Short-Term Forecasting of Inflation in Bangladesh with Seasonal ARIMA Processes

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Abstract

The purpose of this study is to forecast the short-term inflation rate of Bangladesh using the monthly Consumer Price Index (CPI) from January 2000 to December 2012. To do so, the study employed the Seasonal Auto-regressive Integrated Moving Average (SARIMA) models proposed by Box, Jenkins, and Reinsel (1994). CUSUM, Quandt likelihood ratio (QLR) and Chow test have been utilized to identify the structural breaks over the sample periods and all three tests suggested that the structural breaks in CPI series of Bangladesh are in the month of February 2007 and September 2009. Hence, the study truncated the series and using CPI data from September 2009 to December 2012, the ARIMA(1,1,1)$(1,0,1)_{12}$ models were estimated and forecasted. The forecasted result suggests an increasing pattern and high rates of inflation over the forecasted period 2013. Therefore, the study recommends that Bangladesh Bank should come forward with more appropriate economic and monetary policies in order to combat such increase inflation in 2013.

JEL: E17, E31, C22

Key words: Inflation, Forecasting, SARIMA, Bangladesh

Introduction

Over the past five years, Bangladesh has experienced skyrocketing inflation, which is the major threat to the country's economic stability. Enormous efforts have been made by Bangladesh Bank to control this rising inflation. Nevertheless, inflation upsurge continues and hit the highest point 11.97% in the month of September 2011.[2] Hence, an accurate and timely inflation forecasting is imperative for Bangladesh Bank. This study thus, aims to model and forecast short-term inflation rates of Bangladesh. The study possesses an importance for two specific reasons. First, the

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[2] See Bangladesh Bank "Monthly Economic Trends" http://www.bangladesh-bank.org/econdata/index.php for details information about Inflation in Bangladesh 2011.

results of this study would give a prior indication about the future direction of inflation, which might be helpful for the Bangladesh Bank to design their current economic strategies and monetary policies. Secondly, an accurate forecast of near-term inflation would help the government and its policy makers to formulate appropriate forward-looking fiscal and monetary policies to control any hyper inflation in the near future.

There are a number of approaches have been used in empirical works for forecasting short-term inflation. One of the most popular and widely used univariate models is Auto-regressive Integrated Moving Average (ARIMA) proposed by Box and Jenkins (1976). Typically, an ARIMA model is a tool for modeling and forecasting time series data based on their past values. Following Box and Jenkins (1976) original identifications, a number of papers have attempted to fit the CPI series to an ARIMA model for forecasting short-term inflation. Aidan, Geoff and Terry (1998), employed ARIMA models to forecast Irish inflation. The authors find that ARIMA performed accurate forecasting for Irish CPI series. Muhammad, Shazia, and Mete (2006) used ARIMA models to forecast inflation series in Pakistan. The study shows that the selected ARIMA models had sufficient predictive powers in forecasting CPI series of Pakistan.

However, one intrinsic problem arises in ARIMA class models for forecasting inflation when the CPI series contains changeable and unclear seasonality. To explore this seasonal effect, later, Box, Jenkins, and Reinsel (1994) extend ARIMA models including both seasonal and non-seasonal component which is called SARIMA (Seasonal Autoregressive Integrated Moving Average) models. Several studies examine the efficacy of SARIMA models for forecasting short-term inflation in different countries. For example, Junttila (2001) employed SARIMA model to forecast Finish inflation and Pufnik and Kunovac (2006) used SARIMA model to forecast short term inflation in Croatia. The authors show that the SARIMA represents an accurate out-of-sample forecast for CPI series compared to any other time series models. Gokhan (2011) employs SARIMA model for forecasting Turkey inflation series. The author suggests that the selected SARIMA models provide accurate representation of the Turkish inflation.

In this study, an attempt has been made to forecast inflation series of Bangladesh using SARIMA models. While CPI series of Bangladesh clearly exhibits seasonality in deterministic, therefore SARIMA was appropriate for modeling short-term inflation series of Bangladesh.

However, a major problem occurs in forecast CPI series for any country when the series contains significant structural breaks in the sample period . In order to quantify the structural breaks in Bangladesh's CPI series, the study uses more elaborate structural break tests, such CUSUM test, the Quandt likelihood ratio (QLR) test and Chow test. CUSUM test and the Quandt likelihood ratio (QLR) test suggest that the break point in CPI of Bangladesh are in the month of February 2007 and September 2009. To complement the QLR test, single Chow tests have been conducted and F-statistics confirm that the second peak in September 2009 was more significant than the first peak in February 2007. Hence, the study splits the sample by three different periods. The first sample constructed considering without any break and using full sample from January 2000 to December 2012. Second sample constructed with the first significant break and using the CPI data from February 2007 to December 2012. The third sample constructed considering the second significant break and using the CPI data from September 2009 to December 2012.

In order to identify the final model, several models with different order were considered to estimate the three samples. Finally, based on the minimum AICs and BICs, ARIMA $(1, 1, 1) \times (1, 0, 1)_{12}$ was selected for the full sample and ARIMA $(1, 1, 1) \times (1, 0, 1)_{12}$ and ARIMA $(1, 1, 1) \times (1, 0, 1)_{12}$ were selected for the sample with the first and second significant break respectively. After estimate the final models, diagnostic and forecast accuracy in different models suggest that only residuals in third sample satisfying all the model assumptions. Hence, the study chose the third sample as a final model and using this sample (September 2009 to December 2012) forecast conducted up to December 2013.

The estimated result shows that the chosen models give accurate prediction and can represent the data behavior of inflation in Bangladesh very well. Based on the selected model, a twelve month forecast suggests that the next peak of Bangladesh's inflation is in the month of July 2013. Therefore, the study recommended that Bangladesh Bank should come forward with appropriate fiscal and monetary policies to control any hyper inflation in the near future.

The rest of the article is organized as follows. Section 2 provides an overview of the inflationary scenario in Bangladesh. Section 3 briefly describes the data collection and Methodology and deduces the principals the SARIMA modeling, Section 4 describes the results and the forecasting performance and Section 5 presents the concluding remarks which include findings, comments and recommendations.

Overview of inflation scenario in Bangladesh

The experience of high inflation is not new in Bangladesh. Over the last five years, Inflation increased several times due to the contractionary monetary policies, orthodox exchange rate management, the rise in import bills and internationally price hikes in food. The average inflation in 2001 was 1.90% while it is found 9.07 % in 2007. After the 2007 global financial crisis, Bangladesh Bank decided to ease monetary policy in order to limit the impact of the crisis on the domestic economy. As a result, in 2009 the average inflation declined to 5.42%. But it went up again 10.68% in 2011. Further, to control this hyper inflation Bangladesh Bank took more restrained monetary policies in 2011.

In the national budget and monetary policy of FY 2011-12, the rate of inflation was targeted at 7.5 percent whereas; it stood at 10.6 percent (12- month average) and 8.56 percent (point to point inflation). In FY 2012-13, the government has targeted the rate of inflation at 7.2 percent while the prior experience suggests that it might be hard to maintain inflation below 9% in 2013. Therefore, careful revisions are essential to conduct an effective monetary policy which can successfully control any hyper inflation in 2013.

The graph of InCPI and inflation is depicted in figure 1.1 and 1.2 . From figure 1.2 it can be seen that the inflation increased with a stable rate before 2007 and the dispersion of inflation was larger after 2007. Figure 1.2 also provides visual evidence that the structural breaks can be presumed in the year 2007 to 2010. In order to gather more detailed information, the study performed more elaborate structural break test, such as, CUSUM test, the Quandt likelihood ratio (QLR) test and Chow test to identify the the exact year and the corresponding month of breaks in inflation series.[3]

In figure 3, CUSUM test result shows that from 2002 to 2007 cumulated sum of residuals lies outside of the 95 percent confidence band. Hence, the null hypothesis of parameter stability of CPI is rejected at the 5 percent significance level. In figure 2, the Quandt likelihood ratio (QLR) test represents the exact date of break for CPI series by using the likelihood ratio statistic (LR). QRL ratio was 5.3153 in February 2007 and 4.35 in September 2009 respectively. Chow test also confirms that the break of CPI series is significant in February 2007 and September 2010. Table 1 represents the results of the chow test for both sample periods, where the p - value is $0.02 < 0.05$ reject the null hypothesis that no break in CPI series.

Data and Methodology

The study uses monthly consumer price indexes (CPI) starting from 2000 m1 to 2012 m12, which comprises 156 observations. The monthly Consumer Price Indexes are collected from series of official publications *'Economic Trend'* of Bangladesh Bank. The estimation was performed on a log series of base price index (1996=100). Considering the significant break in CPI series, the sample divided into three periods, with significant break and without any break. Finally, forecasting conducted up to December 2013 using best fitted models.

[3] CUSUM measure the cumulative sum of the scaled residuals, which is generally used to test for parameter stability of a regression.

SARIMA is a simple extension of ARIMA (Auto Regressive Integrated Moving Average) model which is widely used to forecast seasonal time series data. In ARIMA (p, d, q) model, p shows the number of autoregressive (AR) terms where AR predicts the series from its previous values and q shows moving average (MA) terms where MA predicts the series from previous random errors, or "shocks" and d is the number of non-seasonal difference. In SARIMA model by adding seasonal components, ARIMA extends to (p, d, q) × (P, D, Q)s, where p and q are the order for the non-seasonal AR and MA components and P and Q are the order of the seasonal AR and MA components. D and d are the order of differencing for the seasonal and non-seasonal respectively. If a plot of the time series data suggests that the seasonal effect is proportional to the mean of the series, then the seasonal effect is probably multiplicative and a multiplicative SARIMA model may be appropriate (Box, Jenkins, and Reinsel, 2008). Now, the generalized form of the multiplicative SARIMA model can be written as (Box et al., 2008; Cryer and Chan, 2008):

$$\Phi_p(B)\partial_p(B^s)(1-B)^d(1-B^s)^d Z_t = \theta_q(B)\varphi_Q(B)\varepsilon_t \quad \text{.........(1)}$$

Where,

$$\Phi_p(B) = 1 - \Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p \quad \text{.........(2)}$$

$$\partial_p(B^s) = 1 - \partial_1(B) - \partial_2(B^2) - \cdots - \partial_q(B^Q) \text{.........(3)}$$

$$\theta_q(B) = 1 - \theta_1(B) - \theta_2(B^2) - \cdots - \theta_q(B^q) \text{.........(4)}$$

$$\varphi_Q(B) = 1 - \varphi_1(B) - \varphi_2(B^2) - \cdots - \varphi_Q(B^{Qs}) \text{.........(5)}$$

Where,

ε_t represents white noise error (random shock) at period t.[4]

B represents backward shift operator.

S represent seasonal order.[5]

For example, the SARIMA (1, 0, 1) (1, 1, 1)$_{12}$ model is a multiplicative model of the form:

$$(1-\emptyset_1 B)(1-B^{12})y_t = (1+\theta_1 B)(1+\varphi_1 B^{12})\varepsilon_t \text{.........(6)}$$

Using the properties of operator B, it follows that:

[4] White noise is a series of uncorrelated random variables with zero expectation and equal variance.

[5] s = 4 for quarterly data and s =12 for monthly data.

$$y_t = \emptyset_1 y_{t-1} + y_{t-12} - \emptyset_1 y_{t-13} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \varphi_1 \varepsilon_{t-12} + \theta_1 \varphi_1 \varepsilon_{t-13} \dots\dots\dots\dots\dots..(7)$$

In equation (1) SARIMA models are suitable for modelling time series that include seasonality both changeable and deterministic. The presence or absence of deterministic seasonality in In CPI series can be detected using following regression equation with dummy variables,

$$y_{t+h} = \sum_{i=1}^{s} \gamma_i D_{it} + e_t$$

$$= \alpha + \sum_{i=1}^{s-1} \beta_i D_{it} + e_t$$

$$y_t = \alpha + \beta_1 D_{t1} + \beta_2 D_{t2} + \beta_3 D_{t3} + \dots\dots\dots\dots + \beta_{12} D_{t12} + \varepsilon_t$$

$$(1 - B^{12}) y_t = (1 - 0{,}99\, B^{12}) \varepsilon_t \dots\dots\dots\dots (a)$$

Where, D_{t1}, D_{t2},........D_{t12} are seasonal dummy variables. This means that the SARIMA (1,1,1) $(1,0,1)_{12}$ specification in (a) can mean that seasonality series is deterministic.

The estimation of SARIMA model consists of three steps, namely: identification, estimation of parameters and diagnostic checking. The identification stage involves checking the stationary and identifies the seasonality of the data series. Stationary confirms the existence or nonexistence of a unit root in the data series. Unit root shows whether a stochastic or a deterministic trend is present in the series. There are several statistical tests used for testing the presence of a unit root in a series such as Augmented Dickey- Fuller (ADF) test and Phillips–Perron (PP) test (1988).[6] If the original series is not stationary then first difference will be appropriate to transform the series into stationary. Further, the graphical presentation of time series can also confirm the stationary and seasonality of the data series.

The next step in model identification stage is to determine the order of the model which is AR, MA, SAR and SMA terms. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) plot is often used to determine the order of the stationary series. The ACF gives the information about covariance between past realizations. PACF helps to determine the appropriate lags p in an AR (p) model. Particularly, an AR-process has a (exponentially) declining ACF and spikes for the PACF and an MA-process has spikes in the

[6] The study uses both tests but eventually focus on PP test results because PP tests ignore any serial correlation in a time series data. Besides, the advantage of PP test over ADF test is that the user does not need to specify the lag length for PP test.

ACF and (exponentially) declining PACF, where the number of significant spikes suggests the order of the model.

Although the ACF and PACF assist in determining the order of the model but that information are not adequate for modeling SARIMA. In this case several models with different order can be considered to estimate the inflation series. But the final model will be selected based on a penalty function statistics such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC).[7] The AIC and BIC are a measure of the goodness of fit of an estimated statistical model. Given a data set, the study ranked several competing models according to their AIC or BIC. The model with the lowest information criterion value will be the best. In the general case, the AIC and BIC take the form as shown below:

$$\mathrm{AIC} = 2\mathrm{k} - 2\mathrm{log}(\mathrm{L})\mathrm{or}\ 2\mathrm{k} + \mathrm{nlog}\left(\frac{RSS}{n}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$\mathrm{BIC} = -2\mathrm{log}(\mathrm{L}) + \mathrm{klog}(\mathrm{n})\mathrm{orlog}(\alpha_{\varepsilon}^{2})\left(\frac{K}{n}\right)\log(n) \ldots\ldots\ldots\ldots\ldots (9)$$

Where,

k: is the number of parameters in the statistical model.

L: is the maximized value of the likelihood function for the estimated model.

RSS: is the residual sum of squares of the estimated model.

α_{ε}^{2} is the error variance.

The next step in SARIMA model is to estimate the parameters of the chosen model using the method of maximum likelihood estimation (MLE). To satisfy ARIMA conditions, the absolute value of the coefficient must be always less than unity.

After estimating the parameters, the last step is model diagnostics. At this stage the study will determine the adequacy of the chosen model. These checks are usually based on the residuals of the model. One assumption of the SARIMA model is that, the residuals of the model should be white noise. When the residuals are white noise, then the ACF of the residuals is approximately zero. If this assumption is not fulfilled then the different model must be searched to satisfy the

[7] See Sakamoto et. al. (1986); Akaike (1974) and Schwarz (1978).

assumption. Several statistical tests such as Ljung- Box Q statistic and Shapiro normality test also used to check for autocorrelation and normality among the residuals in the model.

If the model passed the entire diagnostic test, then it becomes adequate for forecasting. To choose a final model for forecasting, the accuracy of the model must be higher than that of all the competing models. The accuracy of each model can be checked to determine how the model performed in terms of in-sample forecast. The study tested the quality of the obtained forecasts against two standard measures: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which were defined as follows. If $x_{1,.............}x_n$ are actual values and $\bar{x}_{1,.............}\bar{x}_n$ a random variable x, then:

$$MAE = \frac{1}{n}\sum_{i=0}^{n}(x_i - \bar{x}_i)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(x_i - \bar{x}_i)^2}$$

A model with a minimum of these statistics will be considered as the best for forecasting.

Results and Discussions

The statistical tests ADF and PP in Table 2.1 and 2.2 confirms the existence of unit root with constant and constant with linear trend in InCPI which indicates that for all three samples, InCPI series is not stationary at level. Considering the first non-seasonal differenced series, ADF and PP tests confirm the non-existence of unit root with constant and constant with linear trend, which indicate that the series is stationary at first difference i.e. InCPI data are integrated of order (1).

Moreover, non stationarity of InCPI can also be confirmed from the sets of figure 4. The plots illustrate the slow decay in the ACF of the InCPI series and very statistically significant spikes at lag 1 of the PACF with marginal spikes at few other lags such as 2, 3, 8 and 10 for three samples. Thus, looking at the sample ACF and PACF of InCPI, it is hard to identify any pure AR or MA structure for SARIMA models. The sets of figure 4 also confirms that the InCPI is stationary at first difference. The sample ACF and PACF plot of dICPI shows the statistically significant spike at lag 1 and 12, 24 for three samples, which indicating the strong seasonal variation in InCPI series of Bangladesh.

In the identification stage, time series plot of ACF and PACF helps to determine the order of the SARIMA models . For the first sample, considering first differenced of InCPI, figure 4.3 and 4.4

shows that ACF tails of at lag 1 and the PACF spike at lag 1, suggesting that p=1 and q=1 describe the non-seasonal autoregressive process and moving average for CPI series. Also looking at the seasonal lags, ACF and the PACF both spike at lag 1 and lag 12, suggesting that a seasonal moving average (SMA) and autoregressive process (SAR) need to include in the model. Hence, ARIMA (1, 1, 1) $(1, 0, 1)_{12}$, may perhaps the possible model for forecasting inflation of Bangladesh using full sample 2000m1 to 2012m12. For the second sample, considering first differenced of InCPI, figure 4.7 and 4.8 shows that ACF tails of at lag 1 and the PACF spike at lag 1, suggesting that p=1 and q=1 describe the non-seasonal autoregressive process and moving average for CPI series. To identify the seasonal lags, ACF and the PACF both spike at lag 1 and lag 12, suggesting that a seasonal moving average (SMA) and autoregressive process (SAR) need to include in the model. Hence, ARIMA (1, 1, 1) $(1, 0, 1)_{12}$, may perhaps the possible model for forecasting inflation of Bangladesh using second sample data from 2007m9 to 2012m12. Following the same way, considering first differenced of InCPI, figure 4.11 and 4.12 shows that ACF tails of at lag 1 and the PACF spike at lag 1, suggesting that p=1 and q=1 describe the non-seasonal autoregressive process and moving average for CPI series. The figures also suggest that, ACF and the PACF both spike at lag 1 and lag 12, confirms that a seasonal moving average (SMA) and autoregressive process (SAR) need to include in the model. Thus, ARIMA (1, 1, 1) $(1, 0, 1)_{12}$, may perhaps the possible model for forecasting inflation of Bangladesh using third sample data 2009m10 to 2012m12.

Seasonality in dlnCPI series also reveals using the seasonal dummy model. Table 3.1 represents that the seasonality of dlnCPI is simply deterministic for all three samples. In order to keep the seasonal effect in forecasted months, the study considers the the seasonal difference D=0.

Although the sample Autocorrelation function and Partial Autocorrelation function is assisting to determine the order of the SARIMA models but this is just an idea about the possible structure of AR, SAR, MA and SMA. It becomes necessary to build the model around the suggested order. In this case several models with different order considered to choose the final models. The study estimates the SARIMA model with the four possible structures of AR,SAR,MA and SMA.

Table 4.1 represents the models with their corresponding values of AIC and BIC. Among those possible models, comparing their AIC and BIC and minimum forecast error RMSE, ARIMA $(1,1,1)(1,0,1)_{12}$ were chosen as the appropriate model for all three samples. Now, from derived models, using the method maximum likelihood (MLE) the estimated parameters of the models with their corresponding standard error is shown in the Table 5.1, 5.2 and 5.3. Based on 95% confidence level seasonal AR and MA coefficients of the ARIMA (1, 1, 1) $(1, 0, 1)_{12}$ models are significantly different from zero for full sample and seasonal MA terms are significant for second and third samples.

After estimate the model, the next step was diagnosed the model to see how well it fits the data. One of the assumptions of ARIMA model is that, for being a good model, the residuals must follow a white noise process. Fig 5.1(a) shows that for the first sample, ACF of the residuals are not white noise, there was a significant spike at lag 12 of the residuals. Fig 5.3 shows that for the third sample, ACF of the residuals are white noise, there was no significant spike in residuals. Furthermore, the p-values for the Ljung-Box statistic in table 6.1 clearly exceeds 5% of all large orders, indicating that the all three models were adequate for representing the data. But the Shapiro - Wilk test in table 7.1 rejects the normality in residuals for first and second samples. In figure 5.1 and 5.2 CUSUM test clearly illustrates that the residuals in first and second models were not stable over the sample periods. Thus, for the first two samples, the selected model ARIMA (1, 1, 1) $(1, 0, 1)_{12}$ does not satisfy all the necessary assumptions for ARIMA model. For the third sample, figure 5.3 shows that ACF of the residuals are white noise. The Shapiro - Wilk test can not reject the normality in residuals for third sample. CUSUM test suggests that residuals were stable over the sample periods September 2009 to December 2012. So the chosen ARIMA $(1, 1, 1) \times (1, 0, 1)_{12}$ models for third sample was an adequate to estimate the CPI series of Bangladesh .

Finally, twelve months forecast conducted using ARIMA $(1, 1, 1) \times (1, 0, 1)_{12}$ model for third sample. Table 8 presents the accuracy test for forecasted model. From the results, it can be seen that, ARIMA (1, 1, 1) $(1, 0, 1)_{12}$ models was adequate to be used to forecast the monthly inflation rate of Bangladesh. Figure 6.1 shows the original CPI and the fitted values produced by the obtained ARIMA (1, 1, 1) $(1, 0, 1)_{12}$ model. The table 9.1 displays the original and the forecasted value of CPI and inflation series of Bangladesh for next twelve months. Column 3 in table 9.1 shows that the next peak of Bangladesh's inflation is in the month of July 2013.

Conclusion

Following the Box, Jenkins, and Reinsel (1994) approach, Seasonal Autoregressive Integrated Moving Average (SARIMA) was employed for forecasting monthly inflation rate of Bangladesh for the coming months of January, 2013 to December 2013. To do so, several statistical tests performed to identify the best fitted model for forecasting inflation series of Bangladesh. structural break in CPI series identified the using CUSUM, QRL and Chow test. The result of structural break tests shows that there were two significant breaks in CPI series of Bangladesh in the year of 2007 and 2009. Hence, the study splits the sample in three different periods. Finally, based on minimum AIC and BIC value, the best-fitted SARIMA models ARIMA$(1,1,1)(1,0,1)_{12}$ were selected for all three samples. After the estimation of the parameters of selected model, a series of diagnostic and forecast accuracy test were performed to check the validity of the models. Only in third sample, residuals satisfied all the model assumptions. Hence, using CPI data from September 2009 to December 2012, the study finds that ARIMA (1,1,1) $(1,0,1)_{12}$ model was the best for forecasting inflation series of Bangladesh.

The forecasting results reveal an increasing pattern and high rates of inflation over the forecasted period 2013. The results show that the next peak of inflation is in the month of July 2013. Therefore, the study recommends that it is high time for the policy makers of the government of Bangladesh and its central bank to come forward with more appropriate economic and monetary policy in order to combat such increase in inflation rate which is yet to occur in the month of July 2013.

The accuracy of inflation forecast is important because it will affect the quality of the policies implemented based on this forecast. In this study, highest attempt has been made to forecast inflation using best fitted ARIMA models. Nevertheless, the study recommends that future research on this topic can utilize other time series models and then compare the performance of the model used in this research in terms of forecast precision.

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Appendix

Table: 1 Chow Test for Structural Break

VARIABLES	2007m2-2012m12	2010m10-2012m12
Dummy_break	0.00410***	0.00354***
	-0.00157	-0.00134
dlCPI1lag	-0.0691	-0.0567
	-0.158	-0.134
break_dlCPI1	-0.149	-0.127
	-0.183	-0.156
Constant	0.00447***	0.00432***
	-0.00111	-0.00121
Observations	151	70
R-squared	0.07	0.09
F-test model	3.76	3.64
P-value of F-model	0.0255	0.0123

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.1 Unit Root Test with Constant

Variable	ADF Test		PP Test Z(t)	
	Level	First Difference	Level	First Difference
InCPI (Without Break)	4.261***	-3.700***	1.940***	-7.654***
InCPI (First Significant Break)	1.020***	-3.109***	-0.464***	-5.32***
InCPI (Second Significant Break)	0.121***	-3.321***	0.349***	-3.599***

Note: *, ** and *** denote rejection of the null hypothesis of unit root. For ADF, the optimal lag length for the full sample is 10 and 2 for half sample, selected using Information Criteria HQIC, AIC. For PP tests, bandwidth is selected based on the Newey–West procedure using Bartlett kernel.

Table 2.2 Unit Root Test with Constant and Trend

Variable	ADF Test		PP Test Z(t)	
	Level	First Difference	Level	First Difference
InCPI (Without Break)	-3.371**	-5.337***	-2.429***	-7.803***
InCPI (First Significant Break)	-0.942***	-4.08***	-0.464***	-5.278***
InCPI (First Significant Break)	-2.882***	-3.546**	-3.599*	-3.513**

Note: *, ** and *** denote rejection of the null hypothesis of unit root. For ADF, the optimal lag length for the full sample is 10 and 2 for half sample, selected using Information Criteria HQIC, AIC. For PP tests, bandwidth is selected based on the Newey–West procedure using Bartlett kernel.

Table 3.1 Deterministic Seasonality in dInCPI series of Bangladesh

	2000m1-2012m12	2007m2-2012m12	2009m10-2012m12
VARIABLES	dlCPI1	dlCPI1	dlCPI1
m1	0.00264	0.0038	0.00387
	-0.00272	-0.00447	-0.00327
m2	0.0029	0.00229	-0.00225
	-0.00266	-0.00447	-0.00327
m3	0.00539**	0.00692	-0.00011
	-0.00266	-0.00426	-0.00327
m4	0.00444*	0.00442	-0.00384
	-0.00266	-0.00426	-0.00327
m5	0.00414	0.00289	-0.00418
	-0.00266	-0.00426	-0.00327
m6	0.0110***	0.0171***	0.00538
	-0.00266	-0.00426	-0.00327
m7	0.0116***	0.0191***	0.0144***
	-0.00266	-0.00426	-0.00327

m8	0.0104***	0.0139***	0.0140***
	-0.00266	-0.00426	-0.00327
m9	0.0131***	0.0155***	0.0122***
	-0.00266	-0.00426	-0.00327
m10	0.00963***	0.00937**	0.00135
	-0.00266	-0.00426	-0.00327
m11	-0.000261	-0.000508	-0.00343
	-0.00266	-0.00426	-0.00302
Constant	-0.000862	-0.000897	0.00387*
	-0.00188	-0.00301	-0.00214
Observations	155	70	38
R-squared	0.322	0.496	0.776
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Table 4.1 AIC , BIC and RMSE for the Suggested SARIMA Models (2000m1-2012m12)

Model	AIC	BIC	RMSE
$ARIMA(1,1,1)(1,0,1)_{12}$	-1114.431	-1099.214	.00632456
$ARIMA(2,1,1)(1,0,1)_{12}$	- -1114.457	- -1096.197	.00630079
$ARIMA(1,1,0)(1,0,1)_{12}$	-1115.738	-1103.565	.00634823
$ARIMA(0,1,1)(1,0,1)_{12}$	-1116.406	-1104.232	.00632456

Table 2.2: AIC , BIC and RMSE for the Suggested SARIMA Models (2007m2-2012m12)

Model	AIC	BIC	RMSE
$ARIMA(1,1,1)(1,0,1)_{12}$	-462.7233	-451.4808	.00843208
$ARIMA(2,1,1)(1,0,1)_{12}$	-461.7865	-450.3562	.00859878
$ARIMA(1,1,0)(1,0,1)_{12}$	-464.6042	-455.6102	.00845577
$ARIMA(0,1,1)(1,0,1)_{12}$	-464.2455	-455.2516	.00850882

Table 2.3: AIC , BIC and RMSE for the Suggested SARIMA Models (2009m10-2012m12)

Model	AIC	BIC	RMSE
$ARIMA(1,1,1)(1,0,1)_{12}$	-275.2109	-267.023	.00556776
$ARIMA(2,1,1)(1,0,1)_{12}$	-267.769	-259.5811	.00618061
$ARIMA(1,1,0)(1,0,1)_{12}$	-274.2488	-267.6984	.00575326
$ARIMA(0,1,1)(1,0,1)_{12}$	-270.069	-263.5186	.00627694

Table 5.1 Estimates of Parameters for ARIMA $(1,1,1)(1,0,1)_{12}$ (2000m1-2012m12)

VARIABLES	(1) ARMA	(2) ARMA12	(3) sigma
L.ar	0.0487	0.821***	
	(0.272)	(0.0887)	
L.ma	0.248	-0.354***	
	(0.231)	(0.129)	
Constant			0.00629***
			(0.000232)
Observations	155	155	155

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.2 Estimates of Parameters for ARIMA $(1,1,1)(1,0,1)_{12}$ (2007m2-2012m12)

VARIABLES	(1) ARMA	(2) ARMA12	(3) sigma
L.ar	0.499*	0.860***	
	(0.302)	(0.195)	
L.ma	-0.197	-0.475	
	(0.366)	(0.361)	
Constant			0.00788***
			(0.000733)
Observations	70	70	70

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.3 Estimates of Parameters for ARIMA $(1,1,1)(1,0,1)_{12}$ (2009m10-2012m12)

	(1)	(2)	(3)
VARIABLES	ARMA	ARMA12	sigma
L.ar	0.827***	0.740**	
	(0.201)	(0.333)	
L.ma	-0.478*	-0.0281	
	(0.275)	(0.519)	
Constant			0.00500***
			(0.000757)
Observations	38	38	38

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.1 Ljung-Box statistic for ehat

	2000m1-2012m12	2007m2-2012m12	2009m10-2012m12
Portmanteau (Q) statistic	46.2572	19.6971	15.8773
Prob > chi2(40)	0.2297	0.9675	0.5325

Table 7.1 Shapiro-Wilk W test for normal data

Variable	Observation	w	v	z	pro>z
ehat(2000m1-2012m12)	155	0.9199	9.585	5.133	0
ehat(2007m2-2012m12)	70	0.96172	2.356	1.864	0.03119
ehat(2009m10-2012m12)	38	0.9699	1.144	0.282	0.38911

Table 8.1 Forecast Accuracy Test on the Suggested SARIMA Models

Model	ME	MAE	MSE	MAPE	RMSE
ARIMA $(1,1,1)(1,0,1)_{12}$	0.001632	0.004287	0.000031	0.077584	0.005568

Table 9.1 ARIMA$(1,1,1)(0,0,1)_{12}$ Forecasting Results for Monthly Inflation Rates

Month	Forecast CPI	Observe CPI	Forecast Inflation	Observe Inflation
Jul-12	274.43	275.18	8.79	8.03
Aug-12	279.00	280.26	7.75	7.93
Sep-12	284.70	284.43	8.04	7.39
Oct-12	285.45	285.14	6.49	7.22
Nov-12	285.55	286.30	7.14	7.41
Dec-12	286.43	288.50	7.68	8.32
Jan-13	292.80		9.21	
Feb-13	292.90		7.36	
Mar-13	294.47		8.75	
Apr-13	294.85		8.91	
May-13	293.91		8.61	
Jun-13	295.68		9.31	
Jul-13	300.06		9.34	
Aug-13	304.54		9.15	
Sep-13	308.29		8.29	
Oct-13	309.03		8.26	
Nov-13	310.12		8.60	
Dec-13	311.96		8.91	

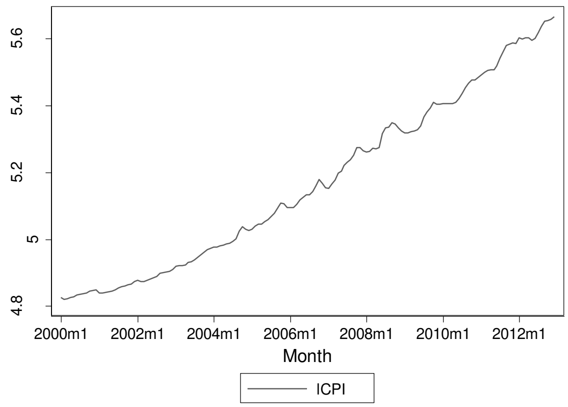

Figure: 1.1 lnCPI of Bangladesh (2000m1-2012m12)

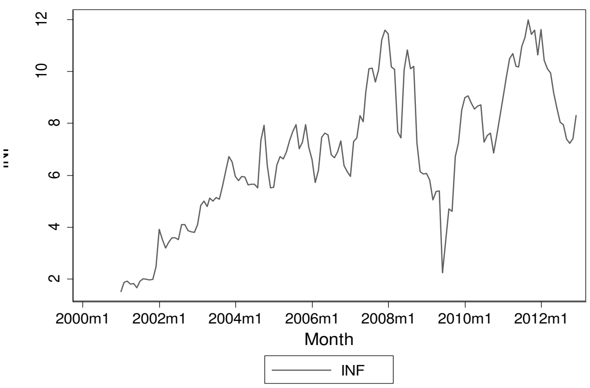

Figure: 1.2 Inflation of Bangladesh (2001m1-2012m12)

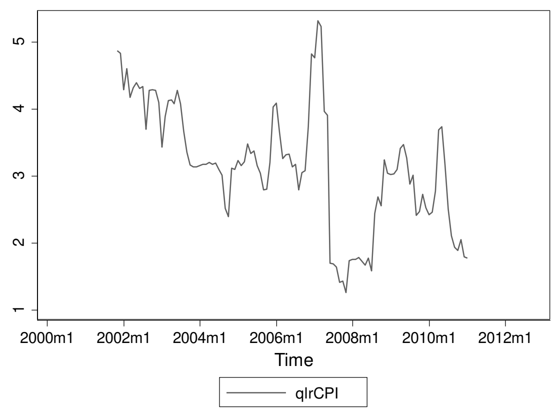

Figure 2: QLR test to identify the break in CPI of Bangladesh

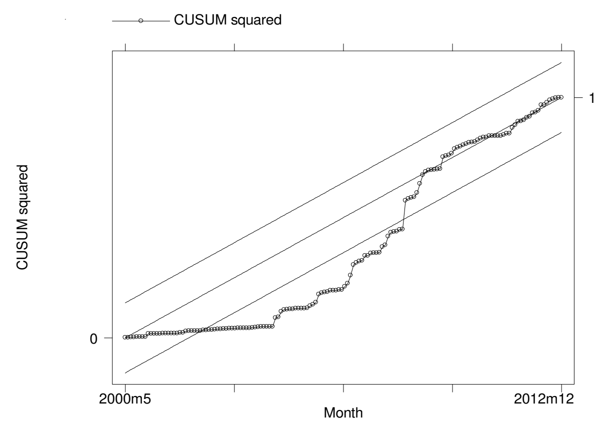

Figure:3 CUSUM test for parameter stability

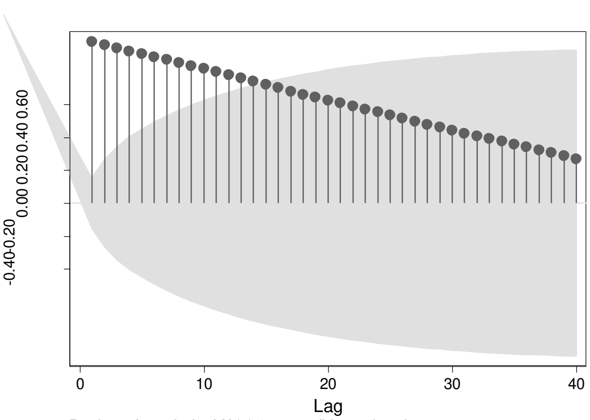

Figure 4.1: Autocorrelation in lnCPI of Bangladesh 2000m1-2012m

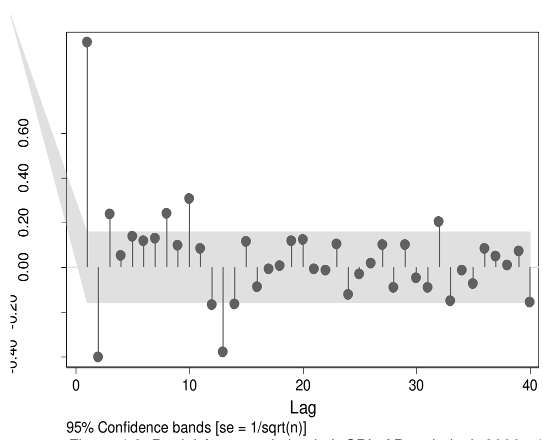

Figure 4.2: Partial Autocorrelation in lnCPI of Bangladesh 2000m1-2012m

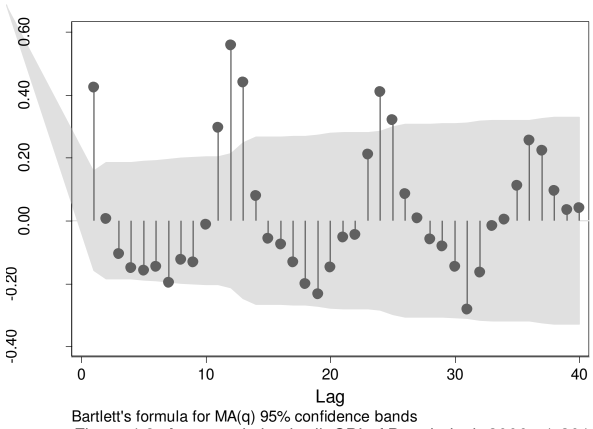

Figure 4.3: Autocorrelation in dlnCPI of Bangladesh 2000m1-2012m

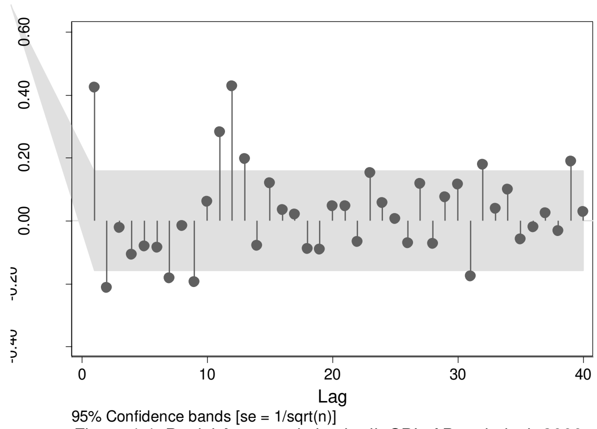

Figure 4.4: Partial Autocorrelation in dlnCPI of Bangladesh 2000m1-2012m

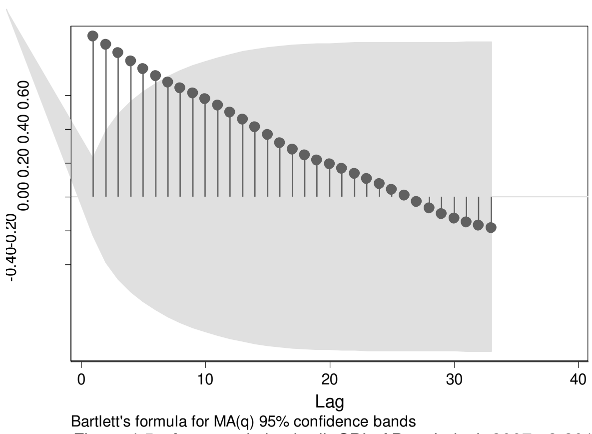

Figure 4.5: Autocorrelation in dlnCPI of Bangladesh 2007m2-2012m

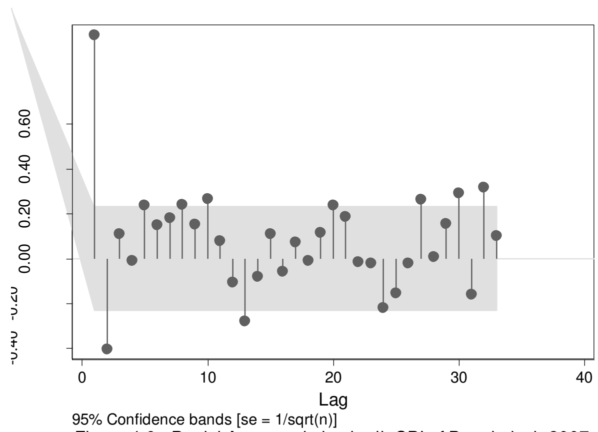

Figure 4.6: Partial Autocorrelation in dlnCPI of Bangladesh 2007m2-2012m

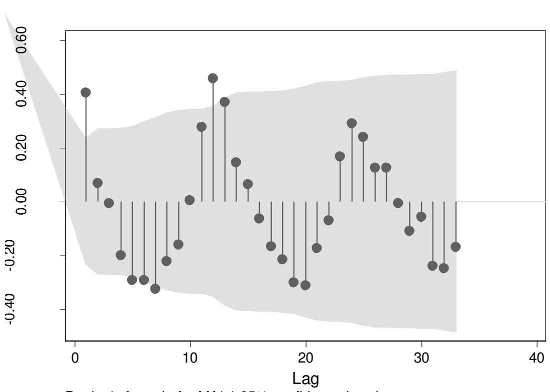

Figure 4.7: Autocorrelation in dlnCPI of Bangladesh 2007m2-2012m

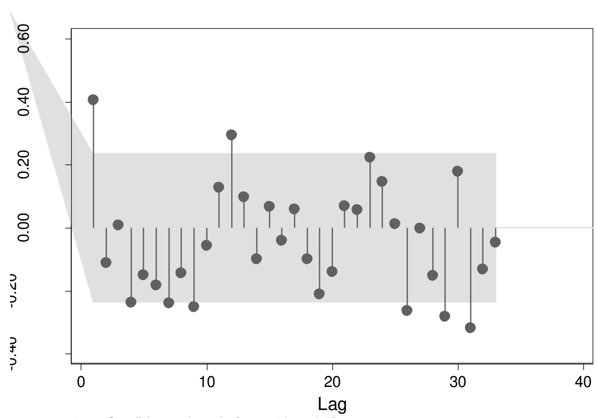

Figure 4.8: Partial Autocorrelation in dlnCPI of Bangladesh 2007m2-2012m

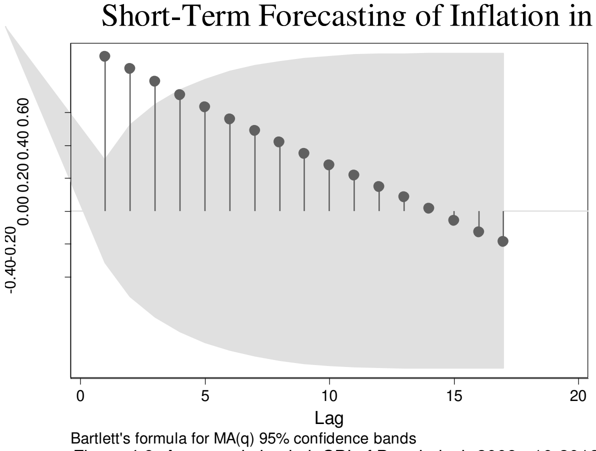

Figure 4.9: Autocorrelation in lnCPI of Bangladesh 2009m10-2012m

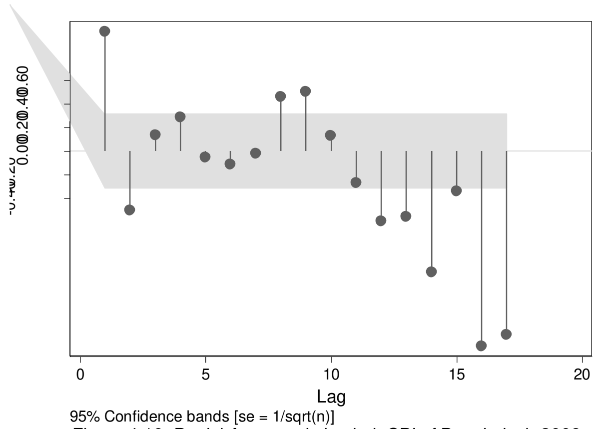

Figure 4.10: Partial Autocorrelation in lnCPI of Bangladesh 2009m10-2012m

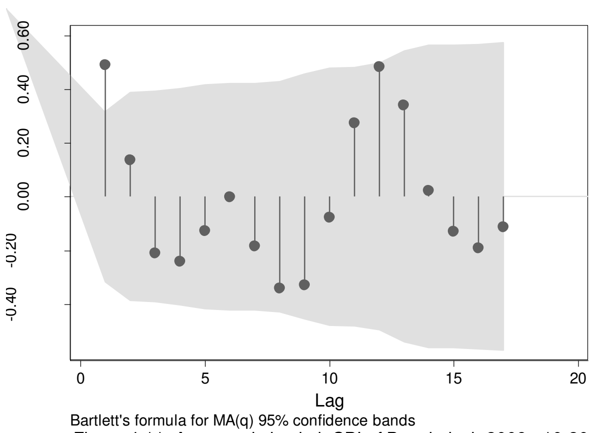

Figure 4.11: Autocorrelation in lnCPI of Bangladesh 2009m10-2012m

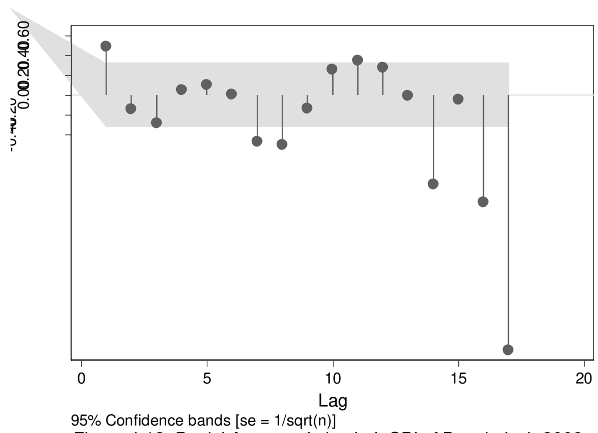

Figure 4.12: Partial Autocorrelation in lnCPI of Bangladesh 2009m10-2012m

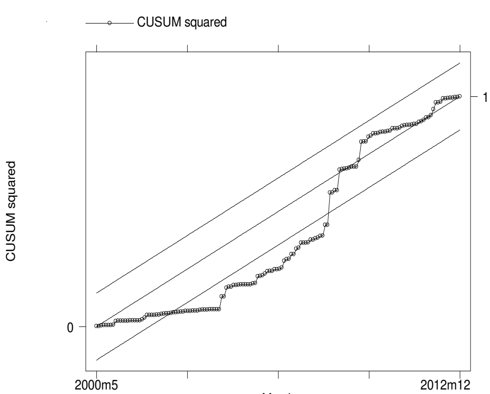

Figure 5.1 CUSUM test residuals of first Sample (2000-2012)

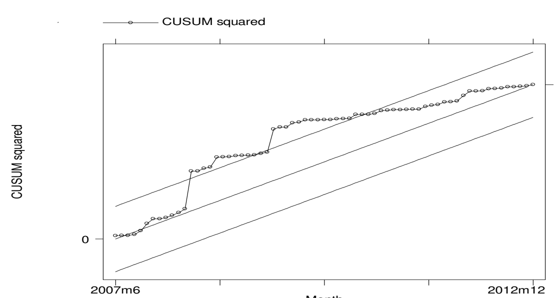

Figure 5.2 CUSUM test residuals of second Sample (2007-2012)

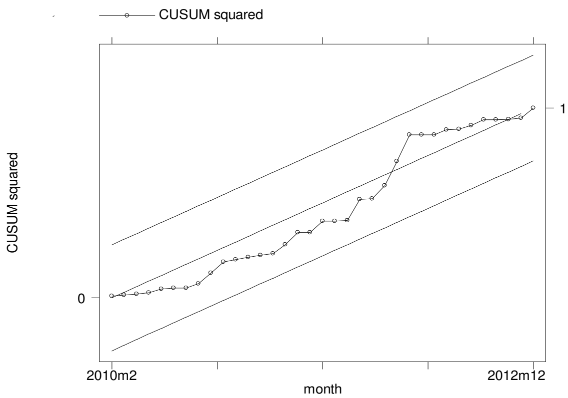

Figure 5.3.1 CUSUM test residuals of third Sample (2009-2012)

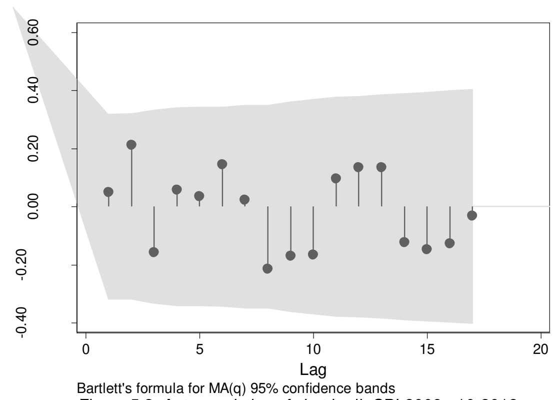

Figure 5.3: Autocorrelation of ehat in dlnCPI 2009m10-2012m

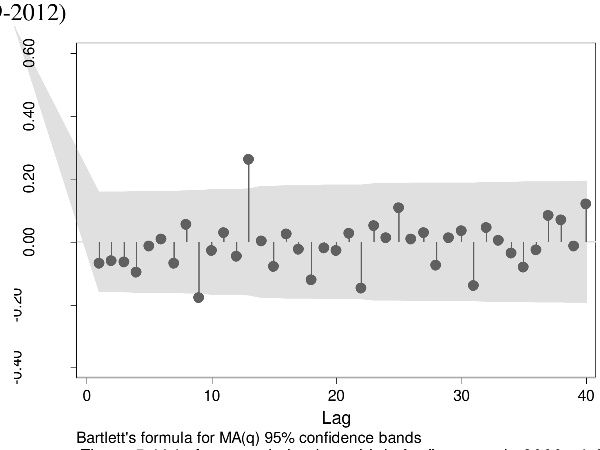

Figure 5.1(a): Autocorrelation in residuls for first sample 2000m1-2012m

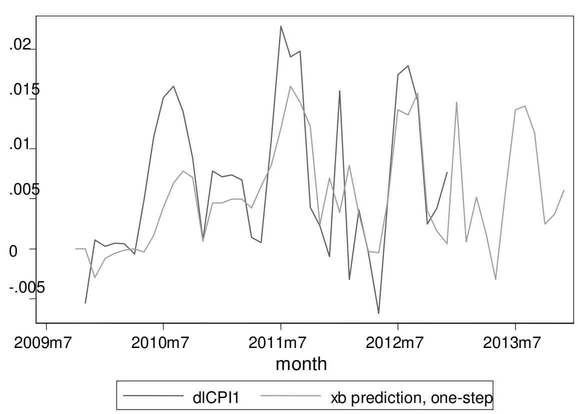

Figure 6.1 Actual and Forecast value of lnCPI of Bangladesh (2009m10-2012m13)