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Behavior of Inflation Rate in Albania Using Time

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ABSTRACT

December 2016. The autoregressive conditional heteroscedastic (ARCH) and their extensions, generalized autoregressive conditional heteroscedasticity (GARCH)) models are used to better fit the data. The study reveals that the inflation series is stationary, non-normality and has serial correlation. Based on minimum AIC and SIC values the best model turn to be GARCH (1, 1) model with mean equation ARMA (2, 1)x(2, 0)$_{12}$. Based on the selected model one year of inflation is forecasted (from January 2016 to December 2016).

Indexing terms/Keywords

Autoregressive Conditional Heteroscedasticity , Generalized Autoregressive Conditional Heteroscedasticity, Inflation.

SUBJECT CLASSIFICATION [MSC]

62P20, 62PO5, 91B84, 62M10

INTRODUCTION

The concept of time series is based on observations that have been collected over a period of time with a particular frequency, see [1]. Modeling and forecasting time series volatility is a crucial area that has received considerable attention during the last two decades. Several models have been suggested for capturing special features of financial data, and most of these models have the property that the conditional variance depends on the past. Various models are introduced to model the volatility of a time series. One such a model is introduced by Engle (1982) named autoregressive conditional heteroscedasticity model (ARCH). This model is generalized by Bollerslev (1986) into GARCH models. Nelson (1991) proposes the exponential GARCH (EGARCH) model which allow for asymmetric effect between positive and negative asset returns. Another model which allow for asymmetric is the threshold GARCH model (TGARCH), proposed by Zakoian(1994). This model allows having differential impacts on conditional variance of the past shocks, see [5]-[9].

Inflation is an important element of measuring macroeconomic performance of a country. Increase in prices of goods and services are an important aspect which is deemed for fluctuations in the economic growth. Inflation can be grouped into four types, according to its magnitude: creeping inflation, walking inflation, running inflation and hyper inflation. Inflation can be defined as the persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money, see [2]. Also inflation can be expresses as a situation where the demand for goods and services exceeds their supply in the economy, see [3]. In reality inflation means that your money can not buy as much as what it could have bought yesterday. Inflation dynamics and evolution can be studied using a stochastic modelling approach that captures the time dependent structure embedded in the time series inflation data, see [4]. The most common measure of inflation is the consumer price index, which measures the inflation of a country over a time period, e.g. monthly, quarterly or annually. Consumer Price Index (CPI) measures the change over time in the general price level of goods and services that households acquire for the purpose of consumption. The inflation rate I_t at time t is calculated as

$$I_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}$$

where CPI_t is the consumer price index at time t and CPI_{t-1} is the consumer price index at time t-1.

The current paper explains inflation modeling using recent monthly data using several ARCH models and a temptation **to** forecast inflation is made. All the data are analyzed by using Eviews 9.

DATA

The inflation data cover the period from January 2000 to December 2016, i.e. 204 observations. Most frequently, the term inflation refers to a rise in the Consumer Price Index (CPI), which measures prices of a representative fixed basket of goods and services purchased by a typical consumer. The inflation rate, I_t, at time t is calculated as

$$I_t = \frac{CPI\,(t) - CPI\,(t-1)}{CPI\,(t-1)} \cdot 100.$$

where $CPI\,(t)$ is the Consumer Price Index in time t and $CPI\,(t-1)$ is the Consumer Price Index in time t-1. The data sets is obtained from INSTAT, Statistics Institute of Albania.

METHODOLOGY

The general form of the ARIMA (*p, q*) is represented by the backward shift operator as

$$(1-\phi_1 L-\phi_2 L^2+\ldots+\phi_p L^p)y_t = (1-\theta_1 L-\theta_2 L^2+\ldots+\theta_q L^q)\epsilon_t$$

and a seasonal ARMA $(p,q)\times(P,Q)_d$ is represented by

$$\Phi(L^d)\phi(L)y_t = \Theta(L^d)\theta(L)\epsilon_t$$

where d is the seasonality period and L is the backshift operator.

Volatility models

The autoregressive conditional heteroscedasticity (ARCH) model violated this conditions assumed that variance of the residual of the mean equation fluctuate on time. ARCH (p) model is defined as follows

$$\sigma_t^2 = \alpha_0+\alpha_1\varepsilon_{t-1}^2+\alpha_2\varepsilon_{t-2}^2+\cdots+\alpha_p\varepsilon_{t-p}^2$$

Bollerslev(1986) developed the ARCH model into GARCH model, which allow the conditional variance to depend not only by the squared residuals of mean equation but even by the previous own lags. The GARCH(p, q) model is

$$\varepsilon_t=\sigma_t a_t,\quad \sigma_t^2 = \alpha_0+\sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{q}\beta_j\sigma_{t-j}^2,\ \alpha_0>0,\alpha_i\geq 0,\beta_i\geq 0 \text{ and } \sum(\alpha_i+\beta_i)<1.$$

Nelson (1991) proposes the exponential GARCH model. The EGARCH (p, q) models is define as follows

$$\ln(\sigma_t^2) = \alpha_0+\sum_{i=1}^{p}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}-\sqrt{\frac{2}{\pi}}\right|+\sum_{i=1}^{q}\beta_i\ln(\sigma_{t-i}^2)+\sum_{j=1}^{r}\gamma_j\frac{\varepsilon_{t-j}}{\sigma_{t-i}}$$

This model allowed capturing asymmetric effects of positive and negative shocks of the same magnitude.

Unit root test

The foundation of a time series is stationarity or weakly stationarity. In order to check for stationarity we use Augmented Dicker Fuller (ADF) test and Philip Perrons (PP) test. The null hypothesis of ADF test is the existence of unit root against the alternative hypothesis of no unit root. The null hypothesis is rejected if the test statistic is greater than the critical value. Null hypothesis is $H_0: \gamma = 0$ in the regression equation

$$\Delta y_t = a_0+y_{t-1}+\sum\beta_i\Delta y_{t-i+1}+\varepsilon_t.$$

The PP test is similar to the ADF test, but correct for any serial correlation and heteroscedasticity in the errors terms. The null hypothesis of PP test is rejected if the test statistic is greater than the critical value.

Test of Heteroscedasticity

In order to apply the GARCH model first we examine the residual of the mean equation for heteroscedasticity, known as ARCH effects, by using ARCH-LM test and Ljung-Box statistic.

The ARCH-LM test is used to test the presence of conditional heteroscedasticity by regressed the squared residual on q lag. The null hypothesis of the test is no heteroscedasticity in the model residual versus the alternative hypothesis of heteroscedasticity in the model residual. The test statistic is

$$LM = NR^2,$$

where N is the number of observation and R^2 is the coefficient of determination of the residual regression. The null hypothesis is rejected if the p-value is less that the significance level.

Ljung–Box Q statistics test the joint hypothesis that the autocorrelation coefficients up to lag q are equal to zero on the squared residual series. This test is defined as

$$\mathrm{Q} = \mathrm{N}(\mathrm{N}+2)\sum_{i=1}^{q}\frac{\rho_i^2}{\mathrm{N}-i}\sim\chi^2(\mathrm{k}),$$

where ρ_i^2 are the autocorrelation on lag q. The null hypothesis, that the autocorrelation function of the series is zero, is rejected if the p-value of the test is less than the significance level.

Test of Asymmetry

Before applied any asymmetric model we investigate for leverage effect by using sign and size bias test for asymmetry in volatility proposed by Engle and Ng (1993). Define S_{t-1}^- as an indicator dummy that takes the value 1 if $\hat{\varepsilon}_{t-1}<0$ and zero otherwise and $S_{t-1}^+ = 1-S_{t-1}^-$. A joint test for sign and size bias based on the regression

$$\hat{\varepsilon}_t^2 = \phi_0+\phi_1 S_{t-1}^-+\phi_2 S_{t-1}^-\varepsilon_{t-1}+\phi_3 S_{t-1}^+\varepsilon_{t-1}+v_t$$

A joint test statistic is formulated in the standard fashion by calculating TR^2 from the regression which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects, i.e. $\phi_1=\phi_2=\phi_3=0$.

RESULTS AND DISCUSSION

As we can see from the value of kurtosis the series do not performs a normal distribution, this results reinforced by Jarque- Bera test with p-value 0.000, see table 1. Before settling the best model for inflation data we first analyzed the data for stationarity. Both ADF and PP test indicate stationarity of the series, see table 2. From the graph, see figure 1, and autocorrelation of the series, figure 2, it seems that the data are seasonality. Significant spikes at lags 12 of the ACF at lags 12 of the PACF suggests for seasonal moving average and seasonal autoregressive components in the mean equation.

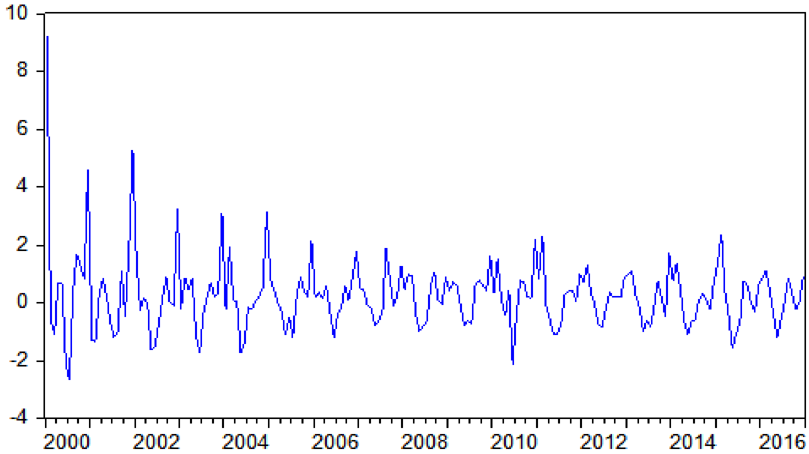

Figure 1: Monthly inflation from January 2000 to December 2016

Table 1. Description statistics of monthly inflation

Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
0.253	0.193	1.228	2.463	17.579	2013.022	0.000

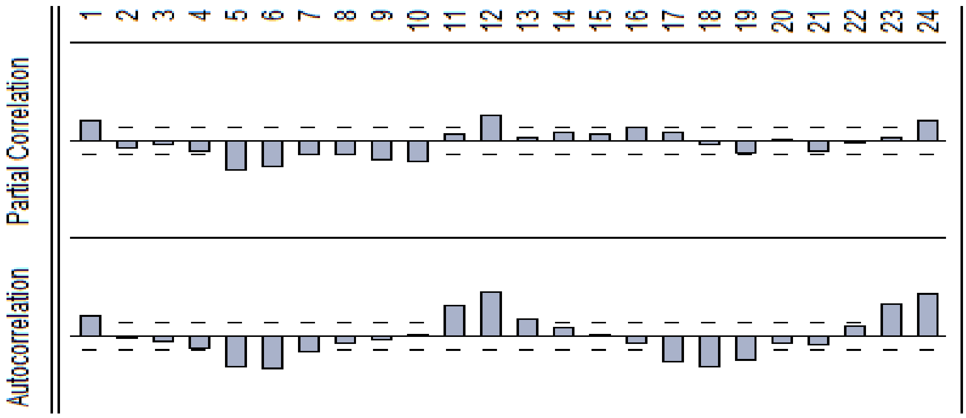

Figure 2: ACF and PACF on the level of inflation series

Table 2. Unit root test on the level

Unit root test	Test statistic	1% critical value	5% critical value	10% critical value
Augmented Dicker Fuller (ADF)	-7.684	-3.464460	-2.876435	-2.574788
Phillips-Perron (PP)	-14.01894	-3.462574	-2.875608	-2.574346

We performed several ARMA $(p,q)x(P,Q)_{12}$ model and according to AIC and SIC value ARMA (2,0,1)x(2,0,0)$_{12}$ was selected as the best model, see table 3. Next we estimate this model. As we can see all the coefficients of the model are significant, Durbin – Watson statistic seems to be nearly to two and $R^2 = 0.518$.

Table 3. Model selection

Model	**AIC**	**SIC**
$(1,0,1)x(0,0,0)_{12}$	3.210005	3.275066
$(1,0,1)x(1,0,0)_{12}$	2.85684	2.938167
$(1,0,1)x(0,0,1)_{12}$	3.034306	3.115632
$(1,0,1)x(1,0,1)_{12}$	2.747022	2.844614
$(1,0,2)x(0,0,0)_{12}$	3.132063	3.213390
$(1,0,2)x(1,0,0)_{12}$	2.775386	2.872978
$(1,0,2)x(1,0,1)_{12}$	2.682230	2.796087
$(2,0,1)x(0,0,0)_{12}$	3.083731	3.271537
$(2,0,1)x(1,0,0)_{12}$	2.755075	2.852667
$(2,0,1)x(1,0,1)_{12}$	2.677698	2.791555
$(2,0,1)x(2,0,0)_{12}$	**2.652278**	**2.766135**
$(2,0,1)x(2,0,1)_{12}$	2.660139	2.790261

Table 4. Estimation of ARIMA $(2,0,1)x(2,0,0)_{12}$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.282903	0.118043	2.396606	0.0175
AR(1)	0.857848	0.099625	8.610781	0.0000
AR(2)	-0.357109	0.053320	-6.697475	0.0000
SAR(12)	0.301642	0.019167	15.73750	0.0000
SAR(24)	0.524954	0.027907	18.81114	0.0000
MA(1)	-0.807488	0.084013	-9.611462	0.0000
SIGMASQ	0.722370	0.052525	13.75297	0.0000
R-squared	0.518620	Mean dependent var		0.253473
Adjusted R-squared	0.503958	S.D. dependent var		1.228012
S.E. of regression	0.864892	Akaike info criterion		2.652278
Sum squared resid	147.3635	Schwarz criterion		2.766135
Log Likekihood	-163.2063	Durbin –Watson stat		2.030475

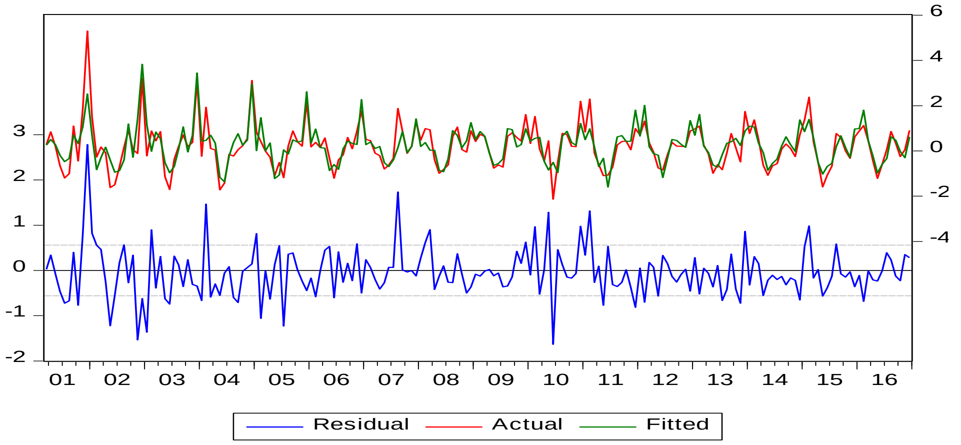

Figure. 3 Graph of actual, fitted and residual series

Applied ARCH test and Q test on the residual of the series the tests strongly suggests for heteroscedasticity and autocorrelation on the residual of the series, see table 5. In order to avoid the heteroscedasticity some ARCH and GARCH model are performed and GARCH(1,1) model was select as the best model, see Table 6.

Table 5. Heteroscedasticity test

Test \ Lag	1	12	24
ARCH Test	13.019 [0.000]	28.654 [0.000]	8.459 [0.000]
Q- Test	6.862 [0.009]	85.795 [0.000]	92.984 [0.000]

Note: p-value is in square breeches

Table 6. Selected best GARCH model

Model / AIC value	ARCH(1)	ARCH(2)	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
AIC	1.553290	1.564131	1.351252	1.381616	1.489729	1.530183

In Table 7 the GARCH(1,1) model evaluated. All the coefficient of the model seems to be significant except the constant coefficient of variance equation. R^2 is equal to 0.7 and adjusted R^2 is 0.69, see table 7.

Table 7. GARCH(1,1) estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.121133	0.046903	2.582631	0.0098
AR(1)	0.949844	0.001654	574.3231	0.0000
AR(2)	-0.278983	0.047476	-5.876347	0.0000
SAR(12)	0.469317	0.058611	8.007312	0.0000
SAR(24)	0.259754	0.069287	3.748979	0.0002
MA(1)	-0.898870	0.000435	-2068.033	0.0000
	Variance Equation			
C	0.004487	0.003035	1.478550	0.1393
RESID(-1)^2	-0.071494	0.022163	-3.225807	0.0013
GARCH(-1)	1.042219	0.017723	58.80618	0.0000
R-squared	0.701690	Durbin-Watson stat		2.115887
Adjusted R-squared	0.693018	S.D. dependent var		0.904409

In order to investigate for asymmetric effects in volatility LM test of asymmetry is performed and the result show no asymmetry on volatility. So non asymmetric volatility model need to be implemented. The ARCH-LM test and Ljung-Box statistic on the residual of GARCH(1,1) model suggests for no heteroscedasticity and no autocorrelation.
So the model turns to be adequate see table 8.

Table 8. Diagnostics tests

Test statistic	**ARCH-LM**	**Q(12) stat**	**Q^2(12) stat**	**LM test of asymmetry**
Test value (p-value)	0.1623 (0.687)	10.357 (0.178)	9.866 (0.628)	3.815 (0.282)

Finale one year out of sample forecasting were obtain for the year 2016 and table 9 shows the various measures of forecasting errors, mean absolute error, root mean squared error and Thiele's U test. The smaller the error, the better the forecaster. The Thail U statistic 0.505 indicates that the forecasts are accurate.

Table 9. Forecast evaluation

RMSE	**MAE**	**Thail inequality coefficient**	**Thail U2 coefficient**
0.288	**0.229**	**0.207**	**0.505**

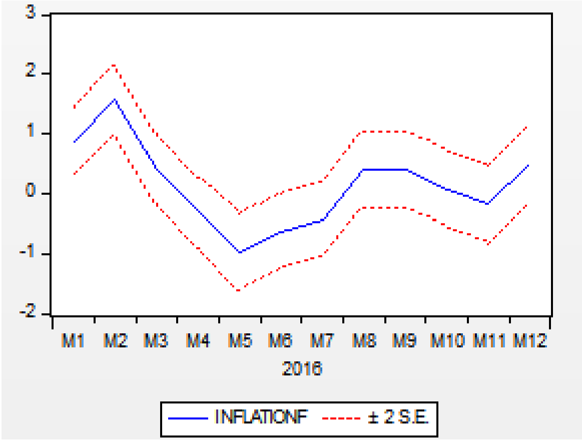

Figure 4. Forecasting performance of GARCH(1,1)

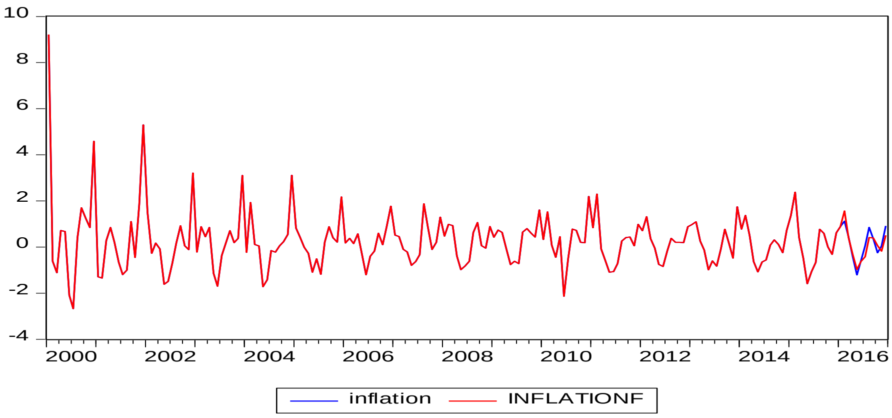

Figure 5. Time plot of inflation and one year forecasts

CONCLUSION

The study attempt to provide empirical evidence of modelling inflation in Albania using the Autoregressive Conditional Heteroscedastic models, i.e. ARCH and GARCH model. Several forms of these models were fitted using the monthly inflation data in Albania and based on the AIC and SIC values the best model was selected GARCH(1,1) with mean equation ARMA(2, 1)x$(2,0)_{12}$. The coefficients of the estimated model are all significant at 5% level, except for the constant in the variance equations. Finale one year out of sample forecasting were obtain for the year 2016 and it can be concluded that the prediction power of the model suitable for forecasting.

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