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Research Article

Forecasting Volatility for Assessment of Yellow Split Peas Products: Analysis in the Frameworks of ARCH Model

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Abstract

Thirty analysed observations of yellow split peas products were collected from Institute of Food Science and Technology (IFST), BCSIR, Dhaka over the year 2007 to 2012 by Single Stage Cluster Sampling method. The work has explored the impact of type of Yellow Split Peas products on testing for ARCH effects and the estimation of ARCH models for analysis data. Our products comprise physiochemical analysis data for Yellow Split Peas. The corresponding p-value is >0.05, which is very high except Purity (%) and Insect damage (%) variables. So we have no difficulty to accept the null hypothesis of no ARCH error in the analysis series. The parameters of Yellow Split Peas analysis are insignificant that means no ARCH effects of the models. The estimation results are given in the Table 1. An outcome of Dickey–Fuller (DF) test confirms that the physiochemical analysis variables series is stationary except Insect damage (%). The results of Figure 1 to 9 indicate that the volatility in the Yellow split peas exhibits almost all of the variable highly volatile in this time period. Our results revealed that the ARCH model satisfactorily explains volatility and the most appropriate model for explaining volatility in the series under analysis.

Keywords: Physiochemical analysis; ARCH effects; Forecasted to Volatility; Dickey–Fuller test.

Introduction

Dry peas, *Pisum sativum*, also referred to as field peas, are a cool-season pulse crop. As a legume, dry peas convert atmospheric nitrogen into soil-borne nitrogen that can be used by subsequent crops. Hence, dry peas may provide benefits in rotations with cereal crops by increasing yields and, to some extent, reducing fertilizer expenditures. Two main varieties of dry peas are produced: green cotyledon and yellow cotyledon. Both varieties are grown in the United States, although U.S. consumers prefer green peas. Yellow peas are widely consumed in India. Seed colors for the two varieties range from light to dark green and from cream to yellow [1].

Dry peas are grown commercially in almost 100 countries, but production is concentrated in Canada, Russia, and China. Jointly, these three countries produce over one-half of the world's dry peas. Canadian dry pea production increased considerably over the past 30 years, expanding from less than 200,000 metric tons per year in the early 1980s to approximately 3 million metric tons in 2012, or 12 percent per year [1].

Canada is the world's dominant exporter accounting for slightly more than 60 percent of world exports between 2008 and 2011. The United States was second in dry pea exports over the same period. France, Russia, and Australia are other important exporting countries. French exports have declined since the early 1990s when France was the world's largest dry pea exporter. Russian exports, generally negligible for most of the post-Soviet period, have increased dramatically since 2009 [1].

India and China import the majority of internationally traded dry peas. Both countries are also important pea producers. Other major importers include Bangladesh and Pakistan where consumers have tastes and preferences similar to those of India. Belgium, Italy, Spain, and Germany use peas for animal feed [1].

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Yellow Split Peas are a great low-fat source of protein and are high in fiber and iron. With a mild, earthy flavor and soft texture, split peas are similar to lentils in terms of their versatility and nourishment. Often referred to as "pulses", split peas (and lentils) are the edible seeds of legume plants. Split peas have been husked and split along a natural seam so that they will cook faster than a whole dried pea. However, this does not significantly impact their nutritional benefits. Yellow split peas are about ¼ inch wide and range in color from medium to pale yellow in color [2].

The analysis of chemical analysis data has received considerable attention in the literature over the last 20 years. Several models have been suggested for capturing special features of this data and most of these models have the property that the conditional variance (or the conditional scaling) depends on the past. One of the best known and most often used is the autoregressive conditionally heteroscedastic (ARCH) process introduced by [3,4]. The theoretical results on ARCH and related properties have played a special role in empirical work in the analysis of data on rates, prices and in inflation rate data to mention but a few [4,5].

This first model is Autoregressive Conditional Heteroskedasticity (ARCH) which was early introduced in the [3,4], it aimed to capture the conditional variance that is why it became the most popular way of describing the unique feature. Later on, for making this model better [4,6,7] put forward, independently of each other, a generalization of this model, called Generalized ARCH (GARCH). And this model have been certificated not only to catch volatility clustering but also to contain fat tails from the volatility data. These are common features about the financial data. Even though the GARCH model is already the extension of the ARCH model, it still has some drawbacks. The main point is that the GARCH model is symmetric, so it has a poor performance in reflecting the asymmetry. Because a fact on an interesting feature of financial volatility data is that bad news seems to have a more significant effect on the fluctuation compared to good ones. In other words, positive and negative information generate different degrees of influence to the changes of financial data. So this asymmetric phenomenon is leverage effect. Considering the stock data, it always exist a strong negative correlation between the current return and the future conditional variance. That is why some advanced GARCH model will be introduced later. Such as exponential-GARCH model [4,8] and GJR-GARCH model, [4,9], are proposed. Except these models, there still have many other extension GARCH models, such as TGARCH model—threshold ARCH—attributed to [4,9,10], FIGARCH model—introduced by [4,11] IGARCH model—proposed by [4,12,13].

This study is to examine the use of ARCH model for forecasting volatility of the physicochemical analysis of Yellow Split Peas products data collected from Institute of Food Science and Technology, Bangladesh Council of Scientific and Industrial Research, Dhaka over the year 2007 to 2012 by the method of single stage cluster sampling.

Materials and methods

Data

The Yellow Split Peas products 30 analysed observations were collected from from Institute of Food Science and Technology (IFST), BCSIR, Dhaka over the year 2007 to 2012 by Single Stage Cluster Sampling method [14]. Data collection methods were non-participant observation of organization included in the study. Archival research included hard-copy issues of reports of analytical documents.

Auto-regressive Conditional Heteoskedastic Model (ARCH) model

ARCH (Auto-regressive Conditional Heteoskedastic) Model is the first and the basic model in stochastic variance modeling and is proposed by [3,4]. The key point of this model is that it already changes the assumption of the variation in the error terms from constant Var (ε_t) = σ^2 to be a random sequence which depended on the past residuals ($\{\varepsilon_1 \ldots \varepsilon_{t-1}\}$). That is to say, this model has changed the restriction from homoscedastic to be heteroscedasticity. This break through is explained by [4,15]. And this is an accurate change to reflect the volatility data's features. Let ε_t as a random variable that has a mean and a variance conditionally on the information set I_{t-1}[16].

Residual Test/ ARCH LM Test

This is a Lagrange Multiplier (LM) tests for autoregressive conditional hetroskedasticity

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(ARCH) in the residuals. The test statistic is computed by an auxiliary regression as given in eq. (1).

$$P_t = \alpha_1 P_{t-1} + u_t \Rightarrow u_t = P_t - \alpha_1 P_{t-1} \quad (1)$$

To test the null hypothesis that there is no ARCH up to order q in the residuals, the regression in eq. (2) is run.

$$u_t^2 = \lambda_0 + \left(\sum_{s=1}^{q} \lambda_s u_{t-s}^2 \right) + v_t \quad (2)$$

Where u_t is the residual. This is a regression of the squared residuals on a constant and lagged squared residuals up to order q. The null hypothesis is that, $\lambda_s=0$ in the absence of ARCH components.

In a sample of T residuals under the null hypothesis of no ARCH errors, the LM test statistic equals number of observations*R-square (TR^2). The test statistic TR^2 follows Chi (χ^2)-distribution with q (lag length) degrees of freedom. If TR^2 calculated is greater than the chi-square table value (TR^2 critical), reject the null hypothesis in favour of the alternate hypothesis. Hence there is ARCH effect in the GARCH model [4,17].

Unit Root Test

In the case of time series analysis, unit root tests are important. Unit root tests help to identify the stationarity and non-stationarity of time series data used for the study. A stationary time series has three basic properties. First, it has a finite mean. This means that a stationary series fluctuates around a constant long run mean. Second, a stationary time series has a finite variance. This means that variance is time invariant and third, a stationary time series has a finite (auto) covariance. This reflects that theoretical autocorrelation decay fast as lag length increases. Regressions run on non-stationary time Series produce a spurious relationship. Hence, to avoid a spurious relationship, there is a need to perform a unit root test on variables [4,18].

Dickey – Fuller (DF) has been widely used to check the stationarity and presence of unit root of a process. The Dickey – Fuller test is valid only for AR(1). We usethe DF test when the residual are not autocorrelated. Dickey – Fuller considered theestimation of the parameter α from the models.

1. $y_t = \alpha y_{t-1} + e_t$(pure random walk)
2. $y_t = \mu+\alpha y_{t-1} + e_t$ (drift + random walk)
3. $y_t = \mu+bt+\alpha y_{t-1} + e_t$ (drift + linear trend)

It assumes that $y_0=0$ and $e_t \sim$i.i.d $(0, \sigma^2)$

The null and alternative hypotheses are:

H_0: α=1 (α(z)=0 has a unit root)

H_1: |α |<1 (α(z)=0 has root outside unit circle) [4], [19], [20]. Using non-stationary time series data in financial models produces unreliable and spurious results and leads to poor understanding and forecasting [4,21].

Result and discussion

ARCH-LM test

To detect the presence of ARCH effect in the mean equation of yellow split peas, we use the ARCH-LM (Lagrange multiplier) test. In our analysis the different value of above variables of the ARCH-LM test; the lags included in the test are only 1. The corresponding p-value is >0.05, which is very high except Purity (%) and Insect damage (%) variables. So we have no difficulty to accept the null hypothesis of no ARCH error in the analysis series. The parameters of Yellow Split Peas analysis are insignificant that means no ARCH effects of the models. The estimation results are given in the Table 1 shows that the values of DF test for all variables p-value <0.05 at 5%, level of significance for all variable except Insect damage (%) which implies that the variables series is stationary. An outcome of DF test confirms that the physiochemical analysis variables series is stationary except Insect damage (%).

Spike Behaviour of ARCH(1) and GARCH(1,1) model estimations

The presence of extreme spikes in our analysis of yellow split peas products is a bad characteristic of food products. Figure 1 shows the conditional and unconditional standard deviation of moisture (%) content over the period July 2008 to August 2011. Conditional standard deviations are over 0.50 during the sample period. The results indicate that the standard deviation almost stable among 2008 to 2011 and volatility in deviations is very low in this time period.

Figure 2 shows the conditional and unconditional standard deviation of purity (%) content over the period August 2007 to August 2011. Conditional standard deviations are over 0.20 during the sample period. The results indicate that the deviations significantly ups and

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down at whole period and also in spike behaviour at September 2008 and December 2010. However, volatility in deviation is low in this time period.

Table 1. ARCH-LM test analysis results of physiochemical analysis parameter of yellow split peas

Variable	LM test for autoregressive conditional heteroskedasticity (ARCH)		Dickey-Fuller test for unit root	
	Chi-square Statistic	p-value	Test Statistic, Z(t)	p-value
Moisture (%)	0.570	0.450	-4.286	0.0005
Purity (%)	6.316	0.012	-4.408	0.0003
Whole peas (%)	0.017	0.895	-5.024	0.0000
Heat damage (%)	0.076	0.782	-5.896	0.0000
Other damage (%)	0.001	0.978	-4.220	0.0006
Foreign matter (%)	0.416	0.519	-7.139	0.0000
Other colour (%)	1.305	0.253	-4.685	0.0001
Insect damage (%)	27.031	0.000	6.987	1.0000
Broken (%)	0.004	0.948	-6.639	0.0000
Husk (%)	0.135	0.7136	-3.532	0.0072
Cotyledon with hush (%)	3.536	0.060	-	-
Standard Plate count (cfu/gm)	1.461	0.227	-	-
Mold (cfu/gm)	0.335	0.5624	-	-

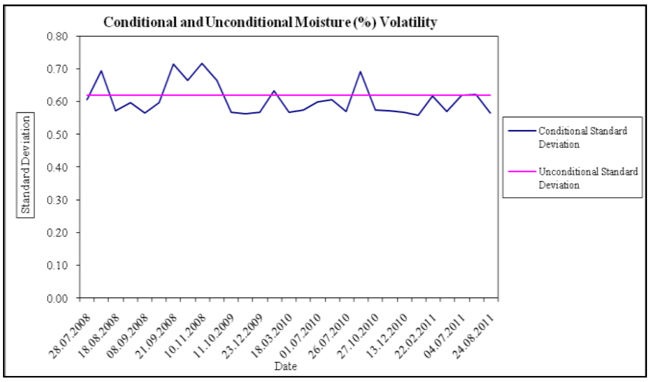

Figure 1. Moisture (%) content of Yellow Split Peas products for the Period November 2007 to February 2010

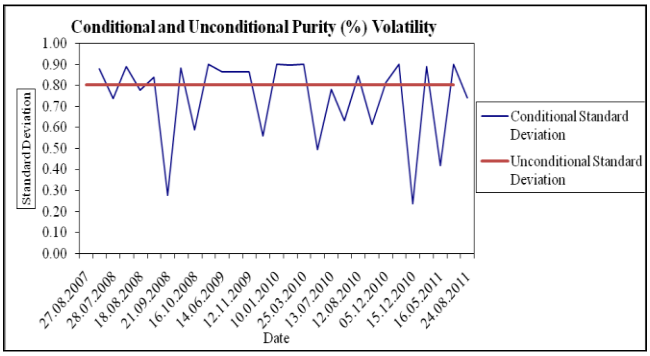

Figure 2. Purity (%) content of Yellow Split Peas products for the Period August 2007 to August 2011

Figure 3 shows the conditional and unconditional standard deviation of whole peas (%) content over the period July 2008 to August 2011. Conditional standard deviations are over 0.7 during the sample period. As can be seen in Figure 3, the deviation has relatively stable then also spike in the period July 2009. However, volatility in deviation is low in this time period.

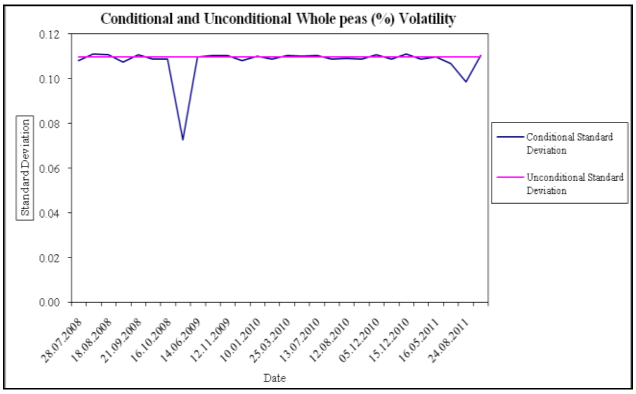

Figure 3. Whole peas (%) content of Yellow split peas products for the Period July 2008 to August 2011

Figure 4 shows the conditional and unconditional standard deviation of Solubility (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.00 during the sample period. The results indicate that the deviations almost stable and spike behaviour at December 2010. However, volatility in deviations is low in this time period.

Figure 5 shows conditional and unconditional standard deviation of Other damage (%) content over the period July 2008 to August 2011. Conditional deviations are over

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0.24 during the sample period. As can be seen in Fig. 5, the deviation has relatively stable during sample period. However, volatility in deviation is low in this time period. The deviation is spike behaviour during the period august to September 2008.

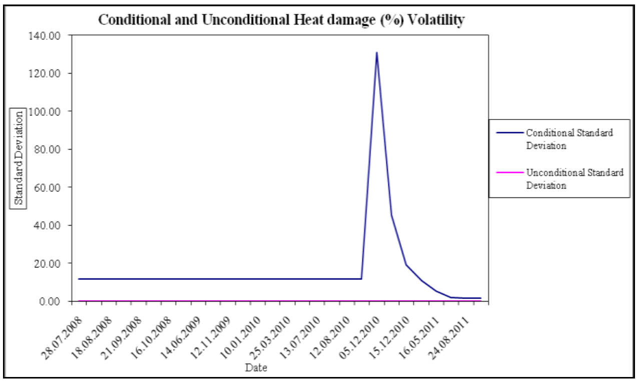

Figure 4. Heat damage (%) content of Yellow split peas products for the Period July 2008 to August 2011

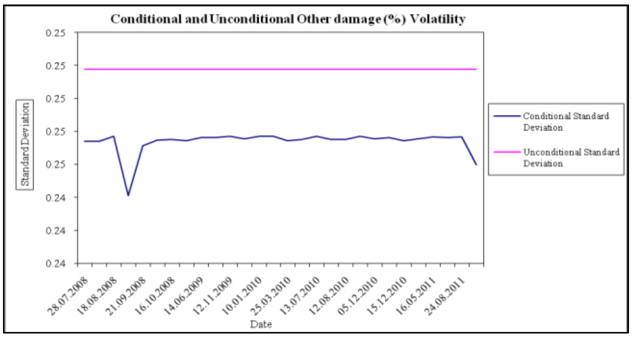

Figure 5. Other damage (%) content of Yellow split peas products for the Period July 2008 to August 2011

Figure 6 shows the conditional and unconditional standard deviation of foreign matter (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.10 during the sample period. The results indicate that the deviations are also stable behaviour. The deviation is volatile during the period 2008 and 2011.

Figure 7 shows the conditional and unconditional standard deviation of other colour (%) content over the period November 2007 to February 2010. Conditional deviations are over 0.00 during the sample period. The results indicate that the deviations are high spike behaviour at the period 2008 and 2011 and relatively high deviation during the whole period. The deviation is high volatile during the period 2008–2011.

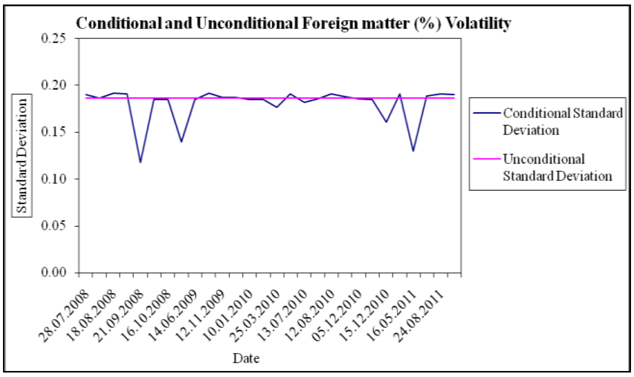

Figure 6. Foreign matter (%) content of Yellow split peas products for the Period July 2008 to August 2011

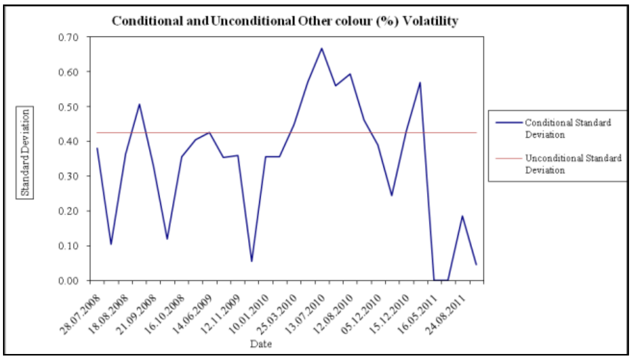

Figure 7. Other colour (%) content of Yellow split peas products for the Period July 2008 to August 2011

Figure 8 shows the conditional and unconditional standard deviation of Insect damage (%) content over the period July 2008 to August 2011. Conditional deviations are over 0.05 during the sample period. The results indicate that the deviations are low spike behaviour at the period 2008 and 2010 and relatively high spike behaviour during the period May 2011.

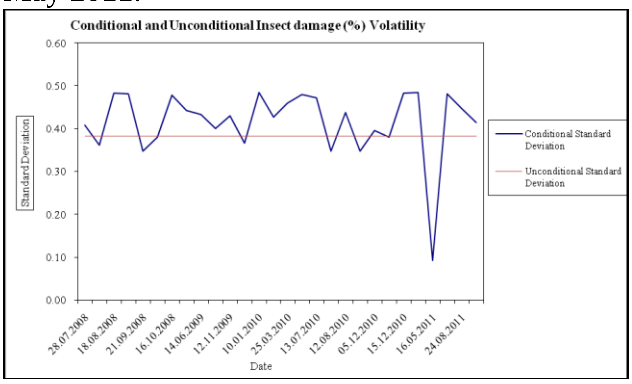

Figure 8. Insect damage (%) content of yellow split peas products for the period July 2008 to August 2011

Figure 9 shows the conditional and unconditional standard deviation of broken (%) content over the period July 2008 to August

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2011. Conditional deviations are over 3.70 during the sample period. The results indicate that the deviations are high spike behaviour at the period 2008 and 2011. The results of figure 1 to 9 indicate that the volatility in the Yellow split peas exhibits the almost all of the variable highly volatile in this time period.

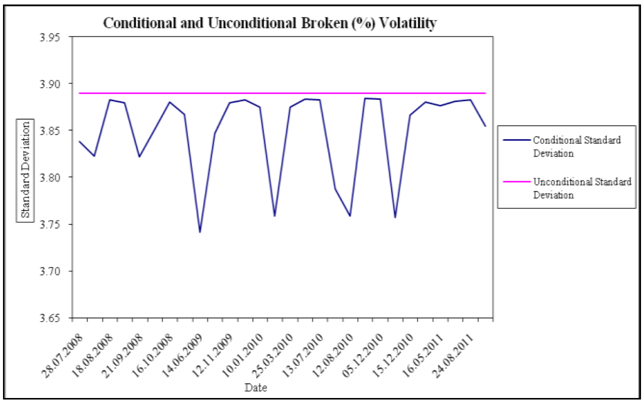

Figure 9. Broken (%) content of yellow split peas products for the Period July 2008 to August 2011

Conclusions

This study has attempted to study the volatility in the quality of food products. The data used for analysis were observations for the period of 2007 to 2011. Empirical results showed that ARCH model can adequately describe the quality of food products. We use ARCH-LM test to test whether there is any further ARCH error in both series. The test results of some parameters in food products show that there is there is an ARCH error in the analysis series. The results suggest that the volatility in the quality of food products exhibits the persistence of volatility behavior. Our results revealed that the ARCH model satisfactorily explains volatility and is the most appropriate model for explaining volatility in the series under analysis.

Conflict of interest

Authors declare no conflict of interest.

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