

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Applications of ARIMA and GARCH models in Sarawak pepper volatility study

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Abstract

This study analyses the Sarawak black pepper price at Kuching spot market volatility using both ARIMA and GARCH models to determine the best fit and accurate forecasting model for the price series. The findings indicates ARIMA (1,1,1) is a good model to forecast the price series but failed to fulfill the white noise assumption. GARCH (1,1) model is found to be the best fit model to model and forecast the price series. Evidence suggests that asymmetry effect is present in Sarawak black pepper price series with long memory volatility persistence.

Keywords: ARIMA; GARCH; Asymmetry; Price Forecast and Sarawak Pepper.

1. Introduction

This study attempts to address the issue of how to effectively overcome the pepper price volatility by analyzing the price series, identifying the best fit and accurate forecasting model on the Sarawak black pepper price series at Kuching market. Understanding the price volatility is important because persistence changes in volatility exposed small pepper famers, traders and commodity dependent country to risk thus affecting the investment and production of the commodity. As very few works has been done on this issue, this study will hopefully enhance the marketing strategies and policy planning for this industry. The pepper industry in Sarawak contributed an income to about 67,000 small pepper farmers in the rural areas (Board, Malaysian Pepper, 2009) [3]. The fluctuation in the pepper price, affect the income and livelihood of the farmers. Malaysia in 2013 ranked the fifth largest pepper producer in the world from third place in 1977 (Board, Malaysian Pepper, 2009) [4]. Malaysian pepper production has declined from its peak of 36,000 tons in 1980s to the lowest level of about 13,000 tons in 1995 before it increased to 26,000 tons in 2013 (Board, Malaysian Pepper, 2009).

Hussain, et al. (2000) [8] found ARMA model is the best fit model to model Sarawak black pepper price series and capable of predicting the future trend of the price movement. Fatimah and Gaffar (1986) [7] identified Box-Jenkins (1976) univariate ARIMA model as a suitable model to forecast agricultural commodity. Besides, ARIMA model was highly efficient in short term forecasting (Fatimah and Gaffar, 1986) [7] and low cost as compared to economic forecasting (Mad Nasir, 1992) [12]. Lalang et. al. (1997) [11] have shown that ARIMA model was the most suitable model to analyze palm oil prices. Sarla et al (2011) [15] found ARIMA model to be suitable for forecasting wheat price in India up to one year.

Based on a review of 58 journal articles using meta analysis method, it was found that ARCH and GARCH models dominated the methodology in forecasting. There were eighteen (31.58 percent) articles using ARCH and GARCH models. The second most commonly used forecasting model was the ARMA model, contributing to 12.3 percent to the total number of articles. Notably, the popularity of the ARCH and GARCH model forecasting tool to forecast commodity price in recent years.

Other time series models used in modeling and forecasting agriculture commodity are autoregressive conditional heteroscedasticity (ARCH) model (Engle, 1982), and general autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986). ARCH model allows the shocks in more recent period to affect the current volatility positively while GARCH models postulate that not only previous shocks but also previous volatilities affect current volatility. EGARCH model (Nelson, 1991) and PARCH model (Ding et al, 1993) were also used to model agricultural commodity prices. The above models are used to analyze the underlying stochastic process generating price series. GARCH model have been extensively used in finance, agriculture and energy commodities. Several articles in energy literature have addressed the modeling and forecasting of crude oil market volatility using generalised autoregressive conditional heteroscedasticity (GARCH) and their variance (Yoon et al, 2009;[20]; Su, and H. Mohammadi; Lixian 2010;[16] , Narayanan, Paresh Kumar Narayan; Seema (2007)[13]. Walid Chkili et al (2014) [17] used linear and non-linear GARCH model to analysed the volatility of crude oil, natural gas, gold and silver. They found the volatility of the commodity returns can be better described by non-linear commodity model which can accomodate long memory and asymmetry features. Similarly Chin Wen Chong et al (2007) [6] investigates the asymmetry and long memory volatility of the Malaysian stock market using GARCH model. The presence of long memory volatility reject the efficiency market hypothesis in the Malaysian stock market. In another case, Walid Mensi et al (2013) [18] employ VAR-GARCH model to investigate the return links and volatility transmission between S&P 500 with energy, food, gold and beverages. Warren G. Dean et al (2010) [19] explore the interdependence of stock and bond markets in Australia using bivariate GARCH to analyse spillover and asymmetry effect. GJR-GARCH model (1993) was employed by



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Amelie Charles (2010) [1] to evaluate whether asymmetry influence is present in the day-of-the week effect volatility. Julien Chelvallier (2011)[10] investigates the existence of ouliers in the volatility of carbon prices during 2005-2008 using EGARCH model. Beum-Jo Park (2010) [5] employ the GARCH type model to investigate the relationship between asymmetric herding and volatility.

Hence we can conclude the popularity of the GARCH model to analyse the volatility and asymmetry effect in commodities.Therefore the author employs the GARCH model to investigate the volatility and asymmetry effect in the Sarawak black pepper price series.

The main objective of this paper is to find the best fit and forecasting model for Sarawak black pepper price at Kuching spot market. Monthly average Sarawak black pepper price data at Kuching spot market from 1977 to 2013 was used in the analysis. Both ARIMA and GARCH models are employed to select the best fit model. The forecast accuracy of the GARCH model for the price series is selected based on the smaller root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

2. Model and statistical properties of data

This study begins with the following representation of the return on Sarawak black pepper price at Kuching spot market.

$$Y_t = a + \alpha' X_t + \mu_t \tag{1}$$

 $\mu_t \sim \text{iid N}(0, \sigma^2) \tag{2}$

In this equation, X_t is a k x 1 vector of explanatory variables and β

is k x 1 vector of coefficients with the assumption that μt is independently distributed with zero mean and a constant variance σ^2 . Table 1 below shows the descriptive statistic of Sarawak black pepper price at Kuching spot market from 1977 to 2013.

Table 1: Descriptive Statistic of Sarawak Black Pepper at Kuching Spot
Market from 1977 To 2013

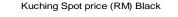
Warket Holli 1977 10 2013			
Statistic	Black pepper Kuching		
Mean	6537.196		
Median	4606.000		
Maximum	19030.00		
Minimum	1361.000		
Std. Dev.	4424.308		
Skewness	1.066247		
Kurtosis	3.022299*		
Jarque-Bera	84.13855		
Probability	0.000000		
Sum	2902515.		
Sum Sq. Dev.	8.67E+09		
Observations	444		
4.01 1.01 F.D.	* 1		

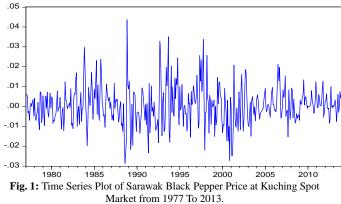
*Significant at 5 Percent Level.

The mean Sarawak black pepper price is RM6537.196 with a maximum at RM19030.00 minimum at RM1361.000 and standard deviation at RM4424.308.

2.1. Analyzing past volatility with autoregressive moving average (ARMA) model

An inferential analysis is carried out on the data series to determine the best fit model for Sarawak black pepper price at Kuching spot market from 1977 to 2013. A time series plot (Figure 1) is also done to further confirm the price volatility. ARMA model is subject to Box-Jenkins procedure (1976), which developed a systematic procedure for identifying and estimating models. It includes statistical test for verifying model validity and statistical measures of forecast uncertainty. This procedure consists of three main stages that is model identification, model estimation and model validation/diagnostic.





However, to confirm the presence of unit root in the series, an Augmented Dickey-Fuller test is performed. The results obtained (Prob* 0.6257) as shown in Table 2 below clearly shows the presence of unit root and therefore the series has to undergo differencing to run further analysis. Therefore, the first differencing is conducted in order to obtain a stationary data before enabling further analysis to be conducted.

Table 2: Result of Augmented Dickey-Fuller Test Statistic for Sarawak
Black Pepper at Kuching Market

Price series		t- Statistic	Prob.*
Black pepper at Kuching spot	Before	-	0.6257
market	differencing	1.310963	
Black pepper at Kuching spot	After	-	0.0000
market	differencing	15.17289	

Since the values of the ACF and PACF after differencing did not clearly shows which model is appropriate, the principle of parsimony is applied. This is done by fitting the simplest model that is ARIMA (1, 1, 1), ARIMA (2, 1, 1), and ARIMA (1, 1, 2) to the data set.

The generic ARMA model equation is:

$$Y_{t} = \emptyset Y_{t-1} + \emptyset_{2} Y_{t-1} + \dots \\ + \dots \\ \emptyset_{q} \mu_{t-q}$$
(3)

The ARMA model after first differencing (ARIMA) is:

$$\Delta Y_t = Y_t - Y_{t-1} \tag{4}$$

2.2. Application of GARCH family model

To test for conditional heteroscedasticity, a Ljung-Box Test is conducted (Table 3) to check whether the magnitude of each residual autocorrelation at their individual lags, are statistically different from 0. In other words, Ljung-Box Test is used to check whether the residuals are independently distributed, which fulfills the main assumption for the error term or the white noise.

 Table 3: ARCH LM Test Result for the Presence of ARCH Effect on Sarawak Black Pepper Price at Kuching Spot Market from 1977 To 2013

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	2.694799	Prob. F(40,401)	0.0000
Obs*R-squared	93.85338	Prob. Chi-Square(40)	0.0000

The results show that the null is rejected to conclude that there is evidence of heteroscedasticity when LM- statistic is bigger than the critical value. The Obs*R-squared statistic is 93.85338 and has a probability limit of 0.0000 limit. This suggest the hypothesis of homoscedasticity is rejected or that ARCH (1) effect is present. It is clear for this equation specification that an ARCH/GARCH model will provide better results.

To remedy the problem of heteroscedasticity, the author follow the work of Eagle (1982) and Bollerslev (1986) and model pepper price return within the ARCH/GARCH framework. One way of allowing for this is to have the variance depend on one lagged period of the squared error terms as follows:

$$\sigma_t^2 = \gamma_o + \gamma_i \mu_{t-1}^2 \tag{5}$$

The advantage of the GARCH (general autoregressive conditional heteroscedasticity) models is that they treat heteroscedasticity as a variance to be modelled. The use of the GARCH model will not only correct the deficiencies of the least squared, but enable prediction to be computed for the variance of each error term. In this analysis, four GARCH models are used and the results are compared to find the best fit model to forecast Sarawak black pepper price series. The GARCH models applied here are GARCH (1,1), TGARCH, EGARCH and PARCH. The variance equations for the different types of GARCH model employed in this study are as shown below:

GARCH(1, 1) model

 $h_t = \omega + \gamma * \text{RESID}(-1)^2 + \varphi * \text{GARCH}(-1)$ (6)

TGARCH model

 $h_t = \omega + \gamma$ *RESID (-1) ² φ + *GARCH (-1)) ²*(RESID (-1) <0) + * δ GARCH (-1) (7)

EGARCH model

 $h_t = \omega + \gamma * ABS(RESID(-1)/@SQRT(GARCH(-1))) + \varphi * RESID(-1)/@SQRT(GARCH(-1)) + \delta * LOG(GARCH(-1))$ (8)

PARCH model

 $h_t = \omega + \gamma * (ABS (RESID (-1)) - \varphi * RESID (-1)) ^ d + \delta * @SQRT (GARCH (-1)) ^ d$ (9)

3. Empirical results

Let us begin the discussion on the result of the ARIMA model as shown in Table 4 below.

 Table 4: Summary Results of the Different ARIMA Models for Sarawak Black Pepper at Kuching Spot Market (1997 To 2013)

Coefficient	Alternative models	•	
	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,2)
С	13051.12 (1.116)	10088.35 (2.548)	36042.35 (0.213) 0.998809
AR(1)	0.994511 (121.777)*	-	(147.648)*
AR(2)	-	0.981547 (80.383)*	-
MA(1)	0.266814 (5.741)*	0.992390 (297.714)*	- 0.003409
MA(2)	-		(0.070)
Diagnostic test			
SSR	1.55E+08	1.67E+08	1.66E+08
AIC	15.61487	15.69140	15.68638
SBC	15.64260	15.71917	15.71411
Adj-R ²	0.982059	0.980657	0.980729

* Significant at 5 Percent Level.

From Table 4 above, only ARIMA (1, 1, 1) and ARIMA (2, 1, 1) models have both AR (1) and MA (1) coefficients significant at 5 percent significance level. However, ARIMA (1,1,1) is the best fit to model Sarawak black pepper at Kuching spot market compared to ARIMA (2,1,1) since it has the smallest value of SBC

(15.64260) and the highest value of Adj-R² (0.982059). Moreover, the coefficient of $\phi 1$ and $\theta 1$ falls within -1 and 1 thus, fulfilling the stationarity and invertability conditions respectively.

However, the model selected must fulfill the white noise assumption. The result as shown in Table 3 above shows that the appointed ARIMA (1, 1, 1) model failed to fulfilled the white noise assumption. This leads us to consider a higher model that is the GARCH model to model the price series.

Next, we consider the results in Table 5 below, using four GARCH models.

Table 5: Estimation Results of Sarawak Black Pepper Price at Kuching Spot Market Using Different GARCH Models (1977-2013)

Spot Warket Using Different OARCH Wodels (1977-2013)				
Data series Sarawak black pepper price at Kuching spot market				
Parameter	GARCH	TGARCH	EGARCH	PARCH
coefficient	(1,1)	10/ittell	Lonixen	mach
Mean equatio	n			
С	2.832404	3.030866	3.041842	3.139424
C	(1.220549)	(1.532531)	(1.577228)	(2.234529)*
AR (1)	1.002411	1.002317	1.002382	1.002737
AK(1)	(162.7345)*	(162.1163)*	(160.9914)*	(168.7511)*
MA(1)	0.394129	0.390578	0.398565	0.3867526
MA(1)	(8.772427)*	(8.171725)*	(8.516455)*	(8.139717)*
Variance equa	ation			
ω	4.63E-05 (2.120677)* 0.202814	4.65E-05 (2.162362)* 0.171340	-0.769295 (- 3.484735)* 0.377002	8.70E-08 (0.144153) 0.152755
Ŷ	(4.737508)*	(3.494026)*	(5.603079)*	(0.0775)
φ	0.768485 (16.00543)*	0.063216 (0.996225)	- 0.011523 (-0.328734)	0.093417 (1.437381)
δ		0.769187 (15.79740)*	0.931567 (34.11235)*	0.714146 (9.419382)* 3.681102
d				(2.013338)*
Dignostic test	t result			
SSR	0.493409	0.493146	0.493601	0.552051
AIC	-4.147831	-4.145720	-4.138402	-4.030227
SBC	-4.092388	-4.081037	-4.073718	-3.965543
Adj-R ²	0.985888	0.985896	0.985883	0.984247
****		1		

*Significant at 5 Percent Level.

The result clearly indicates that GARCH (1,1) model is the best fit model to describe the Sarawak black pepper price volatility at Kuching spot market based on the lowest SBC value (-4.092388). The coefficient γ that measures asymmetry of shocks (Lim et al, 2012), is positive (0.202814) and statistically significant at 5 percent level. The sign is positive, suggesting that positive shocks increase the volatility more than the negative shocks. This suggests that shocks have asymmetric effect on the volatility of Sarawak black pepper price at Kuching spot market.

This imply that when pepper production or supply decreased which is a good news, this will caused the price to increase and become more volatile because traders and producers will speculate in a rising or bullish market either by selling short or taking a long position. An increase in the price in the long run will induce producers to increase production causing the black pepper price to be more volatile.

Combination of coefficient γ and φ that captures persistence of the shocks (Yoon et al, 2009) [20] is positive (0.971299) which is almost one and statistically significant at 5 percent level. The coefficient which is almost one, suggesting that shocks to Sarawak black pepper price at Kuching spot market has high degree of persistence. This implies that positive shocks have permanent effects on Sarawak black pepper price at Kuching spot market volatility. The shocks in the form of speculation, which is due to a decrease in the supply of pepper will have a permanent effect on the price series.

In addition, all three models (TGARCH, EGARCH and PARCH) show high asymmetric leverage coefficient (d) and are all significant with value closer to one. This shows high degree of persistence of the price volatility. The results also shows that the price series is better modeled with conditional variance as the value of the variance coefficient of all the models are all closer to one.

Forecasting analysis results

GARCH (1,1) model is the best model for forecasting Sarawak black pepper at Kuching spot market for twelve months period (January to December 2013) based on the lowest value of root mean squared error (RMSE) (892.5787), mean absolute error (MAE) (673.2440) and mean absolute percentage error (MAPE) (3.950336). Detail summary of out-of-sample forecast evaluation result is shown in Table 6 below.

 Table 6:
 Summary of Out-of-Sample Forecast Evaluation Results for

 Black Pepper at Kuching Spot Market Using Different GARCH Models
 for One Year Period (January to December 2013)

Model	RMSE	MAE	MAPE
GARCH (1,1)	892.5787	673.2440	3.950336
TGARCH	845.7308	663.7630	3.974649
EGARCH	983.0611	697.3144	4.033989
PARCH	895.3849	713.2867	4.349581

4. Conclusion

The main objective of this paper is to select the best fit and most accurate forecasting for Sarawak black pepper price volatility at Kuching spot from 1977 to 2013. ARMA and GARCH models are employed in the analysis and the results are compared to select the best fit model to describe the price series. The study findings are as follows:

- ARIMA (1, 1, 1) is found to be a good model to describe the volatility of the price series as both AR (1) and MA (1) are significant at 5 percent level. However, this model failed to fulfill the white noise assumption. This shows that the model can only describe the mean but not the variance efficiently.
- 2) The findings shows that GARCH (1, 1) model is the best fit model based on Schwarz Bayesian Criterion (Schwartz, 1978). Evidence suggests asymmetry effect is present in the price series and that the positive shocks increase the volatility more than the negative shocks. It also shows that the asymmetry effect is permanent or has long memory. The finding imply that the behavior of the pepper price series tend to very volatile and permanent in nature. Therefore industry players and policy makers should consider the nature of risk involved and take appropriate steps to avoid them.
- 3) The most accurate forecasting model to forecast Sarawak black pepper price at Kuching spot market is GARCH (1, 1) model.

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