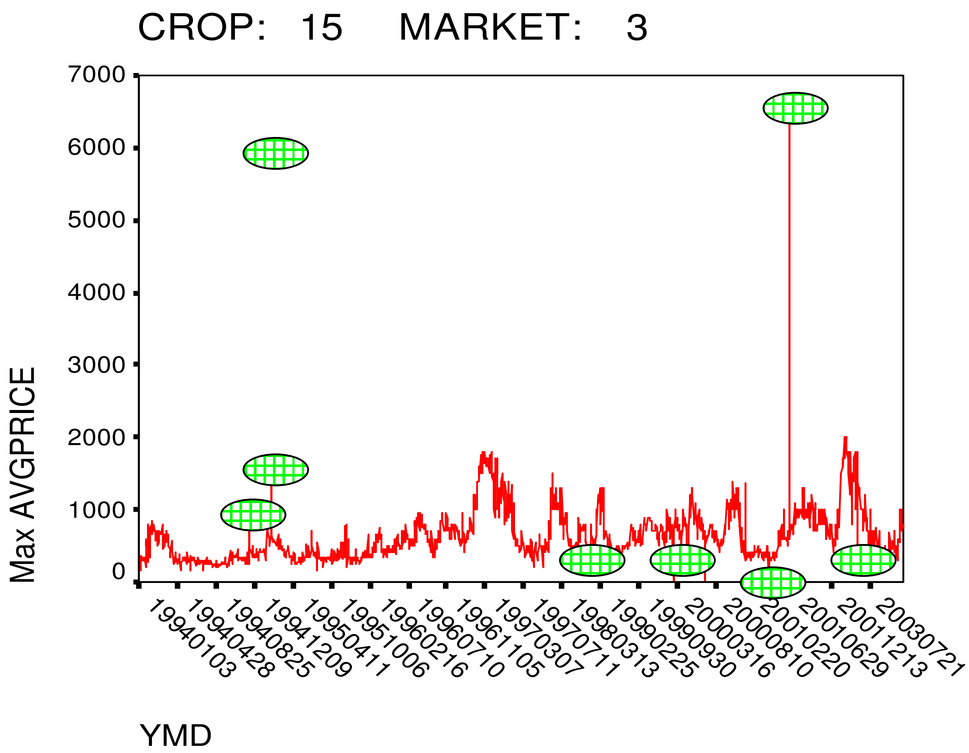
We first calculated a seasonal index for each month in our time series (1994-2003) using the 12-month centered moving average approach:

(1) $$SI_{tm} = P_{tm}/CMA_{tm},$$

where SI_{tm} is the Seasonal Index for month m during year t, P_{tm} is the price during month m of year t, and CMA_{tm} is the 12 month centered moving average of P_{tm}. Because the CMA term "uses up" the first and last six months of a time series, this procedure generates an index for all but the first and last six months. In our case of 120 months of price data, we generated 108 seasonal index numbers.

Plot of uncleaned wholesale prices of dry onions in Mombasa

[2] We used the RMV command with the LINT (linear interpolation) option in SPSS to replace these values.
[3] Note also that we had not daily price data for 2002. Instead, we used monthly averages available in MS-Word files. Because all seasonal analysis is done with monthly data (we "aggregated" our daily data to the monthly level), this created no problems in the analysis.



As can be seen in equation (1), SI_{tm} (i.e., the seasonal index for a specific month during a specific year) shows by what percentage the price for that month lied above or below the prices of the surrounding 12 months. For example, an SI of 1.2 during February 1998 indicates that the price that month was 20% above the average price over the surrounding 12 months[4]. In similar fashion, an SI of, say, 0.87 during June of the same year indicates that, during that year, the price in June was 13% (1.00-0.87) below the average price over the surrounding 12 months.

To obtain a measure of the amount by which a given month "typically" lied above or below its surrounding prices during a specific time period, we calculate the average over our whole time period (1994-2003) of the SI for each month:

(2) $$SI_m = \sum_{i=1}^{n} SI_{tm} / n$$

where n is the number of years in the time series. This operation gives us a single value for each month of the year, reflecting the average amount by which prices during any given month lied above or below their surrounding prices. This is our measure of seasonality; when portrayed in a graph, these twelve values provide a useful visual summary of typical seasonal patterns, and are often referred to as the Grand Seasonal Index (GSI).

[4] Because a 12 month CMA is based on an even number which includes the current month, the actual calculation of CMA_t uses the preceding and following five months, plus the current month (for a total of 11), then weights the sixth preceding month and the sixth succeeding month by one-half. Most common statistical packages such as SPSS will calculate such a CMA automatically.

A final step is to calculate the standard deviation of each monthly value in the GSI (SD_m). Examining SD_m in addition to each GSI value is important to indicate how reliable a given GSI value is. A typical pattern found in agricultural price data is that standard deviations and GSI values during the harvest seasons are both low, while the each tends to be high during the pre-harvest season. These patterns indicate that prices reliably reach seasonal lows during one or two months of the harvest, then rise over the course of the year prior to the next harvest, but that the exact timing and level of the seasonal high is less predictable than the timing and level of the seasonal low. A good example of this pattern is the GSI for Kales in Kisumu (see graph in Results section). GSI values and their standard deviations are both at their lowest levels in October/November, and at their highest levels in March and April. Price movements in April – just prior to the main harvest -- are especially unreliable, as indicated by the very high standard deviation for that month.

Without imposing formal statistical tests, a common rule of thumb in interpreting GSI values is to conclude that a fairly robust seasonal high is reached whenever (SI_m-SD_m) ≥ 1.0 (in other words, whenever the GSI value is at least one standard deviation above a value of 1.0), and that a robust seasonal low is reached whenever (SI_m+SD_m) ≤ 1 (the GSI values is at least one standard deviation below a value of 1.0).

C. Results

The graphs below are organized by crop. For each crop in each market, the graphs on the left hand side show the GSI (middle line), the GSI minus one standard deviation (bottom line), and the GSI plus one standard deviation (top line). Because the GSI always fluctuates around a value of 1.0, we include a horizontal line at that level to facilitate interpretation of the GSI values. To more easily see how reliable the GSI values are for each month, the graphs on the right hand side plot the standard deviations by month. We thus have six graphs for each crop, three for the GSI and three for the standard deviation. Each of these graphs uses the same Y axis values to facilitate visual comparison. Each set of six graphs for a given crop is followed by a summary graph (Figures 1 through 7) that shows the seasonal high and low GSI values, and the typical percentage seasonal price rise that these reflect. We follow each of these summary graphs with a Summary Discussion for the crop. Finally, Figure 8 summarizes average seasonal price rises for each crop in each market.

Table 1 summarizes much of this information. Key patterns include:

- Bananas show no stable seasonal price patterns.

- All other crops show fairly robust seasonality, as indicated by the pattern in the GSI graphs and by the fact that (SI_m-SD_m) is frequently above one during high price months and (SI_m+SD_m) is frequently below one during low price months.

- In nearly all cases, the timing and level of seasonal lows is more reliable than the timing of seasonal highs, as reflected in the standard deviation graphs generally showing high SDs during high price months and lower SDs during low price months.

- With the exception of tomatoes in Nairobi and oranges in all three markets, the timing of seasonal highs and lows for a given crop is very similar across the three markets, generally differing by only one month and sometimes two.

- Cabbages in Kisumu show exceptionally high seasonal price movements, with an average price rise of over 120%; dry onions in Mombasa show a similar seasonal movement.

- Aside from bananas, oranges show the least seasonal price variation.

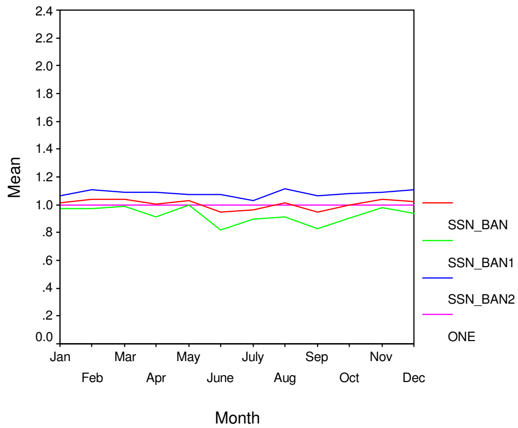
- Onions and cabbages show the greatest differences in seasonality between markets. For example, during our period of analysis (1994 – 2003), onion prices in Mombasa rose nearly 120% on average each year, while in Kisumu the rise was only about 55%. Cabbage prices in Kisumu rose by an average of over 120%, while in Nairobi this seasonal rise averaged less than 60%. Average price rises for other commodities cluster more closely together across markets, with potatoes especially showing consistent behavior across each market.

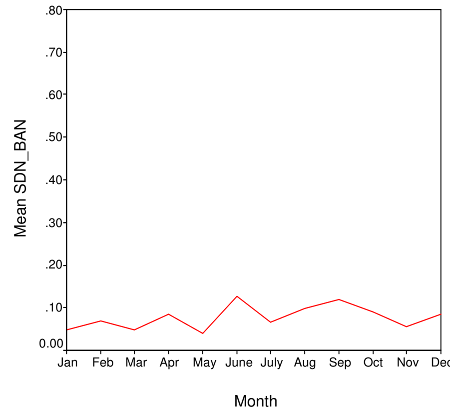
Table 1. Summary statistics for wholesale price seasonality of seven FFV crops in Nairobi, Mombasa, and Kisumu

	Nairobi		Mombasa		Kisumu	
	Seasonal Low	Seasonal High	Seasonal Low	Seasonal High	Seasonal Low	Seasonal High
Bananas						
Month	June/Sep	Feb/Mar/Nov	May	Aug	Oct	Dec
Level	0.95	1.04	0.96	1.07	0.90	1.05
% change	9%		11%		17%	
Kales						
Month	Dec	March	Dec	March	Nov	March
Level	0.81	1.47	0.85	1.26	0.68	1.30
% change	81%		48%		91%	
Onions						
Month	Sep	May	Nov	May	Dec	May
Level	0.77	1.44	0.68	1.48	0.82	1.27
% change	87%		118%		55%	
Tomatoes						
Month	Sep/Oct	May	Sept	Jan	Sept	Jan
Level	0.74	1.32	0.73	1.26	0.83	1.25
% change	78%		73%		51%	
Cabbages						
Month	Dec	Apr	Nov	May	Dec	May
Level	0.77	1.20	0.74	1.30	0.67	1.50
% change	56%		76%		124%	
Oranges						
Month	July	Sept	June	Jan	Oct	March
Level	0.83	1.12	0.80	1.25	0.82	1.26
% change	35%		56%		54%	
Potatoes						
Month	Aug	May	Aug	Apr	Aug	May
Level	0.77	1.28	0.79	1.19	0.80	1.28
% change	66%		51%		60%	

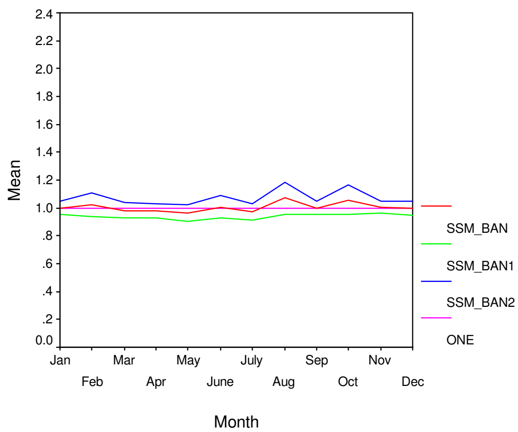
Based on seasonal indices calculated with data from 1994 -- 2003

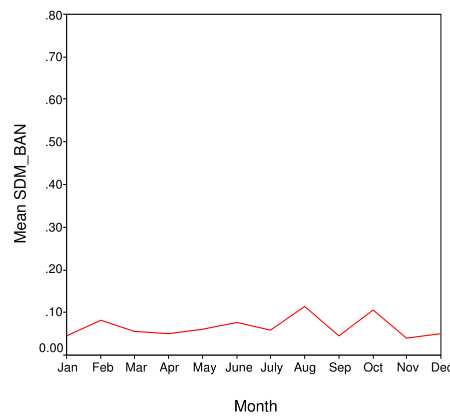
Bananas in Nairobi



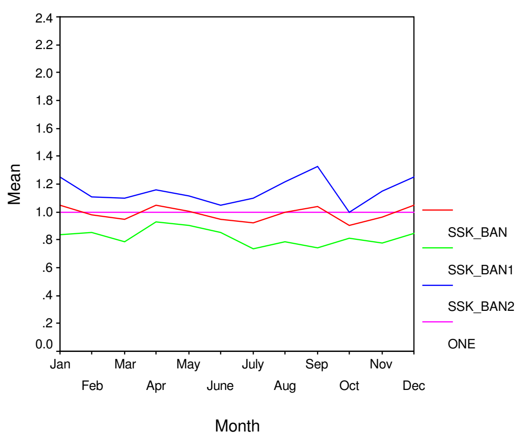


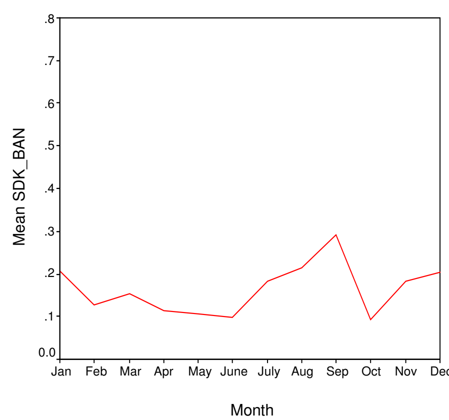
Bananas in Mombasa

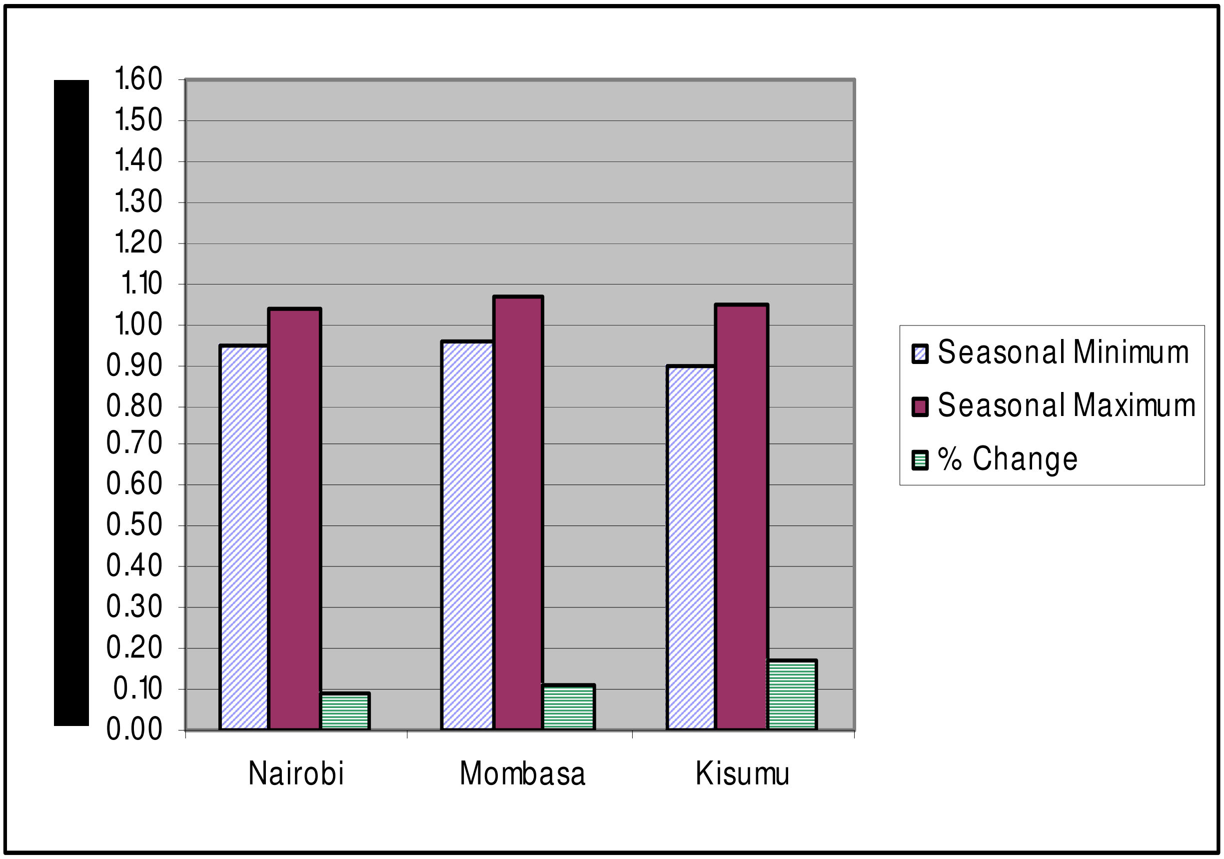




Bananas in Kisumu

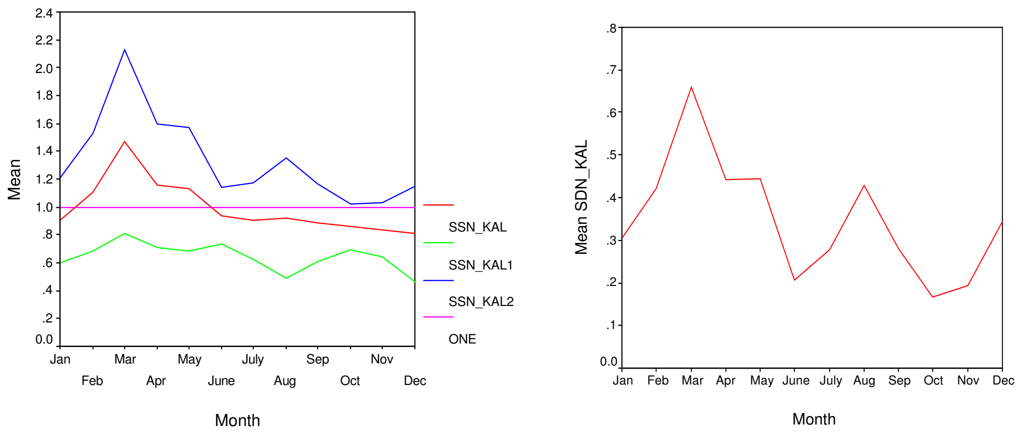




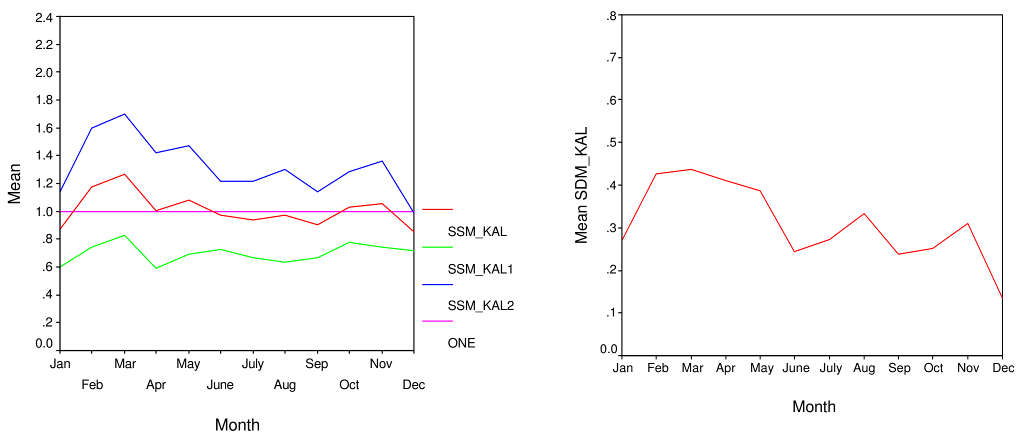


Summary Discussion: Bananas show almost no seasonality in any market. Average seasonal price rises are very low and similar in the three markets.

Kales in Nairobi



Kales in Mombasa



Kales in Kisumu

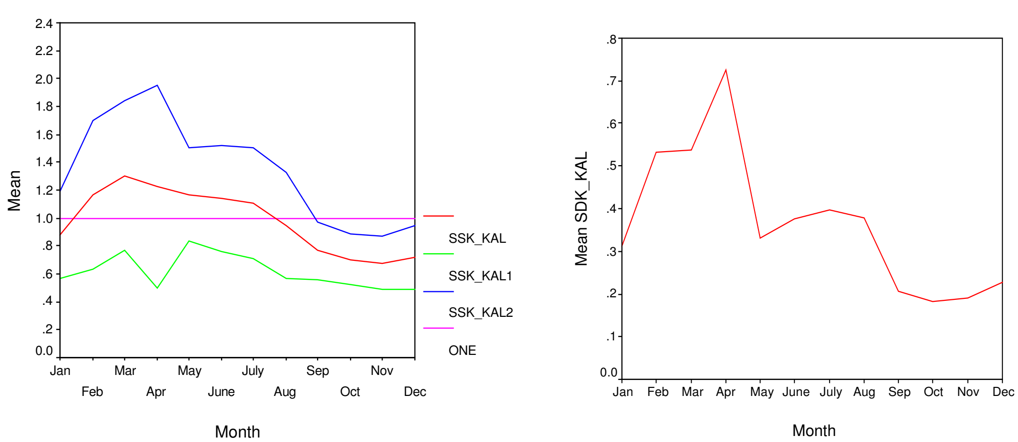
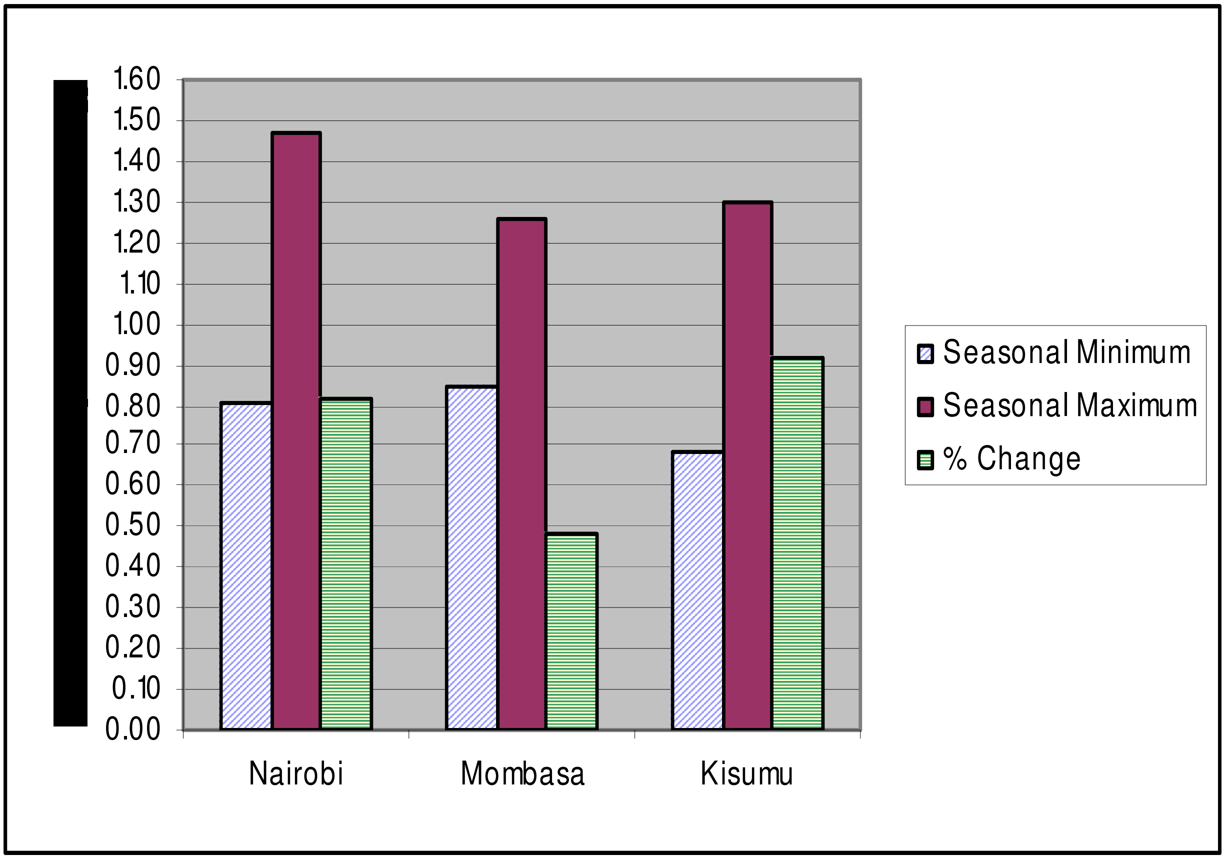
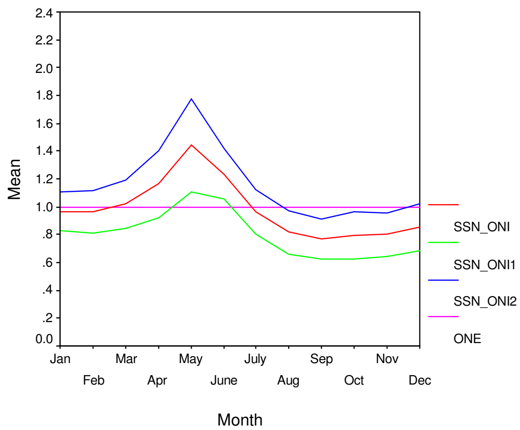


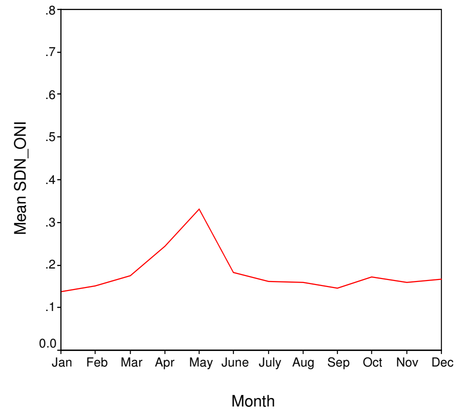
Figure 1. High and low seasonal indices and seasonal % change for kale wholesale prices in Nairobi, Mombasa, and Kisumu



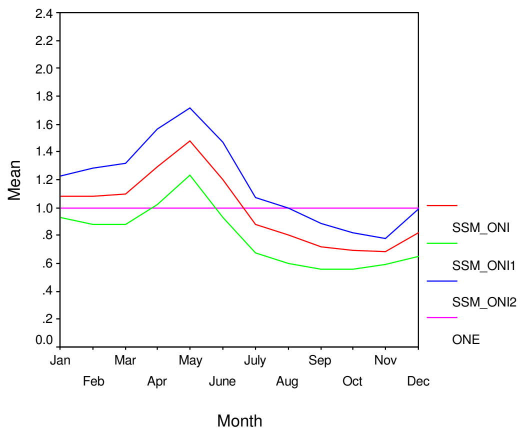
Summary Discussion: Kales tend to show seasonal highs in February-April, depending on the market, and seasonal lows late in the calendar year. But this pattern is unstable, as shown by the fact that SI-SD never exceeds a value of one, and SI+SD falls below a value of one only in Oct-Dec in Kisumu. Mombasa shows substantially less seasonal fluctuation than do Nairobi and Kisumu.

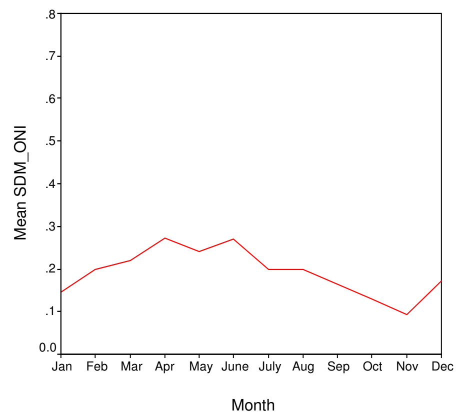
Onions in Nairobi



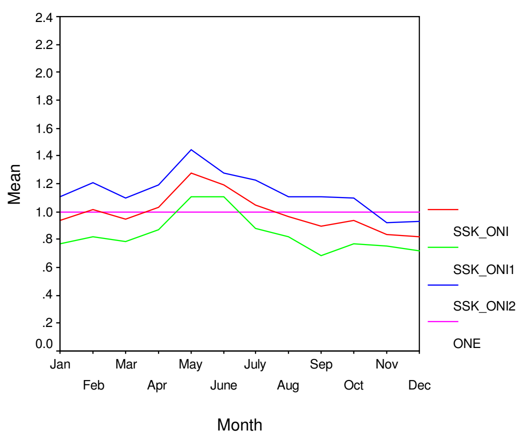


Onions in Mombasa





Onions in Kisumu



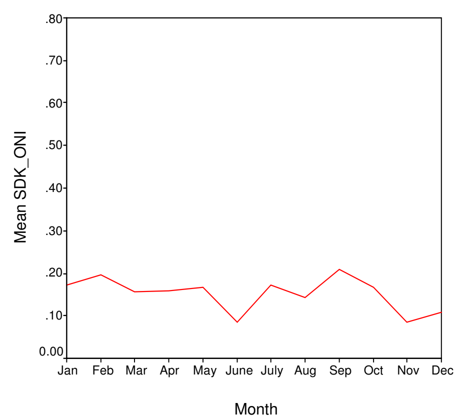
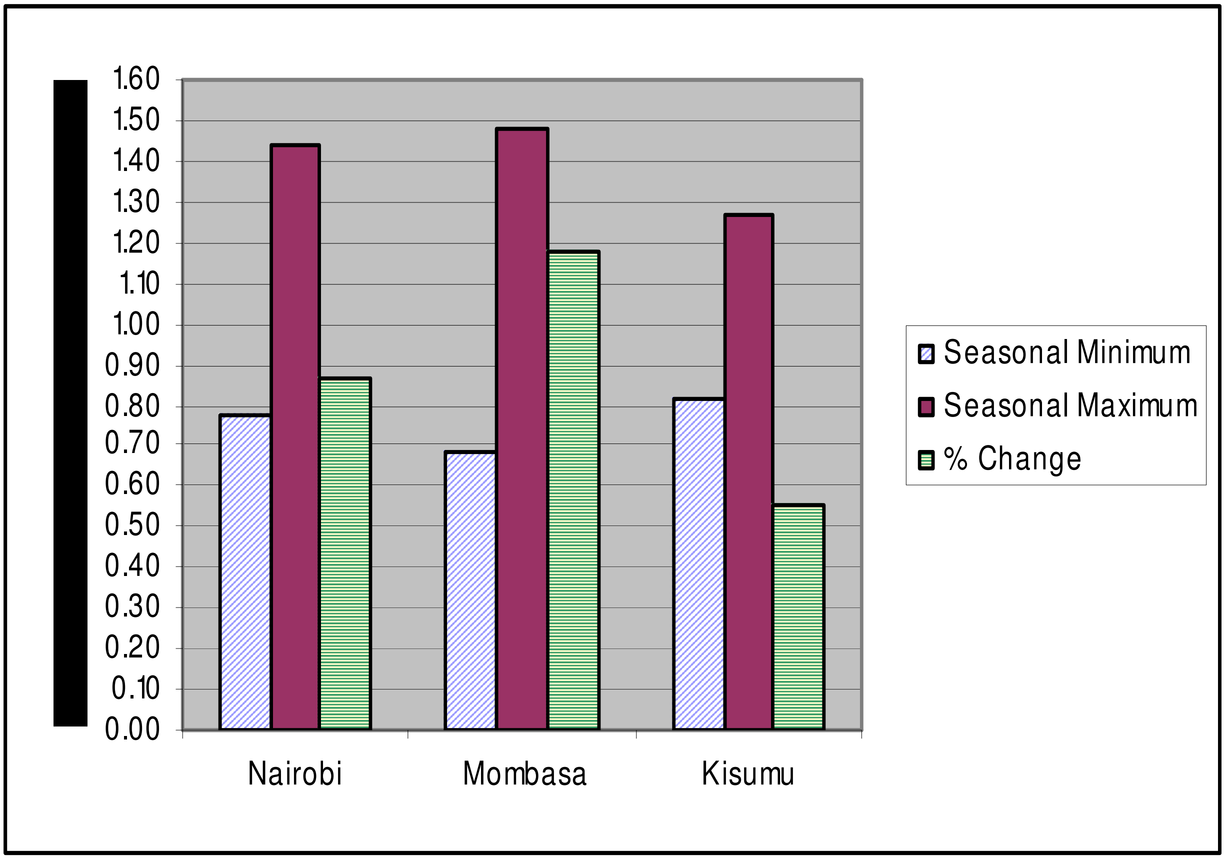
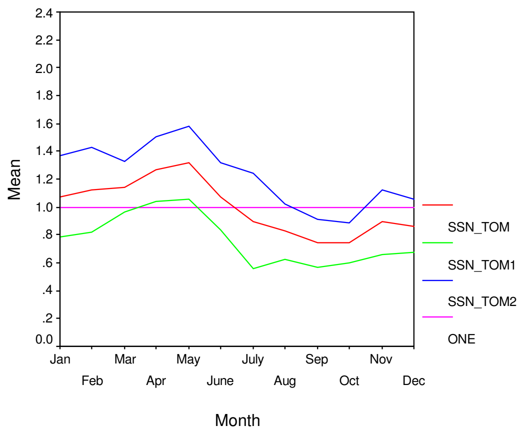


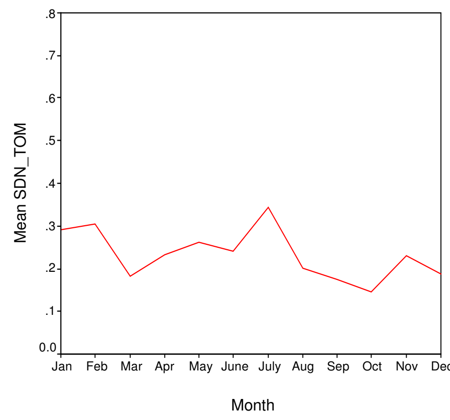
Figure 2. High and low seasonal indices and seasonal % change for dry onion wholesale prices in Nairobi, Mombasa, and Kisumu



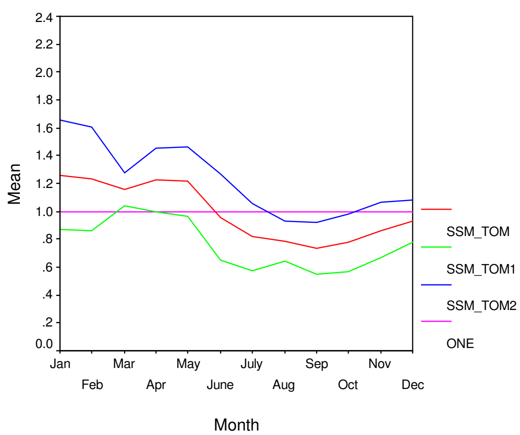
Summary Discussion: Onions show robust and consistent seasonality across all three markets, with seasonal highs in April and lows later in the year. The seasonal pattern in Kisumu is similar to but less accentuated than that in Nairobi and Mombasa. Average seasonal price rises in Nairobi are 87%, and 118% in Mombasa, compared to only 55% in Kisumu

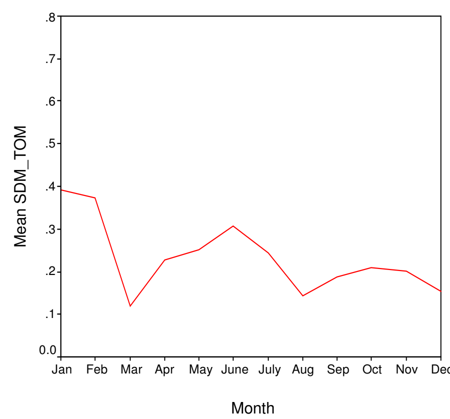
Tomatoes in Nairobi



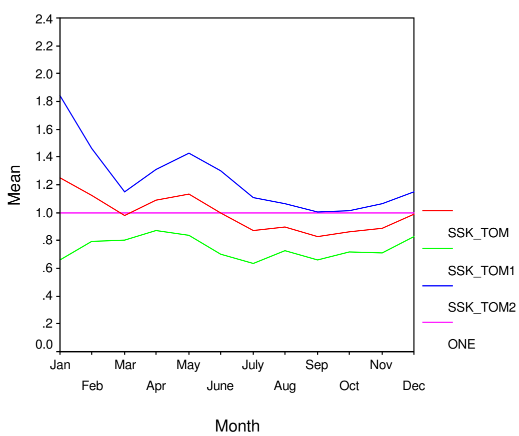


Tomatoes in Mombasa





Tomatoes in Kisumu



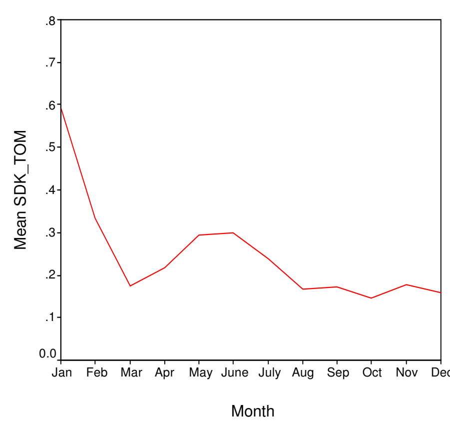
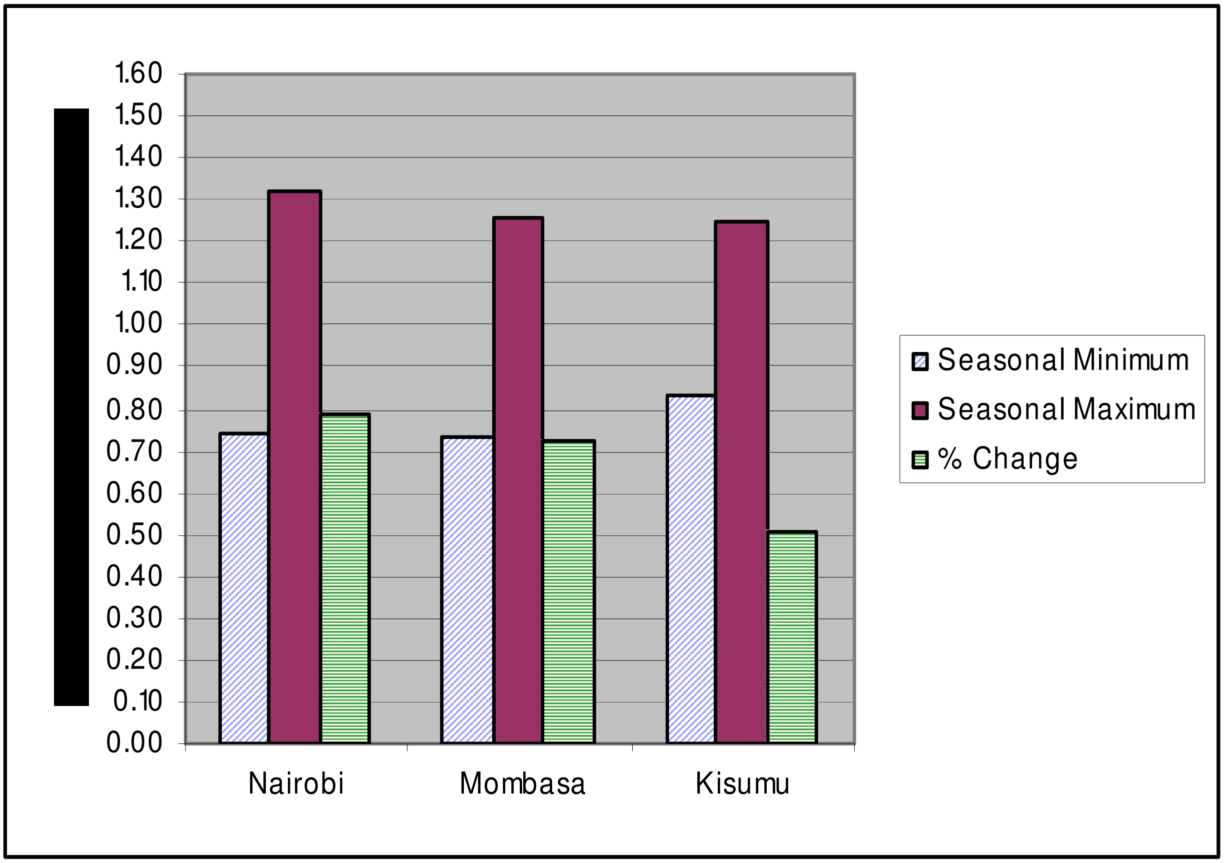
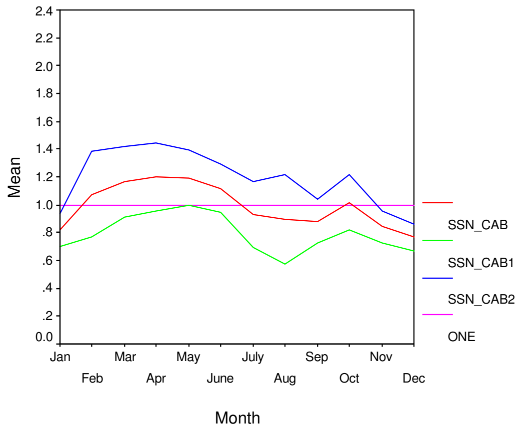


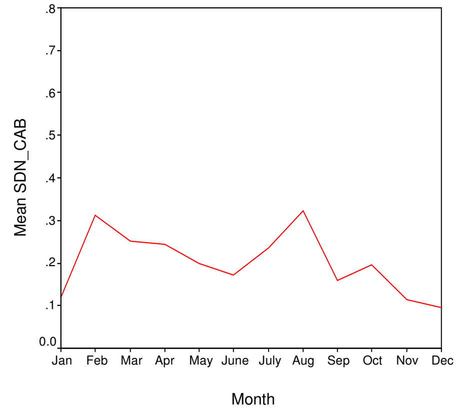
Figure 3. High and low seasonal indices and seasonal % change for tomato wholesale prices in Nairobi, Mombasa, and Kisumu



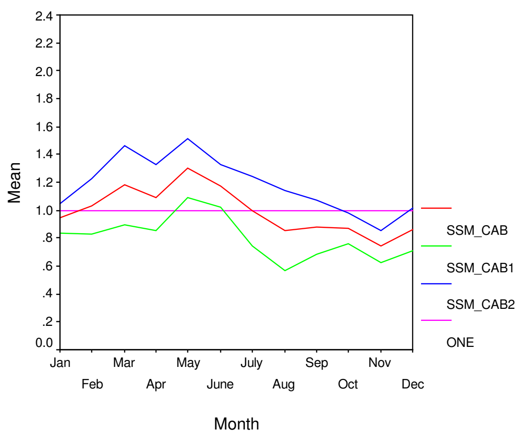
Summary Discussion: Tomatoes show seasonal highs between January and May depending on the market, and seasonal lows around Aug/Sept. This pattern is however less consistent for Kisumu since the SI-SD never goes above one and the SI+SD barely gets to less than one. Average seasonal price rises are relatively close at 78% for Nairobi, 73% for Mombasa and 51% for Kisumu.

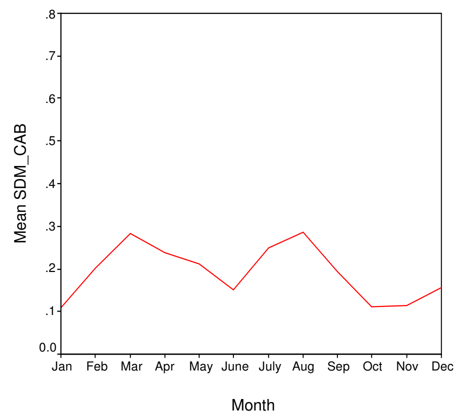
Cabbages in Nairobi



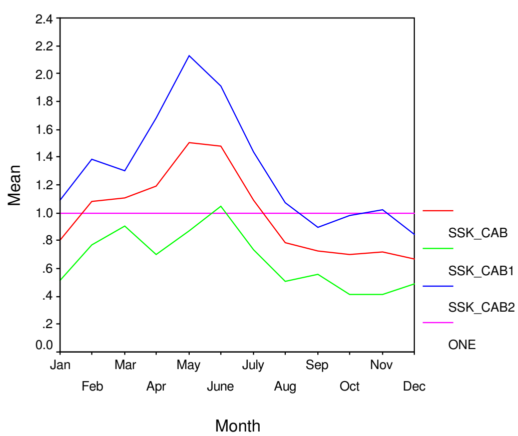


Cabbages in Mombasa





Cabbages in Kisumu



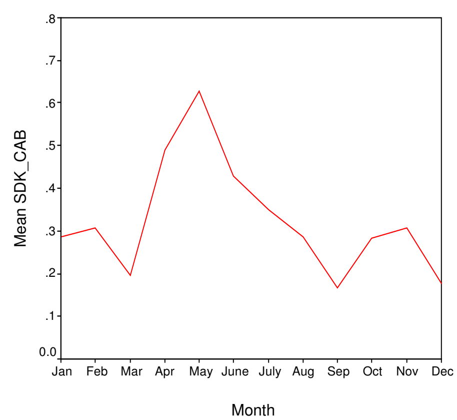
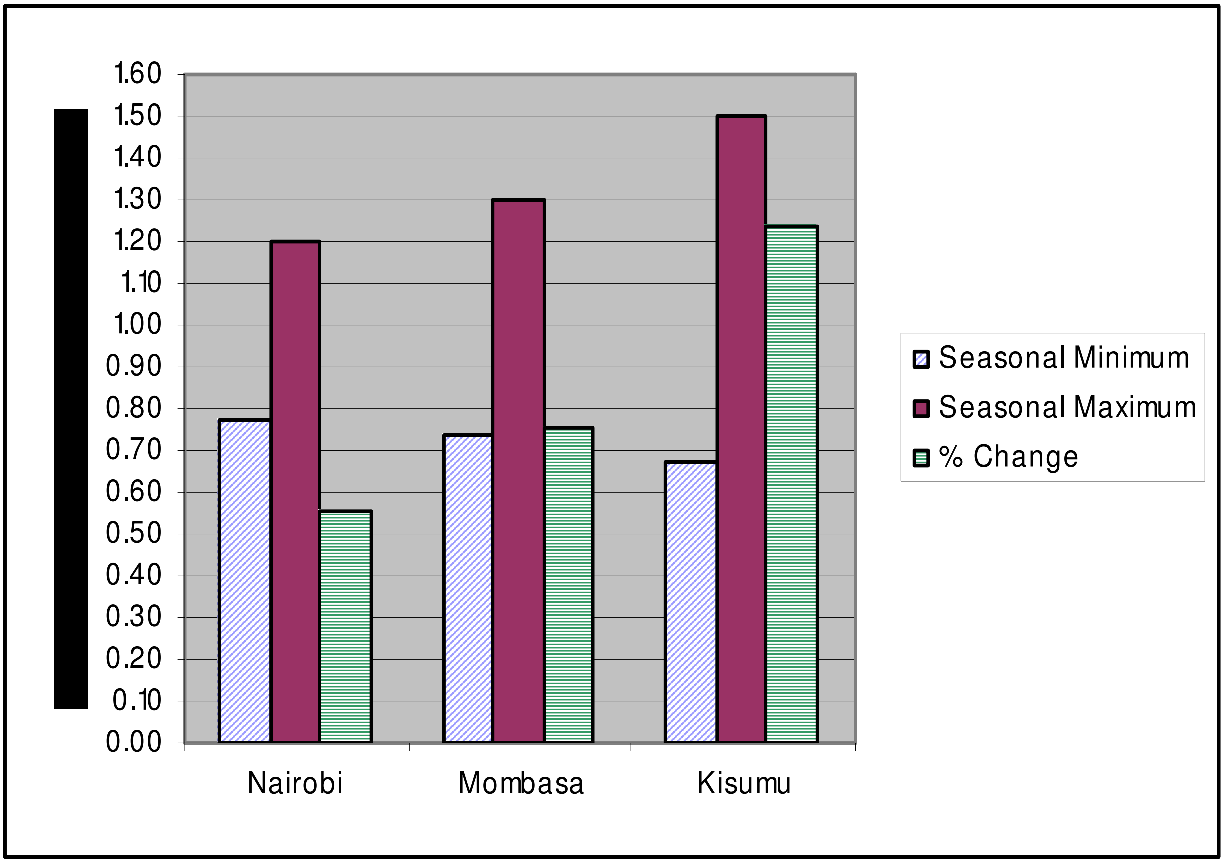
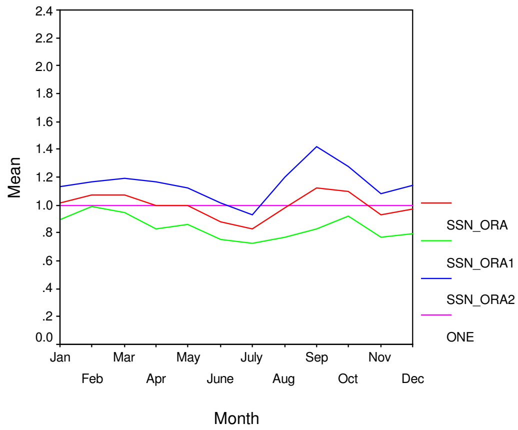


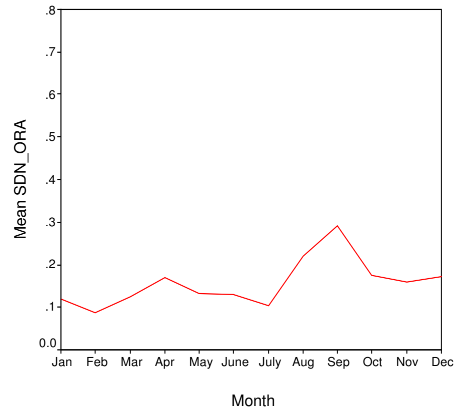
Figure 4. High and low seasonal indices and seasonal % change for cabbage wholesale prices in Nairobi, Mombasa, and Kisumu



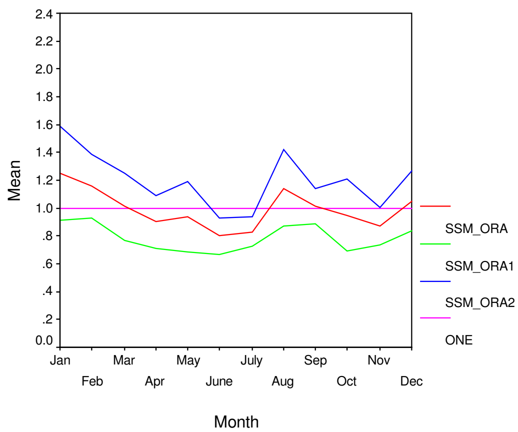
Summary Discussion: Cabbages show a seasonal high between March and June depending on the market. Seasonal lows are found in November and December. The seasonal highs are less stable in Nairobi and Kisumu as the SI-SD barely goes above one. The seasonal average price rise is 56% and 76% for Nairobi and Mombasa markets, respectively, but much higher in Kisumu at 124%.

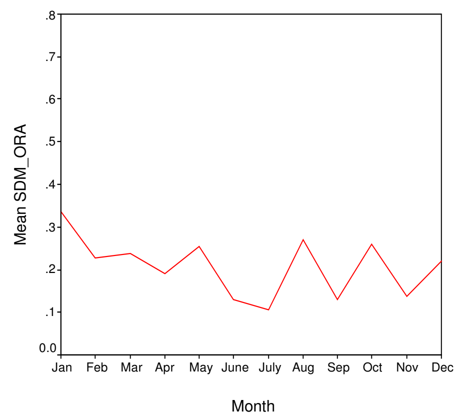
Oranges in Nairobi



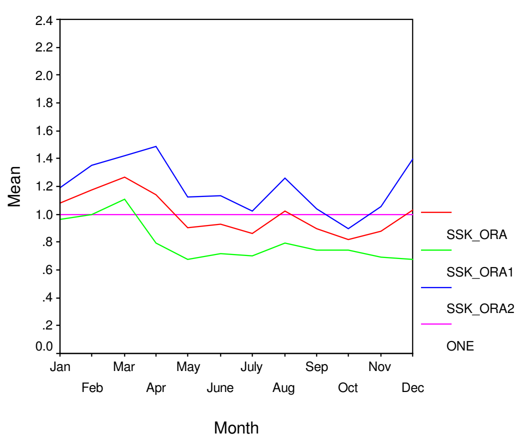


Oranges in Mombasa





Oranges in Kisumu



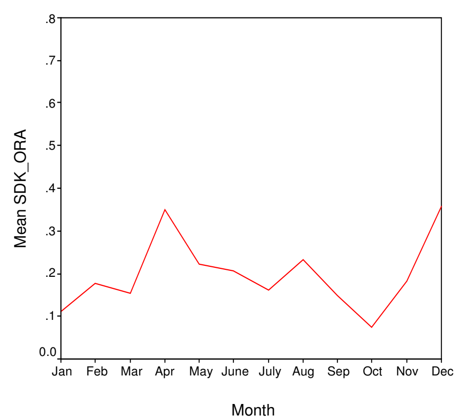
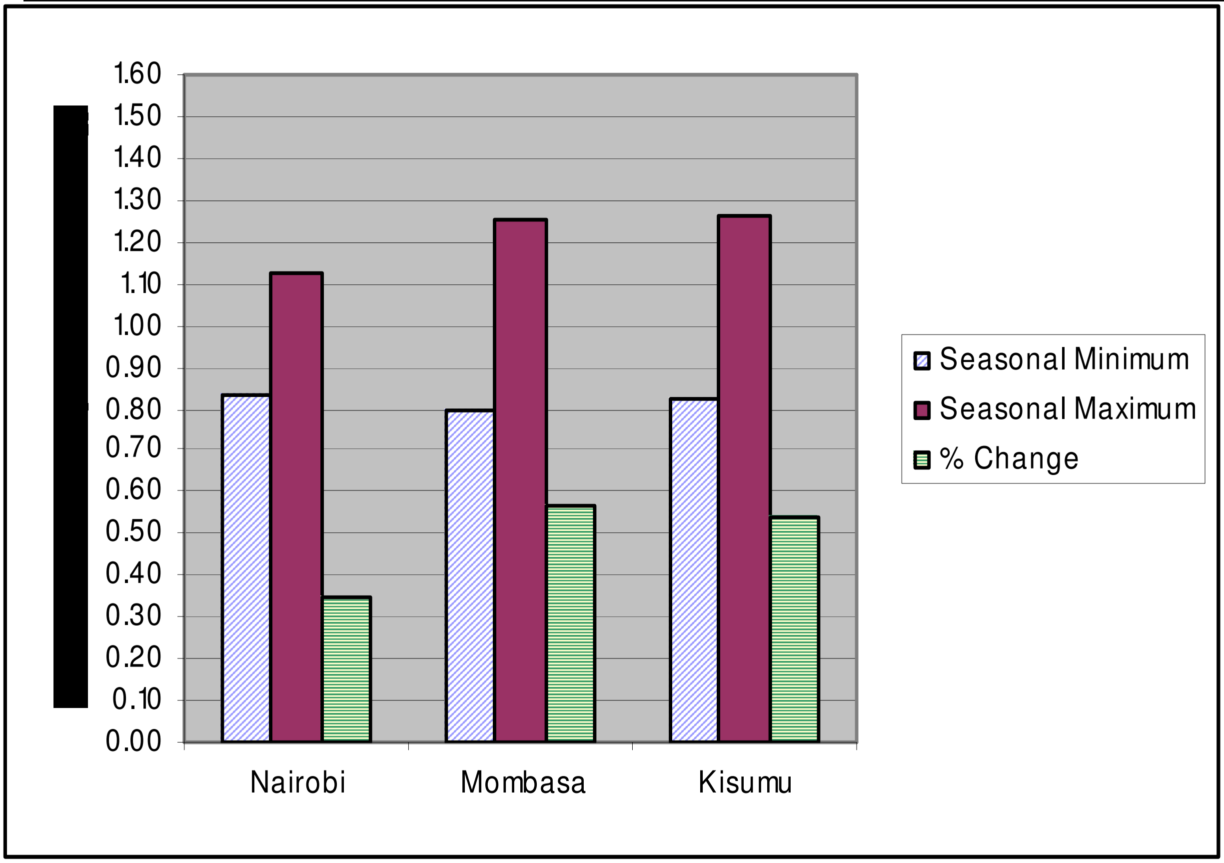
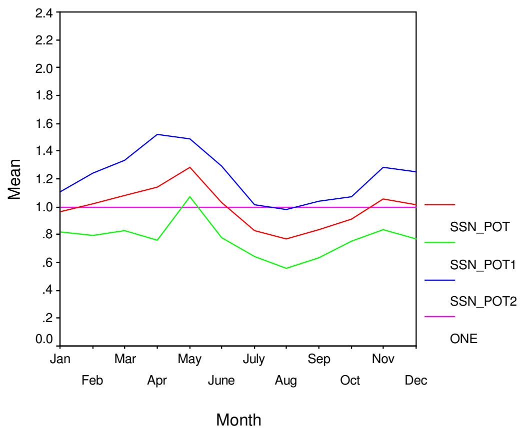


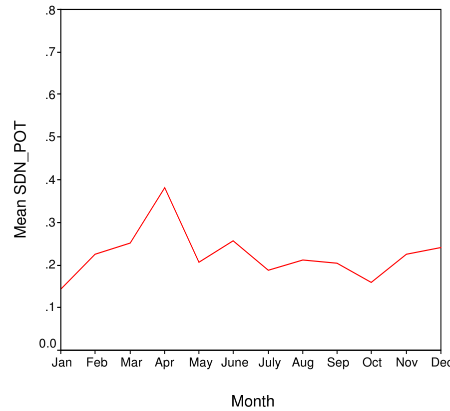
Figure 5. High and low seasonal indices and seasonal % change for orange wholesale prices in Nairobi, Mombasa, and Kisumu



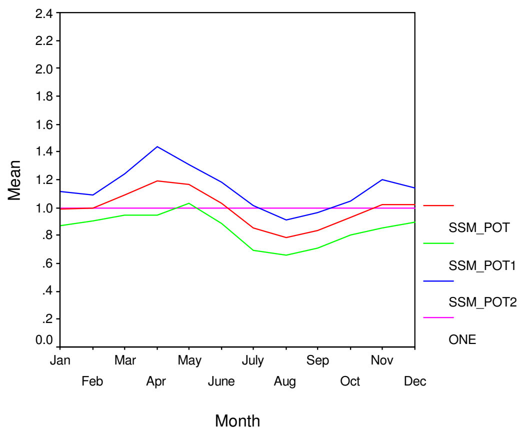
Summary Discussion: The seasonal pattern for oranges is not consistent across the three markets. There is a tendency towards a double low in each market, the first around June/July and the second later in the year. Seasonal highs are very inconsistent, occurring in September in Nairobi, January in Mombasa, and March in Kisumu. Kisumu market shows a stronger seasonal pattern than the other markets, with clear seasonal highs in March and lows in October. The seasonal average price rise is low compared to other crops, especially for Nairobi market.

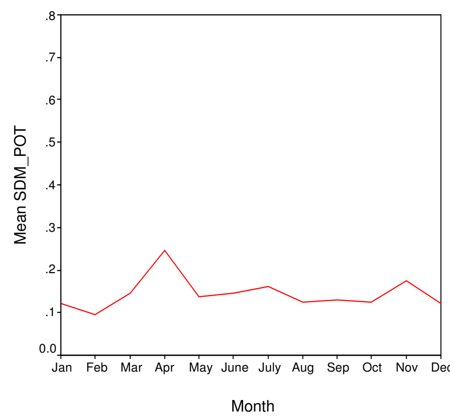
Potatoes in Nairobi



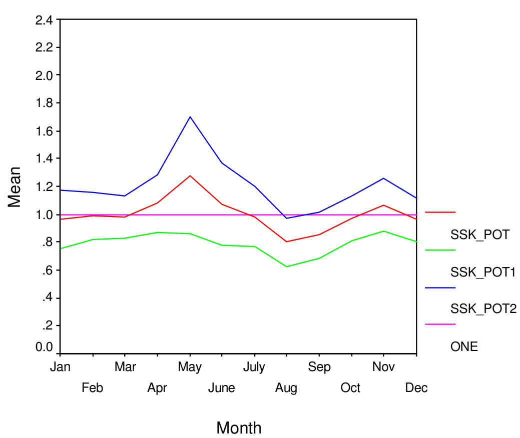


Potatoes in Mombasa





Potatoes in Kisumu



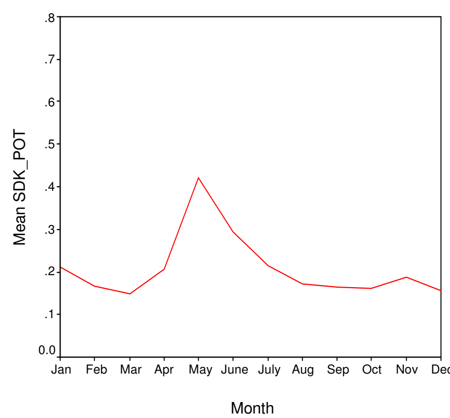
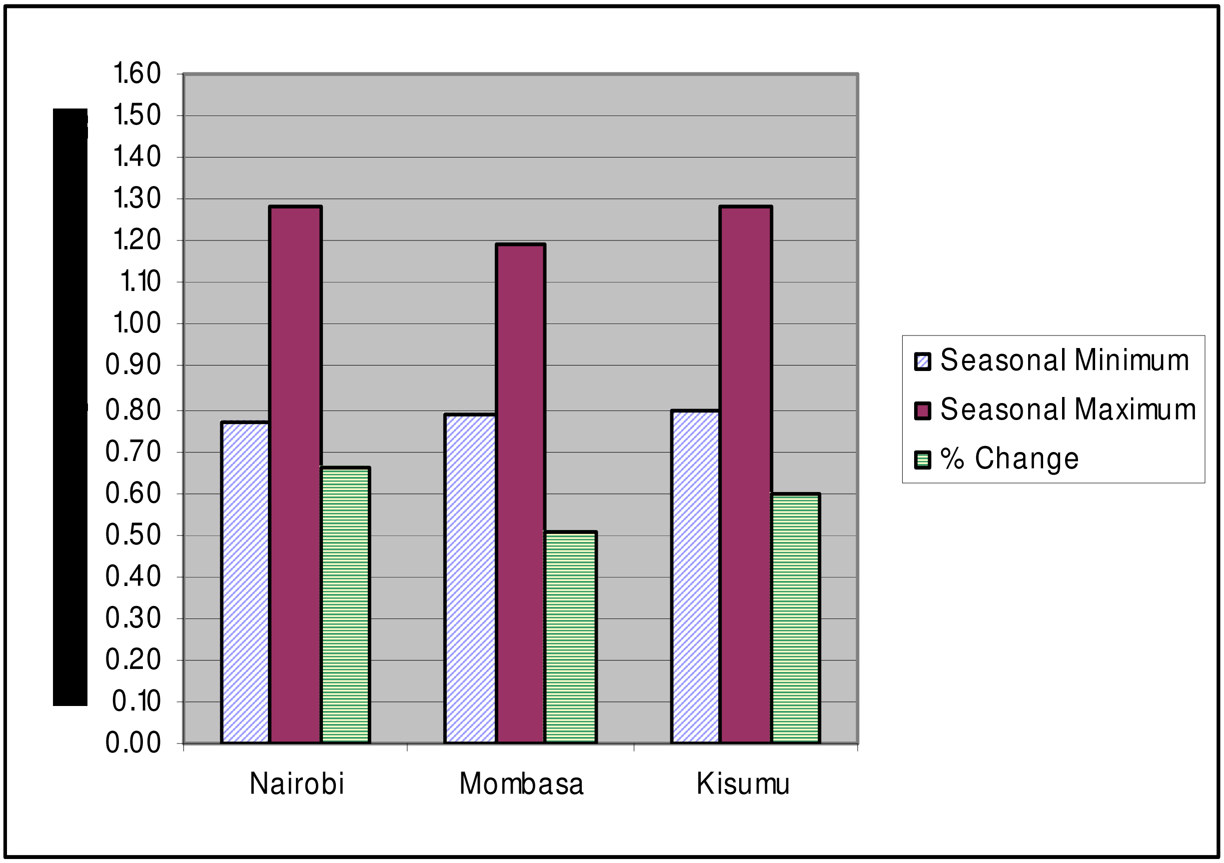
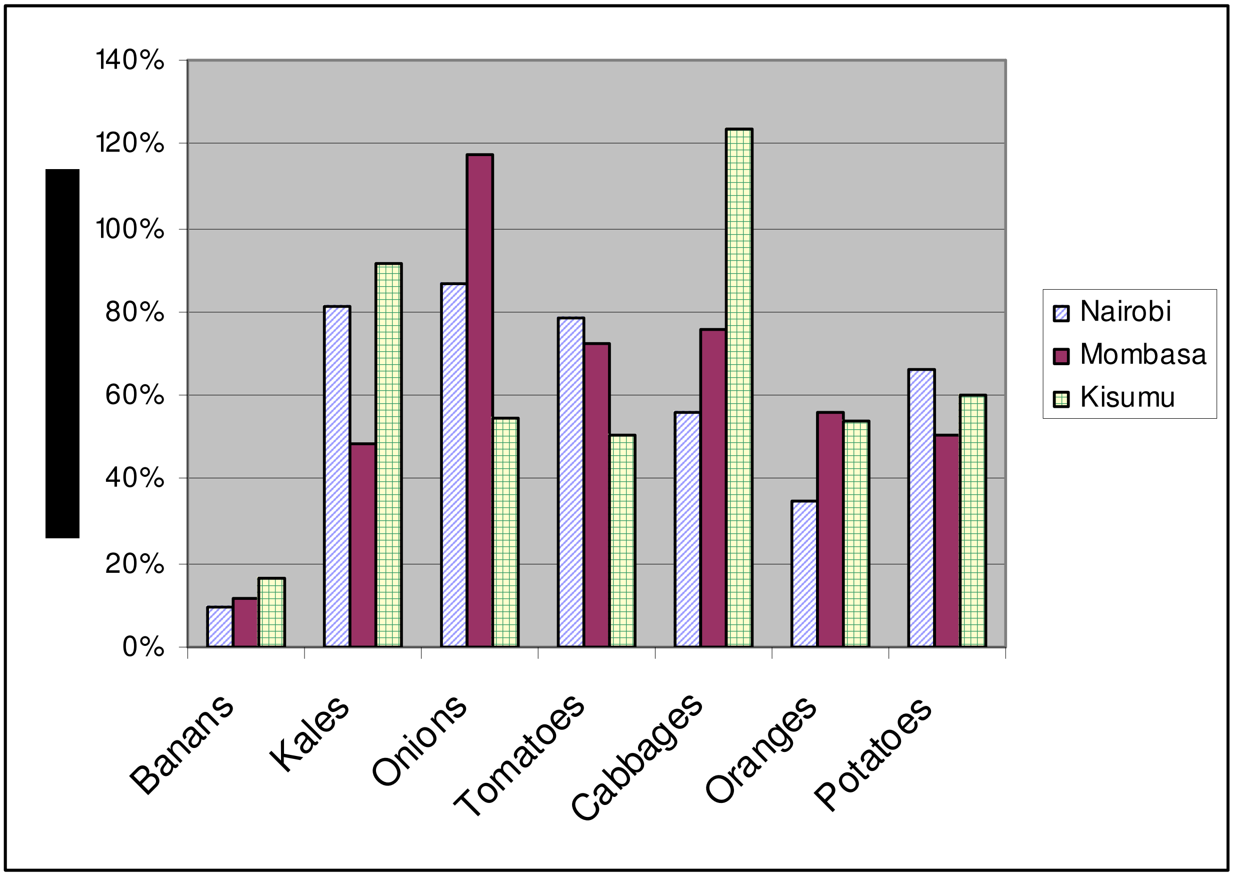


Figure 6. High and low seasonal indices and seasonal % change for white potato wholesale prices in Nairobi, Mombasa, and Kisumu



Summary Discussion: Potatoes show strong and consistent seasonality across all three markets. Clear seasonal highs occur in April/May and seasonal lows in August. Each market also shows a tendency towards a second seasonal high in November, though this is lower than the April/May high. Seasonal highs are less stable in Kisumu and the seasonal lows less stable in Nairobi, as shown by the standard deviations for each.

Figure 7. Typical seasonal price rises for seven FFV crops at wholesale level in Nairobi, Mombasa, and Kisumu



Summary Discussion: Three patterns stand out in this figure. First, besides bananas, oranges show the lowest seasonal price movement of all the crops. Second, seasonal price movements are similar across markets for oranges, potatoes, and tomatoes; seasonal rises vary markedly across markets for the other crops. Finally, onions in Mombasa and cabbages in Kisumu show extreme variability, with average seasonal price rises of about 120% in each.