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Evaluation of Ashley and Patterson Model Diagnostic Tool in selection of ARCH/GARCH Family Models: Case of Natural Rubber Prices at the Colombo Auction

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ABSTRACT: *There is a substantial amount of literature in favor of models in the ARCH/GARCH family as premier class of models for modeling financial and economic returns are of nonlinear form. However, there are many gaps in nonlinear model diagnosis and none of the nonlinearity tests are in wide acceptance. In this study, a new model diagnostic tool proposed by Ashley and Patterson in 2001 was identified as a useful diagnostic technique compared to other techniques in model selection. Moreover, it was found that the model diagnosis was straight forward with Ashley and Patterson test statistic (AP) when it is not straight forward with the use of other methods. Little work was found on the true process generating mechanism of returns of Ribbed Smoked Sheets No. 1 (RSS1) prices in the Colombo auction. In this study, by using AP, it was found that the true process generating mechanism of returns of RSS1 is nonlinear and the EGARCH(1,1) to be the most promising model that correctly generates returns of RSS1.*

Keywords: *Model evaluation, price returns, RSS1, ARCH/GARCH family*

INTRODUCTION

Non-constant volatility is apparent in prices where periods of low and high volatilities are usually not known. The price generating mechanism is generally non-linear. Tracking the true data generating mechanism of non-linear nature is important for many economic and financial processes. Instability of rubber prices has been identified as one of the key economic issue in the Natural Rubber (NR) industry (Samarappuli, 1993). At the macro level, contribution to the foreign exchange earnings from NR as a primary commodity and value-added commodities is affected by the price instability, creating more uncertainty on foreign exchange funds. At the micro level, price instability affects the employment, producer margins and investments. The expanding rubber-based industries in the country will be vulnerable to unstable prices thus, would discourage both local and international investors. It is believed that the micro level issue in price instability is serious due to the associated input demands and spillover effects on the rest of the economy (Samarappuli, 1993). Thus, it is important to study the dynamic behavior of rubber prices with respect to both conditional mean and the variance. Behavior of conditional mean of monthly rubber

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auction prices have been studied by Wijesuriya (1997) and reported that seasonal ARIMA models are not adequate for tracking the true price generating mechanism. Edirisinghe & Herath (2004) have used decomposition techniques to study the seasonal behavior of NR prices which are not adequate to handle the stochastic volatility. There are no any studies reported to-date with regard to modeling the behavior of local NR prices, especially with respect to the stochastic volatility.

The ARCH/GARCH family models are commonly used for modeling economic and financial time series data (particularly returns), which mostly exhibits stochastic volatility and non-linearity. There is a wealth of literature in support of the wide acceptance of this family of models as a principal tool which generates sample data (Hsieh, 1989; Bollerslev *et al.*, 1992; Dhamija & Bhalla, 2010). Empirical evidence from large number of statistical tests *viz.* Engel's LM test, Tsay test and BDS test, easily reject the null hypothesis of a linear process and statistically significant model parameters are found supporting this family of models as very useful (Ashley & Patterson, 2001; 2010).

In non-linear time series analysis, there is a deficiency in comprehensive model identification techniques compared to what has been proposed by Box and Jenkins (1976) for linear processes (Ashley & Patterson, 2001). The reason for not having a widely accepted single nonlinearity test is well explained by Ashley & Patterson (2006). Usually in time series analysis, model selection is done based on the goodness of fit which is tested using criteria such as R^2, FPE, AIC and BIC etc. (Shumway & Stoffer, 2006). Goodness of fit is an important criterion which looks at how well the model fits the sample data. However, it does not look at how close the selected model to the actual data generating mechanism. Further, it is not reasonable to select one model over the others if they produce almost similar goodness of fit. Hence, an alternative approach is used for model selection by evaluating their effectiveness in out of sample forecasting. Generally, non-linear time series models are very sensitive to even a modest model mis-specification, which results in poor out of sample forecasts (Lumsdaine & Serena, 1999; Chan, 2002). Further, these forecasts are distinctive to the period chosen unless the held out sample is long enough. It is not practical to maintain sufficient hold out sample if the given time series is not long enough. However, during the selection process, none of these methods consider the re-generating capacity or actual data of the model. Therefore, there was a necessity to explore alternative approaches used to evaluate non-linear models in this study.

Ashley & Patterson (2006) suggested a new test which can be used complementary to both goodness of fit and out of sample forecasting methods for either evaluating a non-linear time series or determining the choice between two such models. A large number of non-linearity tests can be found in the literature that tests different aspects or forms of non-linearity (Engle, 1982; McLeod & Li, 1983; Tsay, 1986; McLeod, 1994; Monti, 1994; Brock *et al.*, 1996; Hong, 1996; Pena & Rodrıguez, 2002; Duchesne & Roy, 2004; Chen & Deo 2004). Some of these tests are significantly powerful than the other tests against specific alternatives. The new test exploits the diversity of available nonlinearity tests as a new fact to evaluate fitted non-linear model/s, where a "Portmanteau" type of test statistic (AP test statistic) is used in this regard (Ashley & Patterson, 2010). The objective of this study was to evaluate AP in fitting ARCH/GARCH family model, particularly with respect to modeling Ribbed Smoke Sheet No 1 (RSS 1) price series at the Colombo auction.

METHODOLOGY

Data

Rubber prices are determined in the auction at Colombo where about two auctions are held in a week. Average weekly auction prices of RSS1 for the period, 2000 to 2010, which were obtained from the database available at the Biometry Section of the Rubber Research Institute at Agalawatta, Sri Lanka were used in the analysis. However, price returns were used in the actual analysis, which were defined such that, $r_t = (x_t - x_{t-1})$ where x_t and x_{t-1} are price at a given time t and $t-1$ respectively. Further, it can be noticed that $r_t \approx \ln(x_t/x_{t-1}) = \Delta\ln(x_t)$. Generally, r_t is regarded as a lower order serially correlated and a dependent series. The conditional mean and the variance given the information set, I_{t-1}, at time $t-1$ is defined such that $\mu_t = E(r_t|I_{t-1})$ and $\sigma_t^2 = Var(r_t|I_{t-1}) = E[(r_t - \mu_t)^2|I_{t-1}]$.

Model structure

Four types of models in the ARCH family, *viz.* ARCH, GARCH, EGARCH and IGARCH which are commonly used to model volatility in price time series of many commodities (Hsieh, 1989; Pattnaik *et al.*, 2003; Dhamija & Bhalla, 2010; Ou and Wang, 2010) were studied. Various specifications of these model types were evaluated to identify the most compelling RSS1 price generating mechanism. The ARCH (m) model by Engle (1982) is specified as;

$$r_t = \mu + z_t, \qquad z_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i z_{t-i}^2, \qquad t = m+1, \ldots, T \qquad (1)$$

where ε_t is the error term which is standard Gaussian white noise; $\varepsilon_t \sim iid\ N(0,1)$. T is the sample size. z_t is the random component of the mean model which equals to ε_t when $E(r_t) = 0$. Note that $z_t|I_t \sim N(0, \alpha_0 + \sum_{i=1}^{m} \alpha_i z_{t-i}^2)$. Bollerslev (1986) proposed a more generalized version of ARCH model [GARCH(p,q)], which can be detailed as;

$$z_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i z_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2, \qquad t = m+1, \ldots, T \qquad (2)$$

In addition to ARCH conditions (equation 1), there are other conditions *viz.* $\beta_j \geq 0$ and $\sum_{j=1}^{Max(m,n)} (\alpha_i + \beta_j) < 1$ considered in GARCH (equation 2). Both ARCH and GARCH models can capture volatility clustering, leverage effects and heavier tails. However in the case of persistence in volatility, the integrated GARCH (IGARCH) model is frequently used (Shummway and Stoffer, 2006). This is a unit-root GARCH model. An IGARCH(p,q) (Engle & Bollerslev, 1986) model can be described as;

$$z_t = \sigma_t \varepsilon_t, \qquad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i z_{t-i}^2 + \sum_{j=1}^{n} \beta_j \sigma_{t-j}^2, \qquad t = m+1, \ldots, T \qquad (3)$$

where in addition to ARCH constraints there are two other constraints apply *viz.* $\sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{n} \beta_j = 1$ and $1 > \beta_j > 0$. The non-negativity constraints in the GARCH model are too restrictive. The GARCH model imposes the non-negative constraints on the parameters, α_i and β_j, while there are no restrictions on these parameters in the Exponential

GARCH (EGARCH) model (Nelson, 1990). In EGARCH model, the conditional variance σ_t^2 is an asymmetric function of lagged disturbances, z_{t-1} and it is of the form;

$$z_t = \sigma_t \varepsilon_t, \qquad \ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-1}) + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2) \tag{4}$$

where $g(z_t) = \theta z_{t-1} + \gamma[|z_t| - E(|z_t|)]$ and $z_t \sim N(0, \sigma_t^2)$.

Model evaluation

Model evaluation was done using a novel approach proposed by Ashley & Patterson (2001) along with commonly used goodness of fit criteria such as AIC, BIC, and analysis of residuals. The novel approach utilizes information from a set of distinct nonlinearity tests. It can be noticed that there are many ways a time series can be nonlinearly dependent on its past values and thus, many nonlinearity tests are found in the literature, which aim at identifying different effects/aspects of non-linear serial dependencies. Irrespective of the aspect tested, some tests are significantly more powerful than other tests against specific alternatives. If a particular test dominates over all the other tests in terms of power, then it can be used as the non-linearity screening test under that specific hypothesis. Instead, if such a test maintains a high power across all the other alternatives, then it carries less information about the nonlinear specifications because, it cannot distinguish one specific form from another. If one can observe a distinct pattern of test results repeatedly when a set of nonlinearity tests are applied on a set of time series data, then this information can be used as a new stylized fact to specify the respective nonlinear process generating mechanism. For instance, Ashley & Patterson (2010) has applied this principle in support that GARCH(1,1) specification as the only viable model among the ARCH/GARCH family for CRSP equally weighted index of daily returns. Ashley & Patterson (2001; 2006) also provided more empirical evidence in favour of this method as an efficient nonlinear model diagnostic tool.

Let the observed *p*-value of i^{th} test is defined as p_i where $i = 1,2,\dots,r$ at which H_{01}: "Data generating mechanism is linear" is rejected. $E\{p_i\}$ is defined as the expected probability under this null hypotheses. Then a portmanteau type test statistic (AP) can be developed under the null hypothesis (H_{02}) that a particular model choice generated the actual data and is given by (Ashley & Patterson, 2006),

$$AP = \sum_{i=1}^{r} (p_i - E\{p_i\})^2 \tag{5}$$

The test captures the discrepancy between p_i and $E\{p_i\}$, which is obtained over the joint distribution of p_i. During the study, p_i, $E\{p_i\}$, distribution of AP test statistic and corresponding *p*-value under H_{02} were computed by a Monte Carlo simulation. The number of simulations adopted was 1000. In each simulation, 1000 data points were generated using the respective model specification. The first 500 observations were dropped to avoid possible startup transients and to match the original sample size which was 513. The estimated power of the 5% test was the fraction of the 1000 *p*-values which did not exceed 0.05 and $E\{p_i\}$ was the average of 1000 *p*-values.

Nonlinearity tests

Four nonlinearity tests used in this analysis are given in Table1. It can be noted that all these tests share the same platform that if the linear serial dependence is removed by an appropriate pre-whitening process, then any leftover serial dependence is due to a nonlinear process generating mechanism (Ashley & Patterson, 2001).

Table 1. The nonlinearity tests and their focus.

Nonlinearity test	Focus
Engle LM (Engle, 1982)	ARCH/GARCH effect
McLeod/Li (McLeod & Li, 1983)	ARCH/GARCH effect
Tsay (Tsay, 1986)	Quadratic terms (time domain)
BDS (Brock, *et al*., 1996)	General serial dependence

The Engle LM test was carried out using 12 lags of the squared series. The maximum number of lags used in the McLeod/Li test was also 12. In the Tsay test, the order of the AR process was not specified since in R, it can be estimated *via* a function by minimizing AIC. The BDS test was performed with an embedding dimension of two and an epsilon value of one. All statistical computations were done using the R where "FinTS", "TSA" and "rugarch" (Alexios, 2012) packages were used for model fitting and testing.

RESULTS AND DISCUSSION

In the time series analysis, it is customary to investigate the time series diagnostic plots. Those of RSS1 price returns are depicted in Fig. 1 for the period under investigation. In the time series plot of returns, the signs of volatility clustering can be identified and they were later confirmed by the significant Q-statistic ($p = 0.02$). The ACF of the return series looks a white noise while ACF and PACF of squared returns depict an MA(1) process. Initially, this information is not in favour of one to think of an ARCH/GARCH model as the true generating mechanism of RSS1 price returns. However, Engle LM test indicated that there is an ARCH/GARCH effect in data (lag=12, $p = 0.001$). Therefore, a number of models had to be tested and the specifications of those models together with their parameter estimates and commonly used model diagnostics are given in Table 2. For each model, a higher order (for m and n) greater than two was not considered in the analysis, considering a more parsimonious model.

Parameters of most of the models in Table 2; *viz.* ARCH(1), GARCH(1,1), EGARCH(1,1) , EGARCH(2,1) and EGARCH(2,2) were statistically significant and that motivate the empirical investigators to accept these model as adequately fitted to the data. Further, it can be noticed that the LM test for disturbances of each model does not indicate statistically significant dependence out at least at lag twelve, which indicates the respective model can handle the stochastic volatility in the data effectively. If a model is selected based on a goodness of fit criteria such as AIC and BIC, then EGARCH(2,2) is the best fit model for the data. However, some of the model parameters of EGARCH(2,2)are not statistically significant and the model is not very parsimonious compared to some other candidate models. It is not reasonable to prefer this model particularly as the actual data generating mechanism since other contestant models show up goodness of fit criteria (AIC and BIC) which are very close to that of the EGARCH(2,2). Under these circumstances, an insight from a battery of nonlinearity tests together with AP statistic can be effectively used to identify an appropriate data generating mechanism.

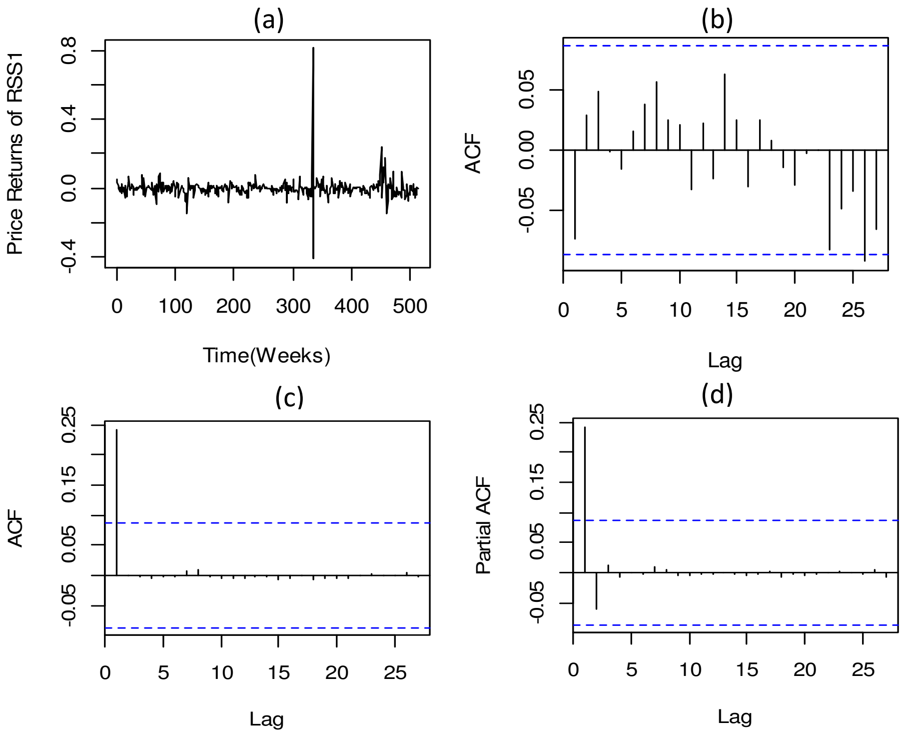

Fig 1. Diagnostic plots of returns of RSS1 prices; (a) Time series plot of returns, (b) ACF of returns, (c) ACF of squared returns and (d) PACF of squared returns.

Table 2. Fitted models, their parameters and model diagnostics in the analysis.

Model	Coefficient							Model Diagnostics		
	α_0	α_1	α_2	β_1	β_2	γ_1	γ_2	AIC	BIC	En.LM
ARCH(1)	0.0005^{**}	0.999^{**}						-3.807	-3.79	0.99
ARCH(2)	0.0004^{**}	0.882	0.117					-3.843	-3.82	0.99
GARCH(1,1)	0.0004^{**}	0.883^{*}		0.116^{+}				-3.842	-3.82	0.99
GARCH(2,1)	0.0004^{**}	0.883^{*}	0.000	0.116				-3.839	-3.81	0.99
GARCH(1,2)	0.0004^{**}	0.904^{*}		0.051	0.044			-3.841	-3.81	0.99
GARCH(2,2)	0.0004^{**}	0.902^{*}	0.050	0.000	0.047			-3.838	-3.79	0.99
EGARCH(1,1)	-2.438^{**}	0.633^{**}		0.613^{**}		1.132^{**}		-3.971	-3.94	0.77
EGARCH(2,1)	-2.899^{**}	0.511^{**}	-0.235^{**}	0.562^{*}		0.915^{**}	0.321	-4.067	-4.02	0.23
EGARCH(1,2)	-2.439^{**}	0.637		0.612	0.001	1.138		-3.969	-3.93	0.15
EGARCH(2,2)	-3.806^{**}	0.507^{**}	-0.130	0.105	0.322^{**}	0.890^{**}	0.717^{**}	-4.087	-4.03	0.44
IGARCH(1,1)	Algorithm did not converge properly									

**Significant at α=0.01, * Significant at α =0.05, $^{+}$ Significant at α =0.1

Table 3 indicates the AP statistic together with respective percentages of $AP_i > AP_{Observed}$ *i.e* p-values for different models fitted. The *p*-value that rejects the null hypothesis; 'the data were truly generated by fitted model' was extracted from the distribution of estimated AP statistics, which were obtained from a Monte Carlo simulation. Actually, it is the fraction of AP values out of 1000 that exceeds the observed AP value (AP statistic computed using actual data).

Table 3. AP statistic and respective $\%(AP_i > AP_{Observed})$ computed for different models fitted to data.

Model	$AP_{Observed}$ (AP Statistic)	$\%(AP_i > AP_{Observed})$
ARCH(1)	0.039	63.0
ARCH(2)	0.035	80.5
GARCH(1,1)	0.042	32.3
GARCH(2,1)	0.043	54.6
GARCH(1,2)	0.043	54.8
GARCH(2,2)	0.039	56.2
EGARCH(1,1)	0.147	81.8
EGARCH(2,1)	0.065	46.7
EGARCH(1,2)	0.126	71.0
EGARCH(2,2)	0.087	44.5
IGARCH(1,1)	-	-

This can be further interpreted as how likely the model will regenerate the observed pattern of the discrepancy of test results in support of rejecting the null hypothesis. The number of simulations (1000) was identified as sufficient enough by observing that the test results were invariant to increasing number of simulations.

This can be further interpreted as how likely the model will regenerate the observed pattern of the discrepancy of test results in support of rejecting the null hypothesis. The number of simulations (1000) was identified as sufficient enough by observing that the test results were invariant to increasing number of simulations.

As indicated in the Table 3, none of the models resulted a statistically significant AP statistic indicating that discrepancies among nonlinearity were not decidedly significant. However, the highest AP statistic was resulted by the EGARCH(1,1) model, which is more than double the AP statistics of other alternative models except EGARCH(1,2) and EGARCH(2,2). The percentage $(AP_i > AP_{Observed})$ can be interpreted as the p-value at which the particular model specification can be rejected as adequately modeled the actual generating process of data. It can be noticed from small percentages $(AP_i > AP_{Observed})$ of EGARCH(1,2) and EGARCH(2,2) that they are comparatively less likely to reproduce the stylized pattern of the observed test results. ARCH(2) and EGARCH(1,1) yielded the highest values for percentage$(AP_i > AP_{Observed})$. Although, they are very similar, ARCH(2) was not selected due to its non-significant model parameters. Consequently, the choice was the EGARCH(1,1) model as the actual generating mechanism of RSS1 price returns. For EGARCH(1,1) specification, observed p-value, estimated p-value and the power of each nonlinearity test (under the null hypothesis that returns are independently and identically distributed) are given in Table 4.

Table 4. Observed *p*-values (using sample data), estimated *p*-values and power (using generated data with EGARCH(1,1) specification in Table 2).

	McLeod/Li L=12	Engle LM P=12	BDS m=2, ε=1	Tsay
p-value for rejection of $H_0: x(t) \sim iid$ (using sample data)	0.0017	0.0023	0.0000	7.65×10^{-15}
Estimated *p*-value , $E\{p_i\}$ (using generated data)	0.116	0.104	0.291	0.194
Estimated power of 5% test (using generated data)	0.794	0.818	0.704	0.565

The results of all four nonlinearity tests provide strong evidence that the returns are nonlinearly dependent in time. Of McLeod/Li and Engle LM tests, the observed pattern of the sample test results (*p*-values) and respective estimated powers are in accordance with their expected patterns. However, with respect to BDS and Tsay tests, there is an apparent discrepancy between sample test results and their estimated powers which is preferably captured by the proposed portmanteau test. Almost 82 % of the 1000 AP test statistic values computed using data generated from EGARCH (1,1) exceeded its observed AP statistic in Table 3. This indicates how well EGARCH (1,1) specification can reproduce the observed stylized pattern of the nonlinearity test results compared to the other alternatives. This is one of the reasons that EGARCH (1,1) is selected as the true generating mechanism of RSS1 price returns over and above the other alternative models.

Power of the nonlinearity tests

Results of this study further helped to identify the differential power of four nonlinearity tests across different models in the ARCH/GARCH family and their implications for model identification. Estimated power of the nonlinearity tests (at 5%) under different alternative processes are given in Table 5.

Table 5. Estimated power of the nonlinearity tests (at 5%) under different alternative processes

Model	Power of Nonlinearity Tests			
	McLeod/Li	Engle LM	BDS	Tsay
ARCH(1)	0.989	0.991	0.843	0.631
ARCH(2)	0.995	0.995	0.868	0.585
GARCH(1,1)	0.998	0.998	0.872	0.583
GARCH(2,1)	0.997	0.998	0.879	0.594
GARCH(1,2)	0.993	0.994	0.865	0.569
GARCH(2,2)	0.993	0.993	0.875	0.601
EGARCH(1,1)	0.794	0.818	0.704	0.565
EGARCH(2,1)	0.846	0.867	0.978	0.451
EGARCH(1,2)	0.795	0.82	0.685	0.595
EGARCH(2,2)	0.800	0.836	0.983	0.395
IGARCH(1,1)	-	-	-	-

If a test has relatively high power against all the alternatives, then it provides inadequate information on which kind of a nonlinear model is appropriate (Ashley & Patterson, 2001). What matters with respect to the identification purpose is lack of consistency of test results across alternative processes. It is very apparent that McLeod/Li test and Engle LM tests show very high power across ARCH and GARCH model specifications which reconfirm that these tests are more powerful to recognize ARCH/GARCH effects. However, their power figures against EGARCH alternatives are comparatively low. Except for two EGARCH specifications, BDS test maintained more consistent powers across the alternative models. However, Tsay test maintained relatively lower powers across all candidate models.

CONCLUSIONS

Often there are difficulties in identifying the exact nonlinear form when the time series is not linear. Tests based on AP provide an effective solution under these circumstances. The method becomes more useful especially when ARCH/GARCH family models are being fitted. Usual goodness of fit criteria often fails in providing information on exact nonlinear form. Modeling RSS1 price returns clearly showed, ARCH/GARCH family models are appropriate for the purpose. Specifically, based on AP, EGARCH(1,1) was found to be the most viable model that generate returns of RSS1 prices in the Colombo auction for the period under investigation indicating volatility apparent in RRS1 price returns are asymmetric. In addition, the study clearly revealed that ARCH/GARCH family model selections are not straight forward and it cannot be done purely based on goodness of fit criteria. This fact should be considered seriously in model fitting and otherwise, model form could have easily been miss–specified. Altogether, it can be concluded that AP statistic has multiple uses and can be used as an effective tool in fitting nonlinear time series models.

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