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Analysis of Price Behavior in Sri Lankan Vegetable Market

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ABSTRACT:
Vegetables are important source of nutrient for the Sri Lankan population and both farmers and consumers are adversely affected by vegetable price volatility. The lack of price analysis and forecasting has made it difficult to establish an effective early warning system for the vegetable farming sector in Sri Lanka. This study investigates the price behaviour of selected fresh vegetables - carrot, cabbage, and tomato - and forecasts the future prices and volatilities using time series techniques. Analysis of weekly price data from 1997 to 2018 revealed that all three - price series had one structural break, but none coincided with the policy change when the government introduced fertilizer subsidies for vegetable producers in the agriculture sector. The autoregressive integrated moving average (ARIMA) model estimations show that the best model for forecasting carrot price is ARIMA (3,1,2)(0,0,2)[52]* capable of predicting retail prices at 71% accuracy while the best model for cabbage prices is ARIMA(1,1,1)(0,0,1)[52] with a prediction accuracy of 55%. All three-price series exhibit serial correlation in residuals; hence GARCH estimations were used to model and predict volatility. Of the fitted ARMA GARCH models, the best model for estimating the volatility of carrot and cabbage were GARCH (1, 2) ARMA (3, 2) and GARCH (1,1) ARMA (3 ,2), respectively. The volatility predictions for the first ten weeks for the year 2019 indicate a gradual decrease in volatility in the carrot price series whilst a gradual increase in volatility in the cabbage price series.

*[52] denotes the seasonal period of ARIMA model for weekly data

KEYWORDS: Vegetable prices; Sri Lanka; Structural breaks; ARIMA; GARCH

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INTRODUCTION

Agriculture in developing countries is often characterized by the presence of many small-scale but resource-poor farmers (World bank, 2020a; Manero, 2017). Lack of income during the lean season, indebtedness and low savings forces the farmers to sell their produce immediately after harvest when the prices tend to be the lowest. With low profits to reinvest, farmers are further entangled in the debt cycle (Mitra, & Boussard, 2011; FAO, & OECD, 2011). As a result, many small-scale farmers in developing regions are experiencing diminishing terms of trade from agriculture (Henegedara, 2016). When commodity prices rise, consumers who spend a large proportion of their disposable income (often more than 30%) on food are exposed to greater risk of seasonal undernutrition (Muhimbula, Kinabo, & O'Sullivan, 2019; Dessys, Herrera, & de Hoyos, 2008). Farmers who are also consumers of what they produce are exposed to the risk of seasonal food and nutrition insecurity. Because of the global food crisis in 2007-2008, the overall living standards of the people in developing countries deteriorated, and about 100 million people were dragged back into poverty (De Hoyos & Medvedev, 2009). Hence, agricultural price stabilization policies play an important role in breaking the poverty cycle and food insecurity in developing regions.

Vegetable farming contributes to the Sri Lankan economy in terms of ensuring food and nutritional security; It is also a source of income, foreign exchange earnings and source employment for the rural community. The average contribution of the vegetable sector to the agriculture - sector GDP was 8 % in 2018 (Ministry of Agriculture, 2019). Total area devoted to vegetable cultivation in 2018 was 84,191 ha (approximately 6.5% of the total arable land), with the corresponding production of 1,167,141 mt (Department of Agriculture, 2019; World Bank, 2019). The export earnings from fresh and dried vegetables in 2018 was 2,286 million USD while the import cost of vegetables was 1.51million USD (World Bank, 2020b).

One of the main production support policies for vegetable farming was the provision of fertilizer subsidies, since mid-2011. Under this scheme, farmers who grow vegetables could purchase fertilizer from the open market at 50% - 60% subsidized rate. Along with the above policy initiative, the fertilizer subsidy cost has increased by 200% from SLRs 11,867 million in 2006 to SLRs 49,571 million in 2015 (Marambe, Silva & Athauda, 2017). 2013 -Between 2013 and 2017, the average annual domestic supply of vegetables was 3,322,000 mt with an average annual per capita availability of 139kgs, equivalent to 380g per person per day (Department of Census & Statistics, 2019). However, due to the seasonal nature of production, the availability of all the fresh vegetables varies widely throughout a year. The main growing season "*Maha*" accounts for 60% of the annual production and extends from mid - October to the end of December, with the peak harvesting period falling in February to March. The peak harvesting season of the other growing season ("*Yala*") is generally observed from August to September. The common pattern is that prices of all the vegetables are lowest during the peak harvesting period and highest just before and after the peak harvest (Champika, 2016). Therefore, December, January, May, June, and July are the months in which the prices of vegetables are higher than the corresponding annual average prices. The intake of vegetables (112/g per day) by the Sri Lankans is below the recommended daily intake (200 /g per day), and this is mainly attributed to low purchasing power of the poor segment of the society during the lean period (Jayawardena et al., 2012). Fresh vegetables such as tomato (*Lycopersicon esculentum*) cabbage (*Brassica oleracea*) and carrot (*Daucus carota*) showed high price fluctuations thus frequently used in price analysis and forecasting models in Sri Lanka (Wickramasinghe & Pradeep, 2017; Rathnayake, Razmy& Alibuhtto, 2016; Illankoon & Kumara, 2020).

The price volatility impeded the prospects of increasing vegetable supply, making the sector less attractive to new farmers (Mitra & Boussard, 2011). Compared to non-perishable storable commodities, perishables always show greater price fluctuations, seasonality, and volatility (Reddy et al., 2018; Reddy, 2019; Zhang et al., 2014). Though the Sri Lankan government's socio-economic research institution has been collecting weekly price data of food commodities since late 1970s, limited attempts have been made to develop price forecasting models for perishables vegetables (Perera et al., 2016; Hathurusingha, Abdelhamid, & Airehrour, 2019). Compared to the need for price stabilization in perishable produce within the country, fewer research is being conducted. Therefore, this study aims to fill the existing research gap by analyzing the nature of price fluctuations and out-of-sample forecasts of prices using time series techniques. Effective prices forecasting might help vegetable farmers make rational production decisions (Zhang et al., 2014; Reddy, 2019), such as crop acreage and crop mix at the beginning of production season. Further, it might enable other stakeholders, such as input suppliers and policymakers, to mitigate against price risk. This study complements the existing literature on price volatility of perishable commodities in developing regions. Both farmers and consumers in developing countries are more vulnerable to commodity price volatilities.

LITERATURE REVIEW

Agricultural products are faced with five types of risks: production risk, market risks (uncertainty of prices) institutional risks, personal risks and financial risks (Komarek, De Pinto, & Smith, 2021). Thus, agricultural commodity prices are highly volatile in the international market compared to industrial goods (Myers, 1994). Furthermore, the delayed supply response to price signals in the short run contributes to high price instability (FAO & OECD, 2011). Hence, there has been a high emphasis on predicting agricultural commodity prices and their volatility in the past three decades. Modelling and forecasting the price behaviour of agricultural commodities has been explored by various research using different approaches (Purohit *et al*, 2021; Mitra & Paul, 2017; Yang & Hamori, 2018; Arunraj & Ahrens, 2015). In most of cases, commodity price series violate the stationary properties with mean and variance varying over time (Shumway & Stoffer, 2011). Augmented Dickey–Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) are generally applied to test the stationarity property of a timeseries (Xu, 2020). If there is a structural break in the time series, the stationary tests can be biased towards the existence of a unit root, and the results can be flawed (Lee & Chang, 2005). The structural break occurs when a time series undergo an instant, permanent change in the parameters at a point in time, mainly because of an exogenous shock. Montañés & Reyes, (2000), proved that in the presence of large structural break, the ADF test losses its statistical power. They further emphasized that under the condition of more than two structural breaks in the dataset, the ADF statistics and Phillips–Perron statistics are invalid. Mitra & Paul, (2017) and Kim & Choi (2017), have also made similar comments. Therefore, time series data must be tested for the presence of structural breaks along with testing for the property of stationarity.

Different variations of the autoregressive integrated moving average (ARIMA) model have been used in commodity price analysis. Both simple and seasonal ARIMA models (SARIMA) have been applied in analyzing price behavior of nonperishable commodities in South Asia (Bogahawatta,1988; Ansari & Ahmad, 2001; Hossain, Samad, & Ali, 2006; Kamu, Ahamed, & Yusoff, 2008; Jadhav, Reddy, & Gaddi, 2017). Fewer studies have been conducted on price fluctuations of perishables, compared to nonperishable agricultural commodities. The application of the SARIMA model in anticipating the price behavior of tomato was done by Adanacioglu & Yercan (2012), using monthly wholesale prices from 2000 to 2010 for Antalya, Turkey. Similar models were estimated by Ivanišević et al. (2015), and Perera et al. (2016), using the tomato prices series and fish price series. Arunraj & Ahrens (2015), have applied a combination of SARIMA and regression estimations SARIMA-MLR (SARIMA with multiple regression) and SARIMA with quantile regression (SARIMA-QR) to model and predict the sales of banana in German market.

Agricultural price volatility, which is often caused by external shocks in the production season, can also stimulate price volatility in the next production season. The Autoregressive Conditional Heteroscedasticity (ARCH) and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are broadly applied in analyzing time series data which exhibits serially correlated heteroscedasticity (Engle, 2001). The first use of ARCH model was done by Engle, (1982), which captured the heteroscedasticity in volatility. Bollerslev, (1986), expanded the ARCH class model one step further to GARCH which had the same key properties as the ARCH but added a lagged term of conditional variance and lagged term of squared error (Cryer & Chan, 2008). However, both the ARCH and the GARCH models assume that positive and negative shocks have the same impact (symmetricity) of volatility (Nelson, 1991).

Yang, Haigh, & Leatham, (2001), used daily cash and futures prices of soybean, corn, wheat, oats and cotton and employed the GARCH model to assess the impact of agricultural liberalization policy of 1996 on the price volatility in the USA. Lama et al, (2015), used the ARIMA, simple GARCH and exponential GARCH (EGARCH) models to model volatility in international monthly cotton prices (published by UNCTAD) from 1982 to 2002. Bannor (2016) has analyzed the consequences of futures trading on cluster beans price instability in Rajastan estate of India using data from 2003 to 2015, applying symmetric GARCH (1,1), and asymmetric EGARCH (1,1) and TGARCH (1,1) estimation. The outcome reveales that the futures trading have substatial effect in bringing down the cluster bean prices volatility in considered location. Similarly, Cermák, Malec, & Maitah, (2017), applied the GARCH model to volatility in daily wheat futures prices traded in USA during 2005 to 2015.

METHODS

Data

This study used weekly retail prices for tomatoes, carrots, and cabbage from 1997 to 2019 for analyses. The data was collected at nine major retail markets in the capital city of Colombo by the Agrarian Research and Training Institute of Sri Lanka. All prices are expressed in Sri Lankan rupees (LKR) per kilo. Each price series contains 1144 observations, with a mean and standard deviation of 105.93 Rs./kg and 67.11 Rs./kg for carrot price series, 78.02 Rs./kg and 45.25 Rs./kg for the cabbage price series and 135.86 Rs./kg and 66.91 Rs./kg for tomato price series, respectively. Plots indicate that all three-price series clearly exhibit seasonality and an upward trend. Seasonal indices are calculated to estimate the seasonal variation of prices within a period of year. Stationarity of each series is tested under three conditions: random walk, random walk with drift, and random walk with the trend using the ADF test and the KPSS test (Table 1). The null hypothesis of ADF test is that the series has a unit root, and the alternative hypothesis is stated as the time series is stationary (Wang & Tomek, 2007; Mugera, Curwen, & White, 2008). Yet, there can be instances where the ADF test cannot differentiate unit roots vs. presence of weakly stationarity. Thus, failure to reject the null hypothesis of presences of a unit root may not necessarily indicate existence of a unit root (Xu, 2020). Therefore, the KPSS test (Kwiatkowski et al., 1992), which has a null hypothesis of stationarity around a mean (or a linear trend), was applied to compliment the results of ADF tests.

Table 1 -Results of the ADF, PP And KPSS Tests For The Presence of Unit Root

Unit root test (Model)	Undifferenced	Differenced	Critical values for t-statistic		
			1%	5%	10%
Carrot Price series (log)					
Random walk					
ADF	0.084	-20.09***	-2.58	-1.95	-1.62
Random walk with drift					
KPSS	11.99***	0.0044	0.74	0.46	0.35
ADF	-3.17***	-20.09***	-3.43	-2.86	-2.57
Random walk with trend					
ADF	-6.75***	-20.09***	-3.96	-3.41	-3.12
KPSS	0.13*	0.0044	0.216	0.146	0.119
Cabbage Price series (log)					
Random walk					
ADF	0.26	-20.84***	-2.58	-1.95	-1.62
Random walk with drift					
KPSS	12.13***	0.0059	0.74	0.46	0.35
ADF	-2.79***	-20.84***	-3.43	-2.86	-2.57
Random walk with trend					
ADF	-6.516***	-20.84***	-3.96	-3.41	-3.12
KPSS	0.0995	0.0054	0.216	0.146	0.119
Tomato Price series (log)					

Random walk					
ADF	-0.48	-18.72***	-2.58	-1.95	-1.62
Random walk with drift					
KPSS	8.42***	0.0057	0.739	0.463	0.347
ADF	-6.14***	-18.70***	-3.43	-2.86	-2.57
Random walk with trend					
ADF	-8.76***	-18.70***	-3.96	-3.41	-3.12
KPSS	0.133**	0.004	0.119	0.146	0.216

***, **, * for 1%, 5% and 10% respectively.
Optimum number of lags for ADF tests were selected using AIC criteria

To smooth-out seasonal variations, all the three prices were log transformed. The Box-cox transformation (Cryer, & Chan, 2008) lambda values (between - 0.5 to 0) suggested that log transformation is appropriate.

The null hypothesis of KPSS test, that the observable price series is stationary, is rejected at 1% for all the three prices, indicating non-stationarity when there is random walk with a drift. However, the ADF test results contradict with the KPSS results, indicating all three series are stationary when there is a drift. Further, both the ADF and the KPSS tests indicate that carrot and tomato price series are trend stationary. Yet, two tests give contradicting results for trend stationarity of tomato price series. Montañés & Reyes, (2000) explained that the ADF test loses its power in the presence of a structural break. Therefore, the presence of a structural beak might be the cause of the contradicting results of the undifferenced price series. When all three prices are differenced once, both the ADF and the KPSS test results are consistent implying the prices are stationary (at 1% level) under all these scenarios: random walk, random walk with drift and random walk with trend. The plots of the first differenced (log) prices series are reported in appendix

Modeling Structural Breaks, ARIMA and GARCH Process

All the price series were checked for possible structural breaks by letting the break timing be endogenously determined by applying the Zivot–Andrew's test.

Zivot–Andrews unit root test

When the point of occurrence and the nature of the structural change cannot be known, the Zivot–Andrews unit root test can be applied to determine the exact time of the breakpoint endogenously (Ling et al., 2013). The model selects a breakpoint when *t* statistics reach its minimum by running a multitude of regressions (Zivot & Andrews, 2002; Mugera, Curwen, & White, 2008). The null hypothesis assumes the time series exhibit a unit root without a structural break while the alternative hypothesis assumes that the time series is stationary a one break point (Mugera, Curwen, & White, 2008).

The expression of a one break point in the intercept is given in Equation 1

$$\Delta_{yt} = c + \propto y_{t-1} + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta_{yt-j} + \epsilon_t. \quad (1)$$

The expression of a one break point in the slope is given in Equation 2

$$\Delta_{yt} = c + \propto y_{t-1} + \theta DT_t + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta_{yt-j} + \epsilon_t. \quad (2)$$

The expression of one break point the intercept and slope is given in Equation 3

$$\Delta_{yt}= \mu+ \propto y_{t-1} + \theta DT_t + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta_{yt-j} + \epsilon_{t.} \tag{3}$$

For the three equations, y_t is the log transformed price series and ϵ_t is the white noise; Δ_{yt-j} is the lagged first differences to correct for serial autocorrelation in the error term. The optimal lag length, *k*, can be selected by following the sequential procedure explained by Perron & Vogelsang (1992) and Campbell & Perron, (1991). The change in the level is implied by the dummy variable DU_t, and dummy variable DT_t implies the slope shifter of the trend function.

ARIMA Model

ARIMA models were fitted on each price series, and the best-fitted models were used to predict future prices. The ARIMA process is comprised of both autoregressive (AR) and the moving average (MA) components, usually presented as ARIMA *(p, d, q)*. In the expression, *p* is the order of non-seasonal of autoregressive, *q* is the order of moving average and *d* represents the order of regular differencing. If a time series Y_t follows an ARIMA pattern at d^{th} differencing, $W_t = \nabla dY_t$ is regarded as a stationarized ARMA. When W_t follows an ARMA(*p*,*q*) model, Y_t is said to be an ARIMA*(p,d,q)* process. Generally, *at most, d will take either 1 or 2 values* (Cryer & Chan, 2008).

The ARIMA model can be expanded to SARIMA model as ARIMA (p, d, q) × (P, D, Q)s. Here, *P* implies the seasonal autoregressive order, *Q* implies the seasonal moving average order, *D* represent the seasonal differencing order and "*s"* denotes the seasonal period (for weekly data s=52).
The Box–Jenkins process of constructing an ARIMA model has four steps: identification of the model, model estimation, model diagnostic checking process, and applying the suited models for predicting (Gujarati & Porter, 2009; Jadhav, Reddy, & Gaddi, 2017). Before estimating the ARIMA model, the time series must be made stationary. In the identification process, initial values for seasonal and non-seasonal orders are determined examining the autocorrelation functions (ACF) and partial autocorrelation functions (PACF).

The ACF plot expresses how far the series's current value is related to its later values. PACF plot describes the correlation between the timeseries variable and its lags, in respect of correlation of residuals with the succeeding lag. In the estimation stage, different classes of ARIMA models are estimated precisely by calculating parameters of the model. Diagnostic checking refers to testing the capability of the selected model to explain the variation in the data series. It is a process of checking whether the residuals are purely a white noise. The Ljung and Box "*Q*" statistics (Equation 7) is used to check if the autocorrelations of the errors are not equal to zero.

The null hypothesis is that the first *m* number of autocorrelations are jointly zero; $H_0: \rho_1 = \rho_2 = \cdots = \rho_m = 0$.

$$Q = n(n+2) = \sum_{k=1}^{h} \frac{\hat{r}^{2}}{n-k} \tag{7}$$

In the above equation, *h* represents the maximum number of lags considered, *n* implies the number of observations used and *rk* is the ACF for lag *k*. Then *Q* will follow a *Chi-square* distribution with degree of freedom of *(h-m)*. In the above expression, *m* denotes the number of parameters to be estimated (Gujarati & Porter, 2009; Wennström, 2014).

Akaike's Information Criteria (AIC) are the commonly used select the best model out of group of suited models. One with the lowest AIC, is considered the best one among tested models (Gujarati & Porter, 2009; Wennström, 2014).

The level of precision of the prediction for both *Ex-ante* and *Ex-post* can be evaluated by calculating mean absolute percentage error (MAPE), mean percentage error (MPE) and root mean squared error (RMSE) (Gujarati & Porter, 2009; Jadhav, Reddy, & Gaddi, 2017). The lower the values the better fit the model is:

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left(\frac{|\text{Actual} - \text{Forecast}|}{|\text{Actual}|}\right) \text{; n = sample size}$$

$$\text{MPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left(\frac{\text{Actual} - \text{Forecast}}{\text{Actual}}\right) \text{; n = sample size}$$

$$\text{RMSE} = \sqrt{\sum_{t=1}^{n}\left(\frac{\text{Predicted} - \text{Actual}}{\text{n}}\right)^2} \text{; n = sample size}$$

GARCH Model

The most common representation of the GARCH (1,1) model is given under Equation 8 and 9 (Sendhil et al., 2014)

$$Y_{it} = a_0 + b_1 Y_{it-t} + b_2 Y_{it-2} + \epsilon_{it} \tag{8}$$

where, Y_{it} is the spot - price of the i^{th} commodity in period *t*, starting from 1, 2, 3… to *n*. The random error variance (Equation 9) is defined as the conditional variance (predicted one period - ahead variance, dependent upon the past information)

$$\sigma^2{}_{it} = \omega + \alpha_1 \epsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2 \tag{9}$$

where σ^2 is a function of the mean (ω), the volatility term estimated as the lag of the squared residual from the mean equation ($\varepsilon_t{}^2{}_{-1}$, which is denoted as the ARCH term) and, the former period's predicted variance ($\sigma_t{}^2{}_{-1}$, which is denoted as GARCH term). General ARCH model and GARCH (1,1) model do not consist of lagged forecast variances term in the conditional variance function. Bollerslev, (1986), introduced *p* lags of the model's conditional variance; hence; a higher order GARCH (*p, q*) models can be estimated by choosing either *p* or *q* or both as greater than one. Here, *q* is the number of ARCH terms, and the *p* is the number GARCH terms (Sendhil et al., 2014)
Higher order GARCH (*p, q)* model can be written as in Equation 10.

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \tag{10}$$

The sum of $\alpha_i + \beta_i$ represents the degree to which the persistence of volatility in the price series is. If $\alpha_i + \beta_i$ exceed one, price volatility is likely to persist for long time and the time series is said to be explosive, with a tendency to move away from the mean (Cryer & Chan, 2008; Sendhil et al., 2014). The property of ARCH effects is a prerequisite for estimating a GARCH model. The existence of ARCH effect is checked by applying the Engle's ARCH test (Engle, 1982). If a timeseries of Y_t has

μ_t - the conditional mean and ε_t - is an innovation process with zero mean (Equation 11). The residual series can be written as Equation 12:

$$y_t = \mu_t + \epsilon_t \tag{11}$$

$$e_t = y_t - \hat{\mu}_t \tag{12}$$

The alternative hypothesis is squared residuals are serially autocorrelated (Equation 13)

$$H_a: {e_t}^2 = \alpha_0 + \alpha_1 \epsilon_t e_{t-1}^2 + \alpha_m e_{t-m}^2 + u_t \tag{13}$$

Null hypothesis (H_0) is the error term is white noise $H_0 : \alpha_0 = \alpha_0 = \alpha_1 = \ldots = \alpha_m = 0$

After conducting GARCH model, ARCH test is performed on residuals to check whether there is serial autocorrelation in squared residuals due to a conditional variance. If not, GARCH model is regarded as a good fit. The best fitted GARCH model on each price series was used for forecasting of price volatility.

RESULTS AND DISCUSSION

Seasonal price indices

The price behaviour of all three commodities - carrot, cabbage, and tomato - based on its respective seasonal indices revealed that the highest prices would prevail between week 21 to 29 and week 49 to 52 (figure 1). The two price spikes correspond to two peaks of the two lean seasons for vegetables. Consequently, two notable price drops were observed for all three vegetables. The first price drop occurs in week 8 - week 14 period, when high supplies are received at the market during the onset of the first peak harvesting season. Though the second peak harvesting season for vegetables generally falls between week 37 – 41 (September - mid October), for tomato, it seems to occur one month prior to other two vegetables between week 33 – 36. Of the considered commodities, tomato has the highest fluctuations whilst price variation observed for cabbage was the lowest.

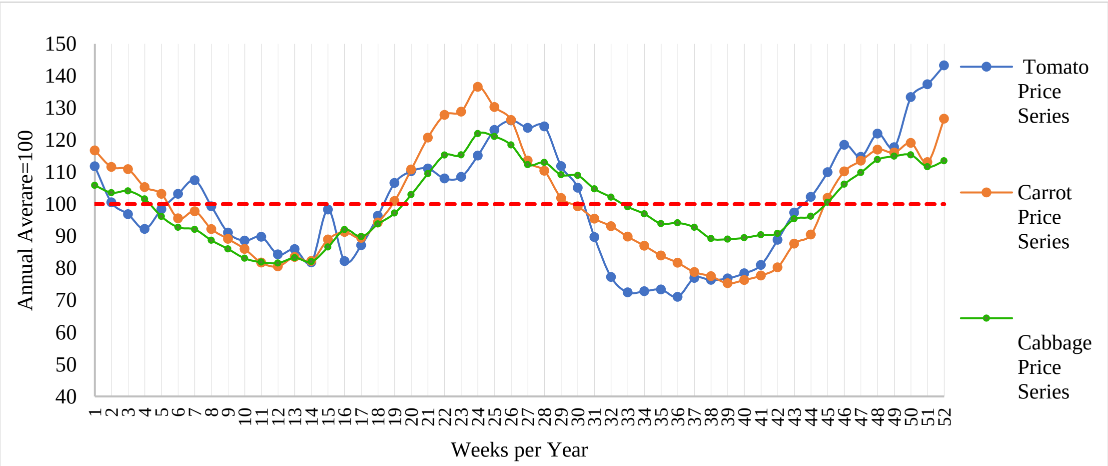

Figure 1- Seasonal Indices of Retail Price Series; Tomato, Cabbage, And Carrot From 1997-2018

Testing for possible structural breaks

All three-price series were checked for possible structural breaks by letting the break timing be endogenously determined by applying the Zivot–Andrew's test. The tion intention was to test whether the policy decision to provide fertilizer subsidy to vegetable farmers in mid-2011 induced a structural changch of the price series. It was assumed that if the above policy change caused a structural change, it should be felt within the period of three growing seasons, immediately after the policy change (starting from mid-2011 to end of 2012). The null hypothesis of Zivot–Andrews model is that the time series exhibit a unit root without a structural break. The Zivot–Andrew's test results, estimated via calculation of potential break points for intercept only, trend only and both intercept and trend for three data series is shown in table 2. The optimal lag length (k) was selected by either increasing the number of lags until the last lag is significant or starting from a large number of lags (e.g 100) and decreasing the number until the last lag is significant (Perron & Vogelsang, 1992; Campbell & Perron 1991). Both procedures were followed, and the optimal k was selected for each timeseries.

Zivot–Andrew's test indicates that all three-price series are stationary when each series is differenced once (the t value is significant). The break dates (both intercept and trend) generated for each price series is: 2014-week-41 (5%) for carrot price series, 2014-week-18 (10%) for cabbage price series and 2006-week-17 (5%) for tomato price series. This result implies that null hypothesis of unit root in each of the time series can be rejected, concluding that each time series is a stationary with a one break point occurring at 41st week of 2014 for carrot price series, 18th week of 2014 for cabbage price series and 17th week of 2006 for tomato price series. It further reveals that none of the three calculated break dates corresponds with the considered policy change. Mugera, Curwen, & White (2008), conducted a similar study to test whether the removal of state monopoly of wheat import in Australia caused any structural change/s in prices of Australian wheat market and concluded that policy change did not trigger any structural change/s in prices. Ling et al; (2013), suggests that changes in macroeconomic variables such as exchange rate and energy prices can trigger structural changes. High increase in input cost of agriculture (pesticides and machinery) due to rapid depreciation of LKR against the USD, started from 2014/2015 (and continued up to 2019), might have trigged a structural break in 2014/2015 period.

Table 2 - Zivot–Andrew's Test Results

Zivot–Andrew's test	t - statistics and break data
Carrot Price series (lag length =4*)	
break in intercept	4.023*** 2014-week-41
break in trend	3.746*** 2005-week-34
Fbreak in intercept and trend	2.843** 2014-week-41
Cabbage Price series (lag length =3*)	
break in intercept	3.310*** 2014-week-18
break in trend	3.040** 2005-week-23
break in intercept and trend	1.852* 2014-week-18
Tomato Price series (lag length =5*)	
break in intercept	3.426***

	2018-week-42
break in trend	2.930**
	2004-week-4
break in intercept and trend	2.964**
	2006-week-17

***, **, * for 1%, 5% and 10% respectively
*Lag length was selected applying the sequential procedure

Estimation of the ARIMA Model

Following the Box–Jenkins process of estimating the ARIMA model, the ACF and PACF plots of differenced price series (figure 2, figure 3 and figure 4 in Appendix 1) were checked to determine the initial values for seasonal and non-seasonal orders. The ACF plot expresses how far the current value in the series is related with its later values, including all components, trend, seasonality, and residual. PACF evaluates correlation of the residual term with the successive lags, in a time series. Significant spikes in the ACF (at low lags) and PACF (at low lags) indicates possible non-seasonal MA and AR terms, respectively. Yet, a significant spike in the ACF and PACF, at higher lags indicates possible seasonal/cyclical MA and AR terms, respectively (Salvi, 2019; Eni & Adeyeye, 2015).

ACF and PACF plots of figure 5 and 6 (in Appendix 2) suggests a possible none-seasonal MA (2) component and a possible nonseasonal AR (2) components. Yet, significant spikes at lag 3 and 4 in ACF and a significant spike at lag 3 in PACF suggest that none - seasonal MA (2) and MA (3), and none - seasonal AR (3) is also possible. Likewise, figure 7 and 8 (in Appendix 2), reveals possible none - seasonal MA (1) or MA (2) component and a possible none - seasonal AR (1) or (2) components. Further, figure 9 and 10 (in Appendix 2), indicates possible none-seasonal MA (1) or MA (2) component and a possible none - seasonal AR (1) or (2) components. Though all three ACF shows a tapering pattern, significant higher order lags indicate the presence of seasonality in all three timeseries.

The conditional heteroscedasticity in each series is tested using the Lagrange multiplier version of Engle's ARCH test. The ARCH test results on differenced (log) price series of carrot, cabbage and tomato rejects the null hypothesis of no ARCH effect at 5% (p=0.0117), 5% (p-value = 0.02317), and 1% (p=0.0001769) respectively. Therefore, it is concluded that all three differenced price series have the property of its present error term varies based on actual value of the immediate past periods' error terms. This changing variance nature makes it difficult to fit a simple ARIMA model. Hence, both nonseasonal and seasonal ARIMA models were tried (Table 3) and the residuals were checked for conditional heteroscedasticity and autocorrelation. The best models were selected using the AIC and loglikelihood criteria.

Table 3 - AIC, and Log Likelihood Values of The Fitted ARIMA Models

Model	AIC	log likelihood
Carrot Price Series		
ARIMA(4,1,2)	-2072.574	1043.29
*ARIMA(3,1,2)(0,0,2)$_{[52]}$	-2096.379	1056.19
Cabbage Price Series		
ARIMA(1,1,1)	-2473.716	1239.86
*ARIMA(1,1,1)(0,0,1)$_{[52]}$	-2476.483	1242.24

Tomato Price Series		
*ARIMA(2,1,3)	-1102.329	510.14
ARIMA(1,1,1)(0,0,2)[52] with drift	-1008.28	557.16

*Best model based on minimum AIC criteria

The ARCH test results on ARIMA residuals for both carrot and cabbage price series fail to reject the null hypothesis of no autocorrelation in squared residuals at 5% level with (p= 0.1665) and (p=0.3148) respectively. However, ARIMA residuals for tomato price series reject the null hypothesis at 1% level with (p = 0.000028), indicating the presence of autocorrelation in squared residuals. Further, Ljung-Box test on best fitted ARIMA residuals for both carrot and cabbage price series fails to reject the null hypothesis and the models do not show lack of fit due to residual autocorrelation at 5% implying white noise of residual series (Figure 11 and 12; Figure 13 and 14 respectively in Appendix 5). The Ljung-Box test on ARIMA residuals for tomato price series rejects the null hypothesis at 1%; (P=0.000216) indicating the presence of autocorrelation in residuals.

Based on the AIC and log likelihood values, it can be concluded that the ARIMA (3,1,2)(0,0,2)[52] is the best fitted model that can be applied in forecasting the carrot price series while ARIMA(1,1,1)(0,0,1)[52] is the best suited model for forecasting the cabbage price series. The best fitted ARIMA model for tomato price series failed to comply with the white noise error, hence cannot be applied for forecasting. Using the selected best models, both *Ex-ante* (in sample) forecast of prices and *Ex-post* (out of sample) forecasts of prices was done for carrot and cabbage series. *Ex-ante* forecasting of carrot prices using ARIMA(3,1,2)(0,0,2)[52] model resulted in MAPE of 1.55, MPE of 0.108 and RMSE of 0.0956. *Ex-ante* forecasting of cabbage prices using ARIMA(1,1,1)(0,0,1)[52] model resulted in MAPE of 1.42, MPE of 0.104 and RMSE of 0.081. *Ex-post* forecasting of both carrot and cabbage price series were done for one - year - period a head (52 weeks) (for the year 2019) and the values were compared with actual values (Table 4 in Appendix 6). MAPE of the forecasted carrot and cabbage prices were 28.86% and 45.20% respectively. It implies that weekly carrot retail prices can be predicted at 71% accuracy by using ARIMA(3,1,2)(0,0,2)[52] model whilst ARIMA(1,1,1)(0,0,1)[52] model is capable of predicting weekly cabbage retail prices at 55% accuracy. ARIMA(1,1,1)(0,0,1)[52] model seem to have overestimated the cabbage retail prices, especially for the first two quarts of the 2019. Figure 15 and 16 depicts the bahaviour of actual vs. forecasted prices for carrot and cabbage prices, respectively.

Seasonal ARIMA models with error margins between 20% and 50% have been observed for perishable commodities. According to Adanacioglu & Yercan, (2012), the best fitted model, SARIMA (1, 0, 0) (1, 1, 1)12 , could predict future monthly prices of tomato with an error margin of 24%. Similarly, Reddy, (2019), has applied ARIMA model including the seasonality effect, to predict monthly tomato prices during the harvesting season in each major growing region in India. According to his analysis, the best fitted models were for Madhya Pradesh - ARIMA(1,0,3) (1,1,0), for Andhra Pradesh - ARIMA(0,0,11) (0,1,1), for Karnataka - ARIMA (1,0,6) (0,0,0), for Maharashtra ARIMA (0,0,1) (1,0,1), and for Gujarat - ARIMA (0,0,1) (0,1,1) The models' MAPE varied between 28.8% to 47.7%.

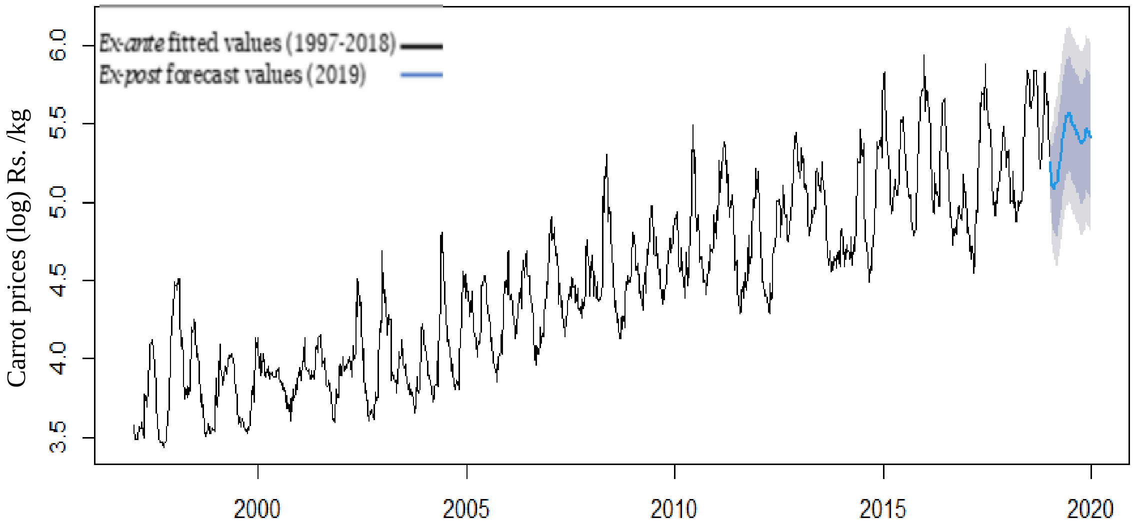

Figure 15 - Actual Vs. Forecasted Prices of Carrot Retail Prices

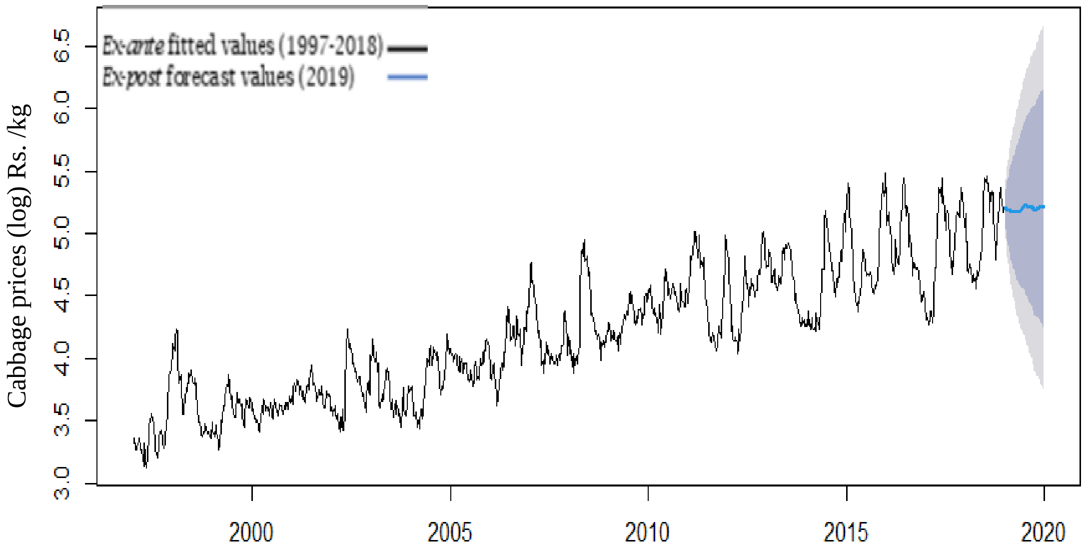

Figure 16 - Actual Vs. Forecasted Prices of Cabbage Retail Prices

Estimation of the GARCH model

Under the GARCH specification, variance at current period is specified as a function of the mean, the volatility from the previous period (ARCH term) and the predicted variance based of the last period's information (GARCH term). Hence, the pre - condition for fitting a GARCH model is that the considered time series should display ARCH effect. The ARCH test results on differenced (log) price series of carrot, cabbage and tomato rejects the null hypothesis of no ARCH effect at 5% (p=0.0117), 5% (p-value = 0.02317), 1% (p=0.0001769) respectively, confirming the presence of ARCH effect.

In the process of estimating the volatility, different variations of ARMA-GARCH models were fitted, starting from the simple GARCH models (GARCH order $\leq$ 1) to higher order GARCH models (GARCH order $\leq$ 2; ARMA order $\leq$ 3) on each of the stationary price series. Estimations was limited to simple ARMA-GARCH models (s-GARCH class) which assume that the volatility of a time series is symmetric overtime (Nelson, 1991). Simple GARCH models indicate that the student t (sst) distribution in the error term is best fitted among the three tested distributions: normal distribution, student *t* distribution and skewed student *t* distribution for tomato price series. The best-fitted error distribution for both carrot and cabbage price series was skewed student *t* (*sstd*) distribution. Of the tested combinations of all the models, 12 ARMA-GARCH models which gave the lowest AIC values under each price series are presented in the Table 5. Based on the ARMA-GARCH estimations, the best model for estimating the volatility of carrot, cabbage and tomato price series are GARCH (1,2) ARMA (3,2) (AIC = -1.9546), GARCH (1,1) ARMA(3,2) (AIC = -2.3134) and GARCH (1,1) ARMA (2,2) (AIC = -1.0675) respectively.

Of the three quantile plots fitted on each model, GARCH (1,1) ARMA (3,2) exhibits the best alignment on the 45^0 line contrast to the fat - tail type distribution of residuals for GARCH (1,1) ARMA (2,2) model (Figure 17, Figure 18 and 19 in Appendix 5).

Table 5 - AIC And Log Likelihood Values for Different ARMA-GARCH Models

Price series	AIC	Log likelihood
Carrot Price Series (log-differenced)		
GARCH (1,1) ARMA(2,3)	-1.9487	1124.676
GARCH(1,2) ARMA(2,3)	-1.9479	1125.217
GARCH(1,2) ARMA(3,2)	-1.9546	1129.039
GARCH(1,2) ARMA(3,3)	-1.8731	1083.461
GARCH(2,1) ARMA(2,2)	-1.8745	1082.304
GARCH(2,1) ARMA(2,3)	-1.9469	1124.676
GARCH(2,1) ARMA(3,2)	-1.9537	1128.535
GARCH(2,1) ARMA(3,3)	-1.9432	1123.559
GARCH(2,2) ARMA(2,2)	-1.8755	1083.835
GARCH(2,2) ARMA(2,3)	-1.9499	1127.363
GARCH(2,2) ARMA(3,2)	-1.9529	1129.084
GARCH(2,2) ARMA(3,3)	-1.8800	1088.431
Cabbage Price Series (log-differenced)		
GARCH(1,1) ARMA(1,1)	-2.2636	1301.630
GARCH(1,1) ARMA(1,2)	-2.2631	1302.380
GARCH(1,1) ARMA(1,3)	-2.2612	1302.300
GARCH(1,1) ARMA(2,1)	-2.2631	1302.365
GARCH(1,1) ARMA(2,2)	-2.2614	1302.372
GARCH(1,1) ARMA(2,3)	-2.2601	1302.654
GARCH(1,1) ARMA(3,2)	-2.3134	1333.098
GARCH(1,1) ARMA(3,3)	-2.3098	1331.277
GARCH(2,1) ARMA(3,3)	-2.3067	1331.277
GARCH(2,2) ARMA(3,3)	-2.3072	1332.591
GARCH(2,2) ARMA(3,2)	-2.3105	1333.473
GARCH(2,2) ARMA(3,3)	-2.3072	1332.591
Tomato Price series (log-differenced)	-1.0606	614.139
GARCH(1,0) ARMA(2,2)		
GARCH(1,1) ARMA(2,2)	-1.0675	619.085
GARCH(1,1) ARMA(2,3)	-1.0672	619.921
GARCH(1,1) ARMA(3,2)	-1.0612	616.483
GARCH(1,2) ARMA(2,2)	-1.0659	619.137
GARCH(1,2) ARMA(2,3)	-1.0656	619.982
GARCH(1,2) ARMA(3,2)	-1.0596	616.557
GARCH(2,1) ARMA(2,2)	-1.0657	619.075
GARCH(2,1) ARMA(2,3)	-1.0655	619.919
GARCH(2,1) ARMA(3,2)	-1.0398	605.295
GARCH(2,2) ARMA(2,2)	-1.0641	619.137
GARCH(2,2) ARMA(2,3)	-1.0638	619.971

*Shaded ones are the best fitted ARMA -GARCH model for each price series

The summary statistics of the best ARMA - GARCH estimation on each price series (Table 6) indicates that no autocorrelation in either standardized or squared residuals for both GARCH (1,2) ARMA (3, 2) and GARCH (1,1) ARMA (3, 2) models. However, the best fitted model on tomato price series, GARCH (1,1) ARMA (2, 2), implies a presence of autocorrelation in standardized residuals at lag 11, indicating lack of good fit. The ARCH LM test which checks for the existence of serial autocorrelation in squared residuals due to conditional variance indicates, no autocorrelation in squared residuals in all the models (Table 6). The presence of leverage effect (effect of positive and negative shocks on volatility are different or not) is tested in sign bias test against the null hypothesis of no leverage effect in the data. As p value is higher than 0.05 for all three models, there was not enough evidence to prove the presence of leverage effect in any of the models. Hence the s-GARCH specification is justified for all three models (Filter, 2017).

All the components in the mean model AR and MA terms (*ar1* to *ar3* and *ma1* to *ma3*) in all three models are significant at 1% level, except for *ar3* component in GARCH (1,2) ARMA (3, 2) model, which is significant at 5% level. According to the applied statistical package for calculation of the variance model, ω represents the constant term, α represents the coefficient of the previous residual term whilst $\beta 1$ and $\beta 2$ represents the coefficient of the previous variance term in the standard GARCH model. The insignificant α and β coefficients implies that the variance of GARCH (1, 2) ARMA (3, 2) model does not significantly conditional upon the previous residuals and previous variance, yet the constant (significant ω coefficient) term is. Further, GARCH (1, 1) ARMA (3, 2) model implies that α term is not significant, yet $\beta 1$ term and term ω is. It indicates that, current variance is conditional only on the previous variance term. None of the models were "explosive" as $(\alpha + \beta)$ does not exceeds 1.

Table 6 - Summary Statistics of Best ARMA - GARCH Models

	GARCH (1,2) ARMA (3, 2)	GARCH (1,1) ARMA (3, 2)	GARCH (1,1) ARMA (3, 2)
Mean model			
μ	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)
ar1	1.644^{***}	1.709^{***}	1.719^{***}
	(0.045)	(0.001)	(0.038)
ar2	-0.538^{***}	-0.671^{***}	-0.769^{***}
	(0.087)	(0.000)	(0.045)
ar3	-0.144^{**}	-0.065^{***}	-1.603^{***}
	(0.070)	(0.000)	(0.000)
ma1	-1.715^{***}	-1.718^{***}	-1.603^{***}
	(0.000)	(0.000)	(0.000)
ma2	0.717^{***}	0.716^{***}	0.602^{***}
	(0.001)	(0.000)	(0.000)
Variance model			
ω	0.001^{***}	0.000^{**}	0.008
	(0.000)	(0.000)	(0.011)
α	0.116	0.079	0.194^{**}
	(0.223)	(0.053)	(0.093)
β1	0.347	0.837^{***}	0.480
	(0.291)	(0.009)	(0.433)
β2	0.397		
	(0.247)		
Skewness	1.276^{***}	1.172^{***}	4.378^{***}
	(0.050)	(0.039)	(0.668)
Shape	5.281^{***}	6.320^{***}	
	(0.814)	(1.140)	
Model diagnostics			
$\alpha + \beta$	0.86	0.931	0.674
L,Box test on residuals			
Lag[14]	4.564	4.319	
Lag[24]	12.398	10.535	
Lag[11]			7.328^{**}

Lag[19]			12.218	
L,Box test on squared residuals		2.707	0.784	***,
Lag[5]		3.394		**,
Lag[8]	3.323		2.566	*
Lag[9]				
Lag[14]	4.842	0.248		
ARCH LM test				
Lag[3]				
Lag[4]	1.37E-05			
Lag[5]		1.588	1.401	
Lag[6]	7.23E-02			
Sign Bias test	0.819	1.512	0.232	

for 1%, 5% and 10% respectively.

The conditional standard deviation or volatility was calculated, applying the respective ARMA-GARCH model. The calculated volatility (in dark blue) vs. absolute value of the respective prices (light blue) is depicted in figure 20 and 21. Both graphs show the typical GARCH type models, in which the volatility varies according to the fluctuations in the prices.

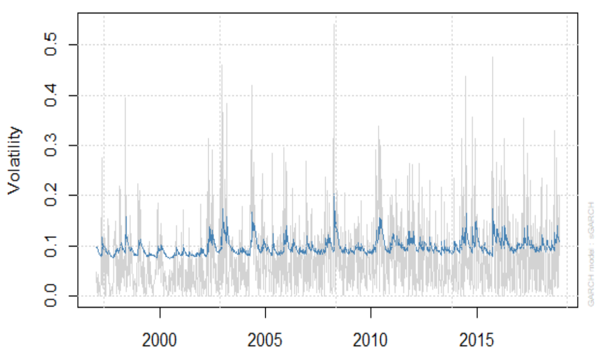

Figure 20 – Volatility vs. Absolute Prices of Carrot Prices (Log-Differenced) for – GARCH (1,2) ARMA (3,2) Model

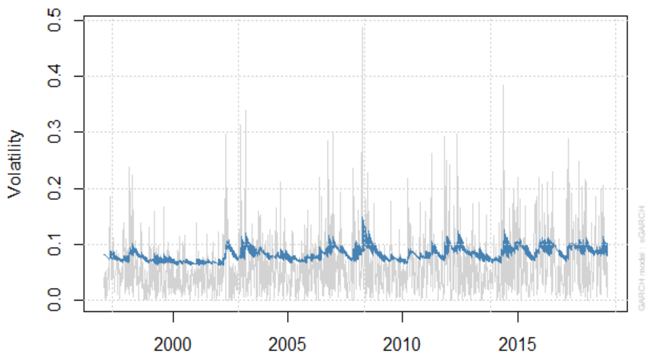

Figure 21 – Volatility vs. Absolute Prices of Cabbage (Log-Differenced) for – GARCH (1,1) ARMA (3,2) Model

Future volatility predictions (Table7) were done using two models that do not show autocorrelation in residuals. The mean and volatility for the first ten weeks of 2019 was predicted for carrot and cabbage price series, applying the respective ARMA-GARCH models. Estimation indicates gradual decrease in volatility in carrot price series from week 1-week 10, whilst gradual increase in volatility in cabbage price series, from week 1 to week 10.

Table 7 - Predicting Future Volatility Using Best GARCH Models

Time	Mean of the price series	Volatility of the Price Series
Carrot price series (log, differenced) GARCH (1,2) ARMA (3,2)		
2019-week1	-0.004012	0.1079
2019-week2	0.003886	0.1072
2019-week3	0.010493	0.1065
2019-week4	0.015792	0.1058

2019-week5	0.019807	0.1053
2019-week6	0.022602	0.1047
2019-week7	0.02427	0.1042
2019-week8	0.024928	0.1038
2019-week9	0.024709	0.1034
2019-week10	0.023753	0.1030
Cabbage price series (log, differenced) GARCH (1,1) ARMA (3,2)		
2019-week1	-0.023156	0.0801
2019-week2	-0.021057	0.0802
2019-week3	-0.018772	0.0802
2019-week4	-0.016393	0.0802
2019-week5	-0.01400	0.0803
2019-week6	-0.011655	0.0803
2019-week7	-0.00941	0.0803
2019-week8	-0.007304	0.0804
2019-week9	-0.005365	0.0804
2019-week10	-0.003612	0.0804

IMPLICATIONS

Managerial implications

The existing market information system and price dissemination network in Sri Lanka could be updated by incorporating the results of this study and similar studies. As weekly carrot retail prices can be predicted at 71% accuracy, study findings can be used to guide present market monitoring system and establishing an early warning system for carrot farming in Sri Lanka. Further research in to prediction of fresh vegetable prices applying different forecasting models might lead the way to find the best fitted model for each type and thereby could develop a price prediction dash – board with real time data. Relevant regional authorities can use such a dash bord to make the farmers aware of the expected prices, before commencing the season. Based on the projected prices, farmers might be able to optimize the decisions on crop acreage and cropping mix.

CONCLUSION

The prices of the considered three fresh vegetables fluctuated widely throughout the year, with two price spikes correspond to two lean seasons and two price drops observed coincides with two peaks of the harvesting seasons. The highest prices prevail between week 21- 29 and week 49 - 52 and the lowest prices were noted in week 8 - week 14 period and week 37 - 41 of the year. Hence, price predictions techniques which consider the trend, seasonality, and conditional volatility were needed for accurate forecasts of price information.

Estimations revealed that each time series is stationary with a one break point; occurring at 41st week of 2014 for carrot price series, 18th week of 2014 for cabbage price series and 17th week of 2006 for tomato price series. The causes for structural breaks were rather unclear. The ARIMA model estimations shows that ARIMA(3,1,2)(0,0,2)$_{[52]}$ is the best fitted model to predict retail prices of carrot while, ARIMA(1,1,1)(0,0,1)$_{[52]}$ is the best suited model for forecasting the retail prices of cabbages. The MAPE of 28.86% and 45.20% for *Ex - post* predictions of carrot and cabbage price series implies that weekly carrot retail prices can be predicted at 71% accuracy by using ARIMA(3,1,2)(0,0,2)[52] model whilst ARIMA(1,1,1)(0,0,1)[52] model is capable of predicting weekly cabbage retail prices at 55% accuracy.

All three-price series exhibited serial correlation in the error term or the ARCH effects. This property allows for fitting GARCH model for predicting volatility. Of the fitted ARMA - GARCH estimations, the best model for estimating the volatility of carrot and cabbage were GARCH (1,2) ARMA (3,2) (AIC=-1.9546) and GARCH (1,1) ARMA (3,2) (AIC=-2.3134) respectively. These two models indicate no autocorrelation in residuals or squared residuals, hence considered as good fit. None of the models were "explosive" as sum of $(\alpha + \beta)$ does not exceeds 1. The volatility predictions for the first ten weeks for the year 2019 indicates gradual decrease in volatility in carrot price series in contrast to the gradual increase in volatility in cabbage price series. Neither seasonal ARIMA nor ARMA - GARCH estimations could model the tomato price series as residual autocorrelation was observed in both cases.

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APPENDIX 1

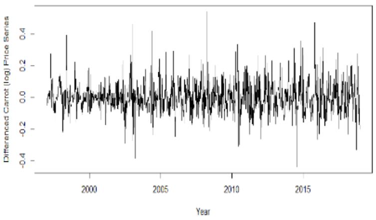


Figure 2 - Differenced Weekly Carrot Retail (Log) Prices, 1997 -2018, (Rs/Kg)

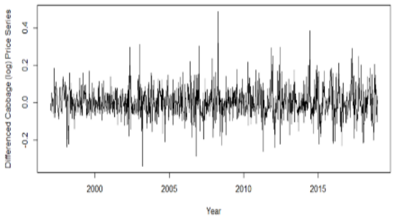


Figure 3 - Differenced Weekly Cabbage Retail (Log) Prices, 1997 -2018, (Rs/Kg)

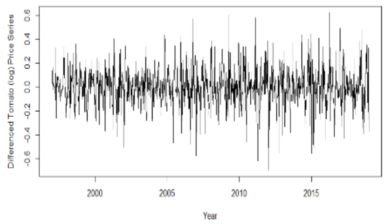
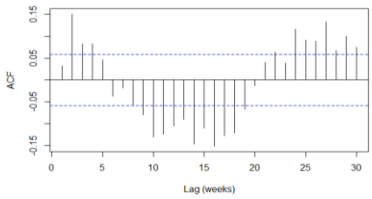


Figure 4 - Differenced Weekly Tomato Retail (Log) Prices, 1997 -2018, (Rs/Kg)

APPENDIX 2



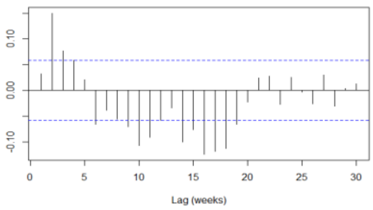
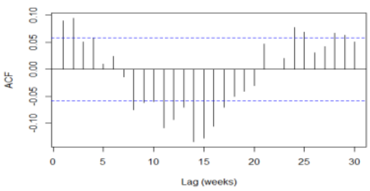


Figure 5 And 6 – ACF (Left) and PACF (Right) Graphs for the Differenced Retail (Log) Carrot Retail Price Series



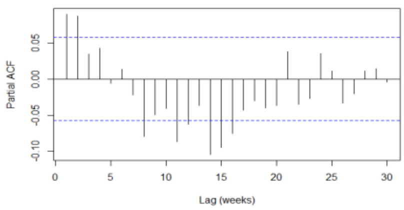
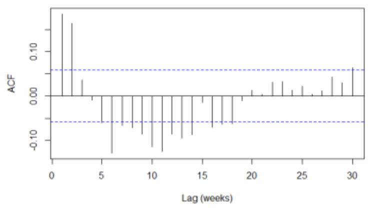


Figure 7 and 8 – ACF (Left) and PACF (Right) Graphs for the Differenced Retail (Log) Cabbage Retail Price Series



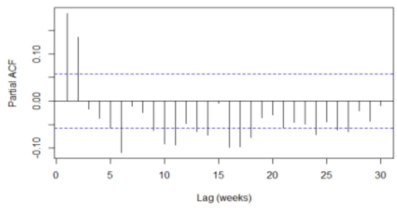
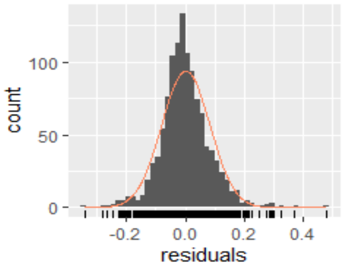


Figure 9 and 10 – ACF (Left) and PACF (Right) Graphs for the Differenced Retail (Log) Tomato Retail Price Series

APPENDIX 3



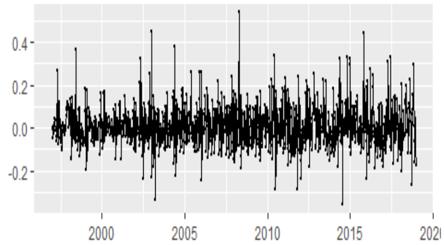
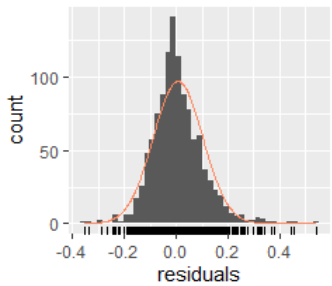


Figure 11 and 12 - Density Plot (Left) and The Plot of Residuals (Right) for ARIMA(3,1,2)(0,0,2)[52] on Carrot Price Series



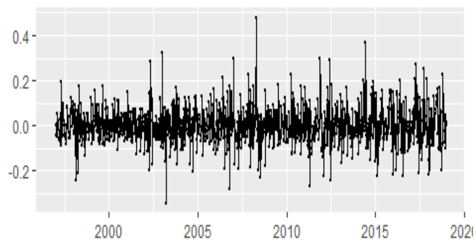


Figure 13 And 14 - Density Plot (Left) and Plot of Residuals for ARIMA(1,1,1)(0,0,1)[52] on Cabbage Price Series (Right)

APPENDIX 4

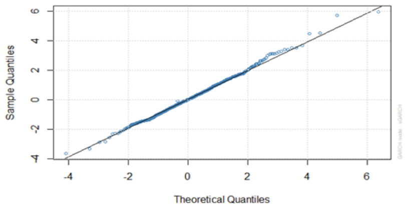


Figure 17 - Q-Q Plot for GARCH (1,2) ARMA (3,2)

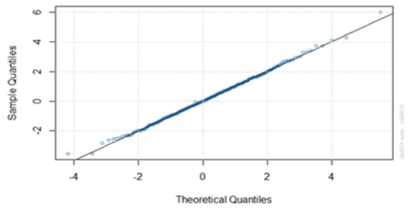


Figure 18 - Q-Q Plot for GARCH (1,1) ARMA (3,2)

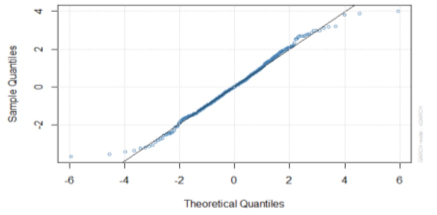


Figure 19 - Q-Q Plot for GARCH (1,1) ARMA (2,2)

APPENDIX 5

Table 4 - *Ex-Post* Forecasted Carrot and Cabbage Retail Prices for The Year 2019 (Rs/Kg)

	Carrot Retail Price (Rs. /kg)		Cabbage Retail Price (Rs. /kg)	
	Actual	**Forecasted**	**Actual**	**Forecasted**
1	166.97	192.15	157.33	182.74
2	155.00	179.62	118.62	180.16
3	140.63	172.96	116.56	179.99
4	144.00	165.68	112.35	177.57
5	145.31	163.58	101.29	177.27
6	128.95	161.83	99.19	177.89
7	126.67	167.27	94.69	177.84
8	149.70	166.01	100.94	177.47
9	136.67	168.37	98.44	176.42
10	137.42	168.87	100.00	176.23
11	138.62	175.38	92.58	176.93
12	129.12	182.40	100.63	176.27
13	127.10	191.98	100.37	176.07
14	138.57	196.73	98.39	176.31
15	152.94	203.95	124.29	175.36
16	153.14	216.89	180.18	176.69
17	153.33	221.70	111.79	175.92
18	151.43	231.87	117.24	176.25
19	190.71	238.24	125.33	176.48
20	201.72	245.96	155.00	176.97
21	212.35	252.75	148.13	177.83
22	200.00	257.86	128.57	178.55
23	181.85	255.32	126.21	179.91
24	179.67	263.89	119.33	181.17
25	173.33	262.36	111.88	182.90
26	172.67	259.25	104.67	185.14
27	184.14	252.27	107.19	185.14
28	171.61	246.86	107.59	184.90
29	174.24	246.28	106.76	184.79
30	155.17	243.42	102.07	185.34
31	145.67	240.95	102.76	184.24
32	149.67	239.55	106.3	183.64
33	133.33	235.75	97.00	182.30
34	128.33	232.92	113.06	184.09
35	128.65	228.81	120.83	184.03
36	132.90	229.79	128.44	184.23
37	127.59	225.15	130.65	184.10
38	136.13	221.62	135.71	181.83
39	138.48	217.43	178.13	180.29
40	155.94	216.87	177.41	178.88
41	162.81	215.33	179.31	177.69
42	167.00	219.30	190.00	179.99
43	243.45	220.04	196.13	180.73
44	229.71	222.67	194.19	181.25
45	252.58	232.82	200.29	182.96
46	360.45	236.00	195.22	183.47
47	253.44	238.72	179.31	184.13
48	244.52	234.01	162.5	183.39
49	277.58	230.21	184.19	183.11
50	308.39	231.37	198.06	181.97
51	328.46	226.40	198.00	182.38
52	412.50	224.64	204.29	182.42
MAPE	**28.82**		**45.20**	
MPE	**42.17**		**51.05**	
RMSE	**45.76**		**58.33**	