Analysing Volatility of Colombo Consumer Price Index using GARCH Models

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Abstract

The objective of this paper is to analyse and modelling the volatility of Colombo Consumer Price Index (CCPI) in Sri Lanka using monthly data from January 2008 to April 2014. Three types of GARCH models (GARCH, TGARCH and EGARCH) were used for this study. Using various specifications for mean equation, study estimated GARCH (1, 1), TGARCH (1, 1) and EGARCH (1, 1) for CCPI. The estimation results reveal that ARMA (1, 0) - EGARCH (1, 1) comes out to be most appropriate specification for modelling CCPI volatility. The study finds that, no evidence of symmetry in the response of CCPI volatility to negative and positive shocks.

Keywords: CCPI, GARCH, Unit root, Volatility.

Introduction

Measuring volatility of CCPI is important for policy maker because it provides them with guidance in formulating polices for achieving price stability. The modeling and forecasting is usually carried out in order to provide an aid to decision making and planning the future. Analysing volatility of CCPI are important inputs for government, businesses sector, policy makers, investors, workers and various individuals for various applications.

This study aims at modeling CCPI volatility using GARCH-family models and choosing the most suitable model among them. The ARCH model was first introduced by Engle (1982) for capturing time variant variance exhibited by almost all financial time series and many economic time series. The generalized version of ARCH model (GARCH model) was formulated by Bollerslev (1986).

Economic literature on issue of CCPI volatility is concerned with the positive relation of inflation level and conditional variance. Goudarzi and Ramanarayanan (2010) employed GARCH model on daily Bangalore stock price index series from 2000 to 2009 and obtained the GARCH (1, 1) model explains volatility of the Indian stock markets satisfactorily. Igogo (2010) used GARCH family models on monthly real exchange rate of Tanzania from 1968 to 2007 and found GARCH (1, 1) model was violated the non-negativity condition and the EGARCH (1, 1) model to measure the real exchange rate volatility. Awogbemi and Oluwaseyi (2011) conducted a study to determine the presence of the volatility in monthly CPI prices of five selected commodities over a period from 1997 to 2007 in Nigerian market. They found that the GARCH (0, 1) model is the best model to determine the volatility of prices. Khalafalla Ahmed (2010) employed GARCH family models to determine the relationship between variability of inflation and it's uncertainty in the Sudan using annual CPI data for the period from 1960 to 2005. The EGARCH (1, 1) model was found to correctly specify and estimate the conditional variance of inflation with possibility of a simultaneous feedback relationship between inflation and uncertainty.

Materials and Methods

Data: The secondary data on monthly CCPI from January 2008 to April 2014 were considered for the analysis and it was collected from Department of Census and Statistics.

Unit Root Test: The stationary of data is usually described by time series plots and correlogram. The unit root test determines whether a given series stationary or non-stationary. The Augmented Dickey-Fuller (ADF) test is mostly used to check stationary. In this paper ADF test has been used.

GARCH Model: The Generalized ARCH (GARCH) model was developed by Bollerslev (1986). The specification of the conditional variance equation for GARCH (1, 1) model is given by:

$$\sigma_t = \gamma_0 + \delta_1 \sigma_{t-1} + \gamma_1 u_{t-i}^2 \qquad (1)$$

where γ_0, δ_1 *and* γ_1 are parameters.

TGARCH Model: The Threshold GARCH (TGARCH) model was introduced by the works of Zakoian (1990) and Glosten, Jaganathan and Runkle (1993). The main target of this model is to capture asymmetric in terms of negative and positive shocks. The specification of the conditional variance equation for TGARCH (1, 1) model is given by:

$$\sigma_t = \gamma_0 + \gamma u_{t-1}^2 + \theta u_{t-1}^2 d_{t-1} + \delta \sigma_{t-1} \quad (2)$$

Where d_t takes the value of 1 for $u_t < 0$ and 0 otherwise. If θ [illegible]ere is asymmetry while if $\theta = 0$ the news impact symmetry.

EGARCH Model: The exponential GARCH (EGARCH) model was developed Nelson (1991), and the variance equation for this model is given by:

$$Log(\sigma_t) = \alpha + \beta \frac{u_{t-1}}{\sqrt{\sigma_{t-1}}} + \delta \left| \frac{u_{t-1}}{\sqrt{\sigma_{t-1}}} \right| + \phi \; Log(\sigma_{t-1}) \quad (3)$$

Where $\alpha, \beta, \delta \; and \; \phi$ are parameters to be estimated. The log of the variance series makes the leverage effect exponential instead of quadratic and therefore estimates of the conditional variance are guaranteed to be non-negative. The EGARCH models allow for the testing of asymmetry. When, then positive shocks generate less volatility than negative shocks.

Model Selection Criteria: The following statistical measures were used to find an appropriate model forCCPI.

$$AIC = \log\left(\frac{rss}{n}\right) + \left(\log(n) * \frac{k}{n}\right) \quad (4)$$

$$BIC = \log\left(\frac{rss}{n}\right) + \left(2 * \frac{k}{n}\right) \quad (5)$$

$$\ln L = -\frac{n}{2} \ln 2\pi\sigma_a^2 - \frac{1}{2\sigma_a^2} S(\phi_p, \theta_q, \mu) \quad (6)$$

Where; k = number of coefficient estimated, [illegible]esidual sum of square, sst = sum of square total, n = number of observations

Results and Discussions

1 Descriptive Statistics of CCPI

The basic analysis of CCPI is shown in table 1.

Table 1: Descriptive statisticsof CCPI

Statistic Measures	Values
Mean	150.40
Median	150.60
Maximum	178.40
Minimum	118.70
Standard Deviation	17.18
Skewness	0.205
Kurtosis	1.776
Jarque- Bera	5.27
Confidence Interval	[0.072]
for CCPI (at 5%)	[146.47,154.32]

From the table 1, the mean of CCPI is 150.40 and its standard deviation is 17.18. According to the Jarque –Bera statistic, the CCPI is normally distributed at 5% significance level, (p=0.072). The mean of CCPI series lies between (146.47, 154.32) at 5% significance level.

The time series plot for the monthly CCPI series is shown in figure 1.

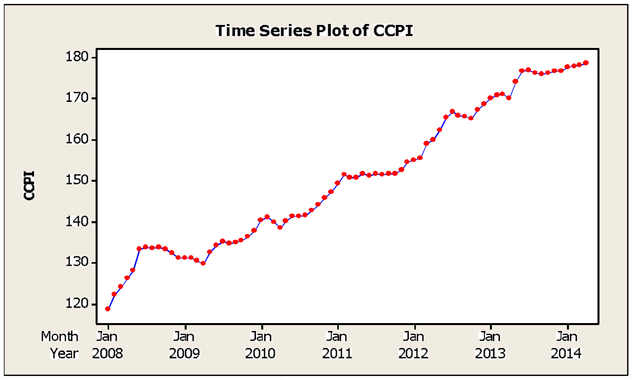


Figure 1: Time series plot for CCPI [Jan 2008 –April 2014]

From the figure 1, it can easily be seen that CCPI has been increasing over time and variance is increasing with time. Thus, it is obvious that the series is not stationary. Also, this result is confirmed by unit root test and this result is shown in table 2.

Table 2: Results of the unit root test for CCPI

ADF Test Statistic		t-Statistics	Prob.
		-2.7773	0.2103
Test Critical Values	1% Level	-4.0868	
	5% Level	-3.4717	

Table 2 indicates that, the null hypothesis of the series is non stationary could not be rejected for CCPI [p=0.2103]. Therefore, CCPI series is non-stationary. Then, the CCPI series was transformed into the log differenced of CCPI series (LogDCCPI) and the time series plot and normality plot of this series were obtained and shown in figure 2 and figure 3 respectively.

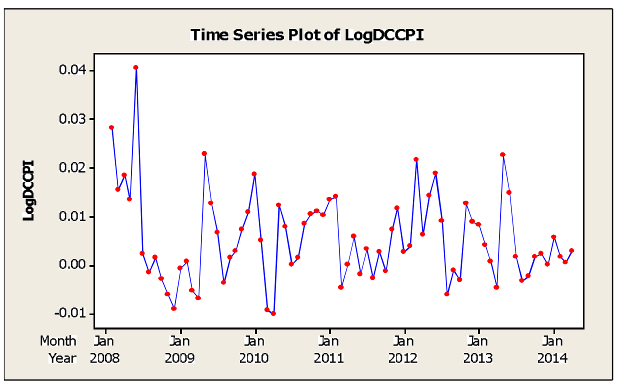


Figure 2: Time series plot for Log difference of CCPI.

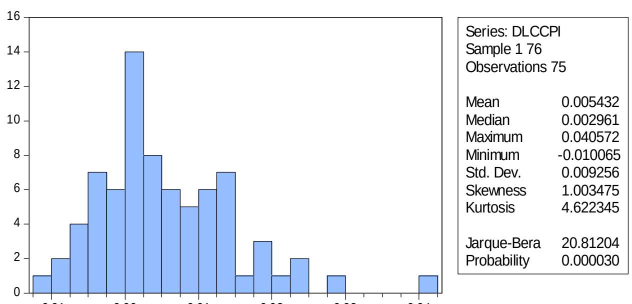


Figure 3: Normality plot for Log difference of CCPI.

From the figures 2 and 3, there is a high volatility exists in log difference of CCPI (kurtosis=4.622).

Table 3: The results of unit root test for LogDCCPI

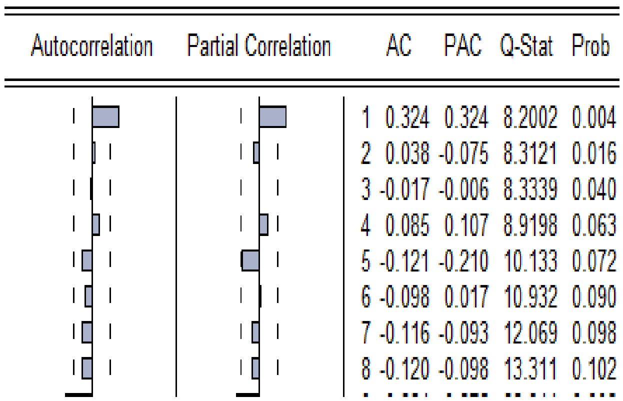
ADF Test Statistic	t-Statistics	Prob.

		-5.4175	0.0001
Test Critical Values	1% Level	-4.0887	
	5% Level	-3.4726	

Table 3 indicates that, the null hypothesis of the series is non stationary is rejected for the log difference of CCPI [p=0.0001]. Hence, the log difference of CCPI series is stationary.

2. ARMA model for log differenced transformed of CCPI

The correlagram of sample ACF and PACF for LogDCCPI series (Figure 4) was considered for identification of suitable AR and MA orders.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.324	0.324	8.2002	0.004
		2	0.038	-0.075	8.3121	0.016
		3	-0.017	-0.006	8.3339	0.040
		4	0.085	0.107	8.9198	0.063
		5	-0.121	-0.210	10.133	0.072
		6	-0.098	0.017	10.932	0.090
		7	-0.116	-0.093	12.069	0.098
		8	-0.120	-0.098	13.311	0.102

Figure 4: Sample ACF and PACF for LogDCCPI

According to the Figure 4, the sample ACF has one significant autocorrelation at lag 1 and sample PACF has one significant coefficient at lag 1. Thus it can be hypothesized in the ARMA model to be fitted MA order to be 1 andAR order to1. Thus, the following models were considered as possible models to represent the original series. They are:(i) ARMA (1, 1), (ii)ARMA (1, 0), and (iii) ARMA (0, 1). The estimates of the above ARMA models were shown in table 4.

Table 4: ARMA models for DLCCPI

Models	Parameter Estimates	P-Value	AIC , SIC	Log likely hood	DW
ARMA (1,1)	C=0.005 AR(1)= 0.222 MA(1)=0.134	0.001 0.385 0.621	-6.658, -6.565	249.136	2.013
ARMA (1,0)	C=0.005 AR(1)=0.327	0.001 0.003	-6.683, -6.621	249.288	1.971
ARMA (0,1)	C=0.005 MA(1)= 0.361	0.000 0.001	-6.618, -6.556	248.195	1.957

Table 4 indicates that the coefficient of AR (1) of ARMA (1,0) model is significant at 5% significance level (p-value = 0.003). Results in table 4 also indicate that of the three models the maximum log likelihood estimate and the lowest AIC and SIC values were obtained by ARMA (1, 0) model. Thus it can be concluded the best model out of these three models is ARMA (1, 0).

3 GARCH models for log differenced transformed of CCPI

This study investigates the issue of CCPI's volatility by using three types of the GARCH-family models. The result of ARMA (1, 0)-GARCH (1, 1) model is shown in Table 5.

Table 5: ARMA (1,0)-GARCH (1,1) Model

Variable	Coefficient	Std. Error	Z-Statistic	Prob.

C	0.0038	0.0013	2.9450	0.0032
AR(1)	0.3137	0.0783	4.0047	0.0001
Variance Equation				
C	3.10×10^{-6}	5.12×10^{-7}	6.054	0.0000
Resid(-1)^2	-0.1023	0.0004	-269.340	0.0000
GARCH(-1)	1.0451	0.0036	294.129	0.0000

[AIC= -6.862, SIC=-6.706, Log Likelihood=258.89]
The table 5 indicates that the coefficient of related with AR (1) in equation for mean of ARMA (1,0)-GARCH(1,1) is statistically significant. Also, the equation for variance, the both coefficients of ARCH and GARCH terms are statistically significant.

The estimated GARCH (1, 1) model is:

$$\sigma_t = 3.1X10^{-6} + 1.045\sigma_{t-1} - 0.102u_{t-1}^2$$

GARCH can capture asymmetric response of negative and positive shocks on volatility. This asymmetric response of volatility is termed as leverage effect. A summary result of ARMA (1, 0)-TGARCH (1, 1) is shown in table 6.

Table 6: ARMA (1, 0)-TGARCH (1,1) Model

Variable	Coefficient	Std. Error	Z-Stat	Prob.
C	0.0034	0.0014	2.3298	0.0198
AR(1)	0.3119	0.0695	4.4857	0.0000
Variance Equation				
C	3.40x10-6	2.04x10-6	1.6630	0.0963
Resid(-1)^2	-0.0955	0.0408	-2.2792	0.0227
Resid(-1)^2*(Resid(-1)<0)	0.0389	0.1408	0.2764	0.7823
GARCH(-1)	1.0193	0.0627	16.2440	0.0000

[AIC= -6.602, SIC=-6.615, Log Likelihood=257.673]

The table 6 indicates that the coefficient related with AR(1) in equation for mean of ARMA (1,0)-TGARCH(1,1) is statistically significant. Also, the equation for variance, the coefficients of ARCH and GARCH terms are statistically significant. Other two terms are not statistically significant. Although, table 6 shows that the coefficient of the [Resid (-1)^2*(Resid(-1)<0)] term is positive and statistically significant, this is evidence of no symmetric response volatility of differenced log CCPI to negative and positive shocks.

The estimated TGARCH (1, 1) model is:

$$\sigma_t = 3.4X10^{-6} - 0.096u_{t-1}^2 + 0.039u_{t-1}^2 d_{t-1} + 1.019\sigma_{t-1}$$

Another model which can capture asymmetry in response of conditional variance to negative and positive shocks is EGARCH. A summary result of ARMA (1, 0)-EGARCH (1, 1) is reported in Table 7.

Table 7: ARMA (1, 0)-EGARCH (1,1) Model

Variable	Coefficient	Std. Error	Z-Stat	Prob.

C AR(1)	0.0038 0.3049	0.0011 0.00714	3.4984 4.2698	0.0005 0.0000
Variance Equation				
C	-18.978	0.5104	-37.185	0.0000
ABS(RESID(-1)/@SQRT(GARCH(-1)))	0.5677	0.1179	4.8145	0.0000
RESID(-1)/@SQRT(GARCH(-1)) GARCH(-1)	-0.0629	0.0882	-0.7136	0.4755
LOG(GARCH(-1))	-0.8812	0.0533	-16.579	0.0000

[AIC= -6.908, SIC=-6.722, Log Likelihood=261.62]

The table 7 indicates that the coefficients related with AR (1) in equation for mean of ARMA (1, 0)-EGARCH (1, 1) is statistically significant. Also, the in equation for variance, the coefficients of three terms are statistically significant. Although, table 7 shows that the coefficient of the [RESID (-1)/@SQRT (GARCH (-1)) GARCH (-1)] term is negative and not statistically significant, this is evidence of no symmetric response volatility of differenced log CCPI to negative and positive shocks.

The estimated EGARCH (1, 1) model is:

$$Log(\sigma_t) = -18.978 + 0.568\left|\frac{u_{t-1}}{\sqrt{\sigma_{t-1}}}\right| - 0.063\frac{u_{t-1}}{\sqrt{\sigma_{t-1}}} - 0.881 Log(\sigma_{t-1})$$

4 Model Selection

In the model selection, the log likelihood, AIC and SIC values from each estimated models were computed. Using these statistics, to estimate which model is a better estimate for CCPI. The model with the lowest AIC and SIC values and the highest value of log likelihood are concluded to be the better model. The results are reported in Table 8.

Table 8: Model selection results

Models	AIC	SIC	Log likelihood
ARMA(1,0)-GARCH(1,1)	-6.862	-6.706	259.89
ARMA(1,0)-TGARCH(1,1)	-6.602	-6.615	257.67
ARMA(1,0)-EGARCH(1,1)	-6.908	-6.722	261.62

Table 8 indicates that both AIC and SIC values from EGARCH (1, 1) model is the lowest compared with other two models. Also, log likelihood value is high for EGARCH (1, 1) model. Therefore, it shows that the EGARCH (1, 1) is the best model to determine the volatility of monthly CCPI series.

5 Diagnostics checking for EGARCH (1, 1) model

To validate the assumptions of residuals, the following hypotheses are to be considered.

1. H0 : There is no serial correlation in the residuals.
2. H0 : There is no ARCH effect in the residuals.
3. H0 : The residuals are normally distributed.

In order to check the serial correlation of residuals, the correlagram of squared residual was carried out and the result is shown in figure 5.

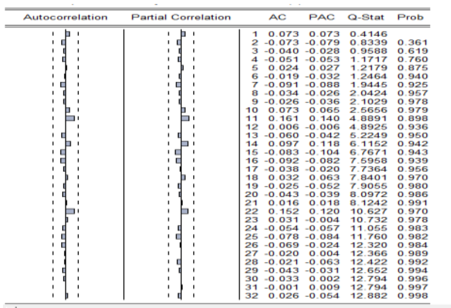


Figure 5: Correlagram for sample ACF and PACF of squared residuals

Figure 5 shows that, the all p-values of autocorrelations are not statistically significant at 5% significance level. Therefore, residuals are not serially correlated.
In order to check the ARCH effect of residuals, the ARCH LM test was carried out and the result is shown in Table 9.

Table 9: Result of ARCH effect

ARCH Test	
F-statistic	0.4478 [0.5056]
Obs*R-squared	0.4575 [0.4988]

Table 9 indicates that the Obs*R-squared is not significant [p=0.4988] at 5% significance level. Therefore, the hypothesis of no ARCH effect cannot be rejected. Hence, there is no ARCH effect in the residuals.

In order to check the normality of the residuals, the Jarque-Bera test was carried out and the result is shown in figure 6.

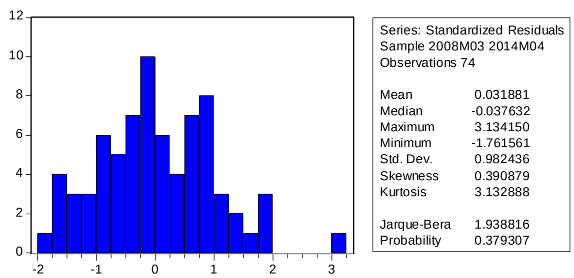


Figure 6: Normality plot

Figure 6 shows that, the respective p-value of Jarque-Bera statistic is not significant at 5% significance level [p=0.379]. Thus, it is confirmed that residuals series is normally distributed. Based on the above detailed analysis of residuals, it can be confirmed that the EGARCH (1, 1) model is satisfied all the diagnostic tests. Hence, the EGARCH (1, 1) model is the best model to modelling the volatility of CCPI.

Conclusions and Recommendations

This study aimed to modeling volatility of CCPI using GARCH family models. The CCPI data is not stationary at level. By differences of log transformed the series of the CCPI data becomes stationary. Then various GARCH models were estimated. The comparative performance of these GARCH models have checked and verified by using the model selection procedure (AIC and SIC). The comparison indicates that the EGARCH (1, 1) model as the best model to modelling the volatility of CCPI.

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