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Retail Price Volatility: The Case of Coconut in Sri Lanka

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ABSTRACT

This study attempted to analyze the volatility of the retail price of coconuts using monthly time series data from January 1991 to July 2020 and forecast the same for July 2020 to June 2021. The analysis found the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) (1,1) model as the best fit model. Coefficients of past values of the error term and conditional variance are positive and significant indicating positive impacts on the prevailing price volatility. Coefficients of lagged values of conditional variance and error terms are 0.771 and 0.179 respectively. The study concludes that the volatility shocks persist, and the model is appropriate to forecast the retail price of coconuts in Sri Lanka.

Keywords: *Coconut, Conditional Heteroscedastic models, GARCH, Price Volatility*

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Introduction

Coconut (*Cocos nucifera*) is an important crop for the Sri Lankan economy as well as other tropical countries. It is a multipurpose crop that generates living capital for society. Coconut plays a vital role in Sri Lankan economy in terms of domestic consumption and export earnings. Coconut production has contributed significantly to the national economy over a long period, which accounted for approximately 11% of all agricultural produce in Sri Lanka with the total land area under cultivation covering 443,538 ha and about 2,500–3,000 million nuts produced annually (Central Bank of Sri Lanka, 2021). Further, it contributes to the Sri Lankan economy in terms of foreign exchange earnings and the generation of employment. A total of 443,538 ha is under coconut cultivation, of which 72,294 ha are under the estate sector, while 371,244 ha are under smallholdings. Approximately, two-thirds of the coconut production in Sri Lanka is consumed locally and the balance one-third is used for coconut-based industries and exported to various destinations as value-added products. Domestic household consumption of coconut was 1,826 million nuts per the year 2020. The coconut sector earned a historic high foreign exchange of US$ million 834.12 in 2021 (Coconut Development Authority, 2021).

Price volatility is used to describe the price fluctuations of a commodity. Volatility provides a measure of price uncertainty in markets. Price volatility is an important factor for all the stakeholders in the coconut sector, however, its impact on the export sector is significant as exports are based on forwarding contracts. The average price increased significantly to a rate of Rs. 83.87 per nut during April 2020 as a result of disruptions to the coconut supply chain. However, by the end of August 2020, the price declined to around Rs. 72.28 per nut (Central Bank of Sri Lanka, 2020). The coconut prices are affected by production, consumption, and marketing. It is important to examine the nature of coconut price volatility in Sri Lanka as well as to determine future coconut prices to enable the government, producers, and the consumer to make correct decisions. Further, the analysis of price volatility is necessary to develop strategies to maximize profits in the sector.

A considerable number of studies related to coconut prices were done. Nyantakyi *et al.*, (2015) examined the individual behaviour of the prices of tea, rubber, and coconut in Sri Lanka using Auto-Regressive Integrated Moving Average (ARIMA) and also the combined effects of those prices using Vector Error Correction models (VECM). The study concluded that ARIMA (0, 1, 3) was the best-fitted model for the annual price series of coconut from 1966 to 2009. Rangoda, *et al.*, (2006) employed a range of conventional time series models including the general decomposition method, Moving Average (MA), Holt-Winters Multiplicative Seasonal (HWMS) model, Single Exponential Smoothing method (SES), Double Exponential Smoothing method (DES), and

ARIMA method to find the appropriate model to forecast prices of coconut and allied products. National average prices of desiccated coconut, coconut oil, and average retail and wholesale prices of fresh coconuts from January 1974 to December 2004 were used in the study. By considering the lowest Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD), authors have concluded that ARIMA and the single exponential smoothing method are better than other models to predict the prices of fresh coconut, coconut oil, and the desiccated coconut.

Abeygunawardena *et al., (*1996) seemed to be the first and only group of researchers who forecasted one-year previous retail and wholesale prices of coconut with a Vector Autoregression (VAR) model, a stochastic process model that captures the linear interdependencies among multiple time series, using twenty-year period monthly data (1973-1992). In this study, the data were best fitted to the VAR model (two-variables VAR model defined by endogenous variables, retail and wholesale price) and one year ahead forecasts made using the model were statistically accepted. Furthermore, the study concluded that although a lagged effect of rainfall on coconut yield is present, it is not contributed significantly to the nut prices consistent with the model statistics. All the above-mentioned studies focused on price forecasting. However, there is a literature gap directly related to the analysis of the retail price volatility of coconut.

In recent years, coconut retail price volatility has increased. During price escalations, the government imposed a price ceiling on coconut retail prices. Hence, the understanding of retail price volatility is important in making policy decisions. The present study focuses on analyzing the retail price volatility of coconuts in Sri Lanka. Specifically, the study focuses on three objectives; 1) to analyze price trends over the period, 2) to estimate the retail price volatility over the last 30 years, and 3) to forecast the future retail price of coconut in Sri Lanka.

The rest of the article is organized as follows. Section two sets out the methodology used for the present study. The empirical results and discussion of the findings are provided in Section three. Finally, Section four draw conclusions and recommendations.

Methodology

Theoretical Framework

ARCH and GARCH Model

Linear models are unable to explain several important features common to financial data including price volatility. That is because of the assumption of homoskedasticity (or constant variance), which is not appropriate when using financial data. In such instances, it is preferable to examine the patterns that allow the variance to depend upon the past data (Floros, 2008; Bova, 2009). For many time series data, especially price data, there is a propensity to clustered volatility (phases of ups and downs). Therefore, Autoregressive Conditional Heteroscedasticity (ARCH) and GARCH models have been introduced as these models are capable of capturing volatility clustering and leptokurtosis. The ARCH model by Engle (1982) is unique in the sense that it indicates the variance of the error term in a regression equation as conditional on squared past errors (McKenzieand Mitchell, 2002).

Such being the case, the volatility within the ARCH specification will effectively demonstrate periods of relative tranquility and volatility and hence it is capable of capturing the features of volatility clustering. The standard ARCH(q) model can be represented by the following equations.

$$r_t = \lambda_0 + \lambda_1 r_{t-1} + \varepsilon_t \dots\dots\dots\dots \quad Eq\ (01)$$

$$r_t = \lambda_0 + \lambda_1 r_{t-1} +$$

$$\sigma_t z_t,\ z_t \sim NID\ (0,1) or\ z_t \sim \text{GED}\ (0,1) \dots\dots\dots\dots \quad Eq\ (02)$$

$$\sigma_t^2 = \omega + \Sigma_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 \dots\dots\dots\dots \ Eq\ (03)$$

where z_t is an independently and identically distributed (*.i.d*) process with $E(z_t) = 0$ and $Var(z_t) = 1$.

GARCH model, a more useful extension of the ARCH model, has been proposed by Bollerslev (1986). This model is broadly applied and therefore, valuable to review thoroughly. According to Obi and Sil (2013), the basic GARCH model for the superb forecaster of the next period's variance (σ_{t+1}^2) is that the weighted average of the long term variance, the constant term (ω), new information about volatility observed in the current period, the ARCH term

(ε_t^2), and the forecast variance for the current period, the GARCH term (σ2 t). Hence, the standard specification of GARCH (p, q) is symbolized as follows.

$$\sigma_t^2 = \omega + \Sigma_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \Sigma_{k=1}^{p} \beta_k \sigma_{t-k}^2 \ldots\ldots\ldots\ldots Eq(04)$$

with the restriction of $\omega > 0$, $\alpha_j \geq 0$, $\beta_k \geq 0$, and $\Sigma_{t=1}^{\max(p,q)}(\alpha_j + \beta_k) < 1$.

Here, the latter constraint on $\alpha_j + \beta_k$ signifies a limit on the unconditional variance of $\varepsilon_t$whereas the conditional variance σ_t^2 changes over time (Goh *et al.*, 2016).

ARCH Effect

The ARCH effect can be tested in pre-estimation and as well as post-estimation analysis. Before applying the ARCH model, the assumption of linear regression is examined by regression diagnostic specification tests for the variables and Autocorrelation function (ACF) in residuals. In post-estimation, it tests the remaining ARCH effect, *i.e.*, whether or not the conditional heteroscedasticity has been removed. Standardized residuals of the fitted model can be used. This is an LM-test for the ARCH effect in the residuals (Engle, 1982). Normality tests are used to test the Behaviour of the ARCH effect if the normality is often described by the conditional error distribution.

Information Criteria

Several information criteria are available to determine the order p of an AR process. An AR process of order prefers a statistic during which its current value depends on its first *p* lagged values and is generally denoted by AR (p). The AR order *p* is usually unknown and thus has got to be estimated via various order selection criteria like the Akaike's information criterion (AIC) (Akaike, 1973), Schwarz information criterion (SIC) (Schwarz, 1978), and Bayesian information criterion (BIC) (Akaike, 1973).

All the information criteria are based on likelihood. The well-known Akaike information criterion (AIC) as Akaike (1973) defines is:

$$AIC = \frac{-2}{T} ln(likelihood) \frac{2}{T} (Number\ of\ parameters) \ldots\ldots Eq\ (05)$$

Where the likelihood function is assessed at the maximum-likelihood estimates and T is the sample size. For a Gaussian AR (l) model, AIC reduces to

$$AIC = \ln(\sigma_l^2) + \frac{2l}{T} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq\ (06)$$

Where (α_l^2) is the maximum-likelihood estimate of (α_a^2) which is the variance of, a_t and T is the sample size. The first term of the AIC considering Eq. (05) measures the goodness of fit of the AR (*l*) model to the data, and also the second term is considered as the penalty function of the criterion because it uses the number of parameters in a candidate model to penalizes it.

Another commonly used criterion is the Schwarz–Bayesian information criterion (BIC). the criterion is,

$$BIC = \ln\left(\sigma_l^2\right) + \frac{l\ln(T)}{T} \dots\dots\dots\dots\dots.Eq\ (07)$$

The penalty function for each parameter used is 2 for AIC and ln(T) for BIC. Thus, compared with AIC, BIC tends to select a lower AR model when the sample size is moderate or large. This makes BIC the main criterion to select the best fit.

Selection Process

In order to employ AIC to select an AR model, AIC (*l*) for l = 0, …, P, was calculated, where P is a pre-specified positive integer and selects the order k that has the minimum AIC value. The same steps were followed in computing BIC.

RMSE (Root Mean Squared Error)

There are different forecasting errors such as RMSE, MAE, MAPE, and Theil's U inequality. The RMSE depends on the scale of the independent variables and was used as relative measures to compare forecasts for the same series. They have been used extensively in the application of theoretical works on forecasting. It indicates that the smaller error in RMSE is the better the forecasting ability of the model.

Empirical Model

Use of nominal output price does not make economic sense if inflation is high, since farmers will be interested in the actual purchasing power of their money and as a result will respond to changes in real output prices rather than changes in nominal prices (Leaver, 2004). Accordingly, as this study uses monthly time series data of price, they should adjust to inflation. Hence, nominal retail prices of coconut were converted into real prices using the Colombo Consumer Price Index (CCPI) of each year using the following formula.

$$Real\ Price = \frac{Nominal\ price}{Price\ Index} \times 100 \dots\dots\dots\dots\dots\dots\dots\dots Eq\ (08)$$

ARCH models are specifically designed to model and forecast the conditional variance of the dependent variable. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables (Green, 1997). The empirical model for the analysis of the volatility of the retail price of coconuts is given below. The model is comprised of two equations, i.e., mean and variance equations.

Mean Equation

$$\mathrm{RPC_t} = \beta_1 + \beta_2 \mathrm{CP_t} + \beta_3 \mathrm{RPC_{t-k}} + \mathrm{e_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathrm{Eq(10)}$$

Where,

RPC_t = Monthly real price of coconuts at time t (Rs/nut)
RPC_{t-k} = k month's lag real price of coconut (Rs/nut)
CP_t = Monthly coconut production at time t (No. of nuts in million)
e = Residual
β_1 = constant
β_2, β_3 = Coefficients of the variables

Variance Equation

$$\mathrm{H_t} = \beta_4 + \beta_5 \mathrm{H_{t-m}} + \beta_6 \mathrm{e^2_{t-m}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathrm{Eq(11)}$$

Where,

$\mathrm{H_t}$ = variance of the residual (error) term derived from the mean equation above
e^2_{t-m} = squared residual derived from equation (1.1) at t-m
$\mathrm{H_{t-m}}$ = GARCH term
β_4 = constant
β_5, β_6 = Coefficients of the variables

The real price of coconut was regressed with independent variables in the model to find the best fit model. Linear regression model and ARCH models were estimated with variables to select the most suitable model. At the first stage, linear regression was carried out to estimate the coefficients. Then the assumptions of the linear regression model were checked for any violations. Regression diagnostic specification tests were carried out to investigate autocorrelation and heteroskedasticity using Durbin-Watson statistic and Bresch-pagan/Cook-Weisberg tests respectively. If the linear regression assumptions are violated and volatility clustering is present, then ARCH models will be tested. The presence of ARCH effect should be detected before applying any ARCH model and this can be done using Lagrange Multiplier test or ARCH test. ARCH models will be again tested for the presence of ARCH effect after estimation of the model and the model should be free of ARCH effect in order to accept it as a suitable model. Volatility clustering and the ARCH effect in residuals was tested in estimated ARCH models before applying GARCH models. Different types of functional forms such as ARCH and GARCH models were tested. Then the best model was selected for forecasting based on the AIC/BIC values and sign of the coefficients. Root Mean Square Error (RMSE) was used to evaluate the appropriateness of the model for forecasting.

Data

Based on the objectives of the study, price volatility was analyzed for a period of 30 years starting from January 1991 to July 2020. The study used secondary data on monthly coconut production and retail prices for the period and these were obtained from the annual reports of the Central Bank and coconut statistics of the Coconut Development Authority.

Results and Discussion

Descriptive Statistics of the Dataset

Descriptive statistics of the dataset are presented in Table 1. The data were obtained for the period, January 1991 to July 2020. Over the period, the mean value of coconut real price is Rs.42.24, while the standard deviation is 8.69. The minimum value for coconut real price is Rs.25.25, while the maximum price reached Rs. 73.02, and the variance is 75.68. Over the period the mean value of coconut nut production reports as 221.89 million nuts per month while the standard deviation is 28.95. The minimum monthly production was reported as 118 million nuts while the maximum production over the period is high as 323 million nuts with a variation value of 838.64.

A regression model that regressed the monthly real price of coconut with the coconut production and one-month lagged real price as the independent variables was estimated as the first step of the analysis and tested for the presence of heteroscedasticity and autocorrelation. The test for heteroskedasticity is significant at a 5% level rejects the null hypothesis and Durbin-Watson statistic is 0.319 which is less than 2 indicated the presence of autocorrelation.

Table 1. Descriptive Statistics

Variable	Mean	Std Dev.	Min	Max
Real Price (Rs)	42.24	8.69	25.25	73.02
Nut Production (million nuts)	221.89	28.95	118	323
One month Lag-Real Price (Rs)	42.24	8.71	25.25	73.02

Source: Calculated by author, 2021

Pre-condition Test for ARCH/GARCH Model

Figure 1 shows the volatility clusters in residuals while Table 2 shows the results of Lagrange Multiplier test. The test results reject the null hypothesis of there is no ARCH effects and hence it can be concluded that there is an ARCH effect in residual clustering. This ARCH effect in residuals is the pre-condition for the ARCH/GARCH model.

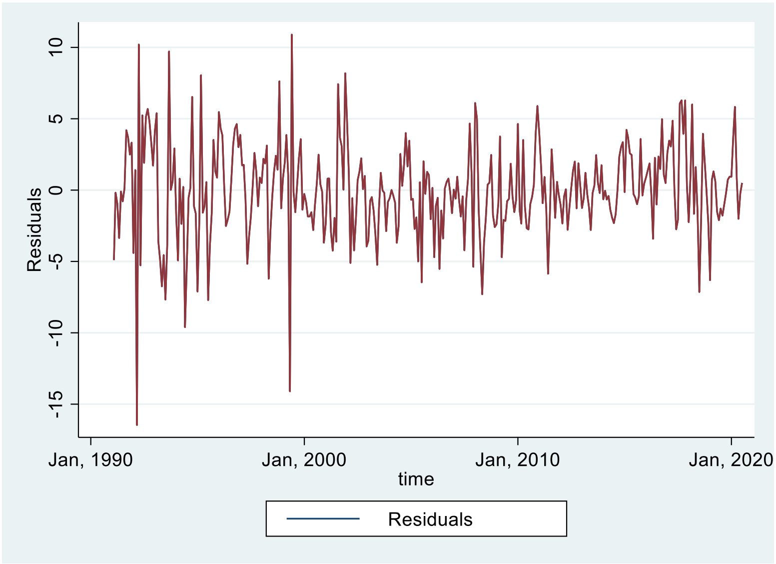

Figure 1. Volatility clustering of residuals
Source: Estimated by Author, 2021

Table 2. Results of Lagrange Multiplier test

lags(p)	Chi2	Df	Prob>chi2
10	28.78	19	0.0014

Source: Estimated by author, 2021

Different ARCH models and GARCH (p, q) models were estimated. After estimating every model, the residual variable was created and checked the presence of ARCH effect in the residuals, and it should be free from ARCH effect. The AIC, BIC and sign of the coefficients were used as model selection criteria. Smallest AIC and BIC values indicate the best-fitted model. The results of the information criteria are given in Table 3.

Both AIC and BIC are minimum for GARCH (1, 1). GARCH (1.1) means the combination of ARCH L1 and GARCH L1. Further, GARCH (1,1) has fully captured the ARCH effect and signs of the coefficients are alined with the theoretical justifications.

Table 3. Model selection criterion

Model	AIC	BIC
arch L1	1841.32	1868.40
arch L2	1835.35	1866.30
arch L3	1833.63	1868.45
arch L1 garch L1	1815.39 **	1846.34**
arch L2 garch L1	1817.38	1852.20
arch L3 garch L1	1830.02	1898.72
arch L1 garch L2	1817.33	1852.16
arch L1 garch L2	18818.63	1857.3

Source**:** Estimated by Author, 2021

Given the values obtained as presented in Table 3, GARCH (1, 1) model was selected as the best fit model. The results of this selected model are given in Table 4 and it indicates that the current month's real price of coconut shows an inverse relationship with the current month's coconut production and a direct relationship with the previous month's real price. In magnitudes, the coefficient of the current month's coconut production resulting in the model is -0.02 while the coefficient of one-month lagged real price is 0.85 and significant at 5% level. These results indicate that the current month's real price of coconut has a positive relationship with one-month lagged price, that is, the higher the previous month's price, it tends to increase next month's coconut price and vice versa. Also, the higher the current month's production, the lower the current month's real price of coconuts which is in far with the demand-supply theory. Coefficients of past values of the error term and past values of conditional variance are positive and significant at a 5% level.

The results indicate that there are positive impacts of the above on the existing price volatility of coconuts. Coefficients of lagged conditional variance and lagged squared error terms are 0.771 and 0.179 respectively where their summation is closer to one indicating volatility shocks are quite persisting.

Table 4. Model estimates for mean and variance components.

Variables	Coef.	Std. Err	Z	P > |z|	[95% conf. Interval]	
Nut Production	-.026	.006	-4.15	0.000	-.039	-.014
Lag Real price	.859	.019	45.18	0.000	.896	.895
Constant	11.54	1.94	5.94	0.000	7.738	15.35
arch L1.	.179	.051	3.46	0.001	.077	.280
garch L1.	.771	.056	13.60	0.000	.660	.882
Constant	.690	.350	1.97	0.049	.003	1.37

Source: Estimated by Author, 2021

Retail Price Forecasting

Monthly price forecasting for the next one-year period was done using the fitted model. The RMSE value was used to test the model validity for price forecasting. The obtained RMSE value is 14.29 which is a lower value indicating a good fit of the GARCH (1, 1) model. The average retail price of coconut for the forecasted period is Rs. 54.40/nut. Figure 2 shows the actual and predicted value of the retail price of coconut. It can be observed that both are following a very similar pattern.

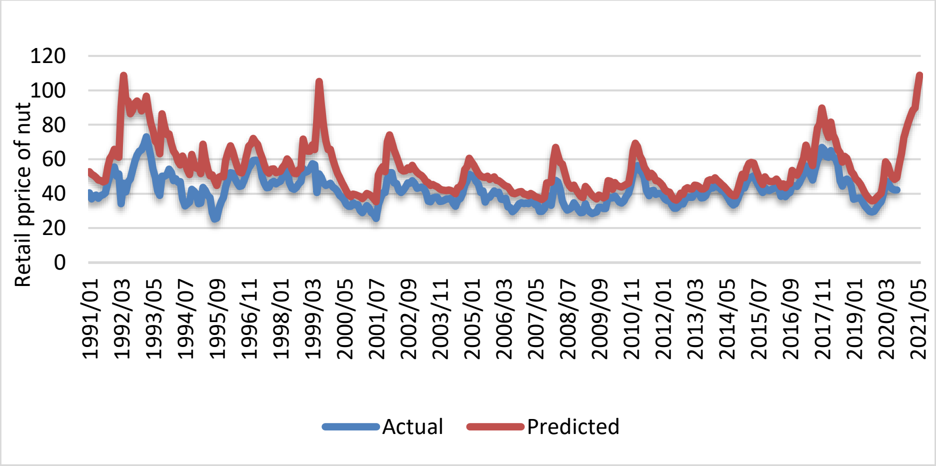

Figure 2. Actual and predicted values of the retail price of coconuts
Source: Estimated by author, 2021

Conclusions and Recommendations

This study investigates coconut price volatility and forecasts future coconut prices for a year ahead. Different ARCH and GARCH models were estimated, and residual diagnostic tests were done. Results showed that the ARCH model has failed to fully capture the ARCH effect in the residuals generated by the mean equation. However, the GARCH (1,1) could fully capture the ARCH effect and left no ARCH effect in the residuals and by using various goodness of fit tests as well as forecast evaluation criteria, the selected model proves to be the best model among all competing models for the analysis of retail price volatility. It is concluded that the retail price of coconut is highly volatile, and the GARCH (1,1) model is suitable for capturing the volatility and its forecasting properties are encouraging and hence can be used in forecasting for a period of one year. The estimates of the RMSE of the price forecasting model, which is used to forecast the prices for a period of one year starting from June 2020 showed the robustness of the prediction. Furthermore, it shows that the average retail price of coconut for the forecasted period is Rs. 54.40/nut. While several models and techniques were employed in this study, there is room for further improvement of the model considering asymmetry in price volatility. In addition, seasonality in volatility, degree of price volatility transmitted to the different markets in the coconut supply chain and the possibility of volatility spillover in the market chain is not explored in this study and including them in a future study is suggested. With an accurate price volatility forecast, the participants in the coconut market can reduce some uncertainties, therefore they can formulate practical plans and necessary decisions in developing the sector.

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