

# An Attempt to Develop a Suitable Model for Forecasting Bank Credit in Pakistan

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## Abstract

An attempt has been made in this study to develop a suitable time series econometric model for forecasting the credit structure in Pakistan. The relevant data has been obtained from the website of State Bank of Pakistan (SBP) regarding the amount of credit given to the private sector for the sake of economic activity and its development. The data thus obtained was of time series type in months starting from July 1990 to June 2010. Keeping in mind, the influence of months' effect, eleven dummy variables have also been introduced in analysis to address this issue. In order to develop a suitable forecast model for credit to private sector, first of all Augmented Dickey-Fuller (ADF) test has been applied to check the level of integration as the data contains a secular trend. It has been observed through ADF test that the credit to private sector data has two unit roots (i.e., it is integrated of order 2). By applying various models like ARIMA, ARCH, and GARCH, decision has been in favor of GARCH (1,1) model as it contains some significant AR and MA terms of specific order along with influential months of the year that describe the possible patterns in the credit to private sector data. Moreover it has been observed that the months of January, February, April, May, June and July are the significant months explaining the variation in the credit data along with AR term of order 12 and MA terms of order 1 being significant.

**Keywords:** Banking Sector, Credit, Central Bank, Monetary Policy, GARCH Model, Investment, Time Series Model

**JEL Classification:** E52, E51, E62, C32, E58

## 1. Introduction

Whenever you make a purchase today with the promise to pay for it tomorrow, you are using credit. Having credit lets you make purchases when you don't have cash available. Before a lender will allow you to use credit, it must first believe that you can be trusted to repay the amount of credit you use. This is considered financial trustworthiness. Lenders use a number of factors to determine your financial trustworthiness. The most commonly used factor is your credit history. To establish credit with a financial institution, you must first make an application. The lender will use identifying information, like your social security number, to look up your credit history. If the lender determines that you are a trustworthy borrower, then it will extend credit to you. Once you have been approved for credit, the lender will give you guidelines, or terms, for using your credit. But the question is who will provide the currency for credit purpose so there must be some authority who will provide it with using a certain policy and for this every country has central bank (which is named as State bank in Pakistan) who uses Monetary policy for this credit facility.

### 1.1 How the Bank Influences an Economy?

A central bank can be said to have two main kinds of functions: (1) macroeconomic when regulating inflation and price stability and (2) microeconomic when functioning as a lender of last resort.

#### 1.1.1 Macroeconomic Influence

As it is responsible for price constancy, the central bank must regulate the level of inflation by controlling money supplies by means of monetary policy. The central bank performs unwrap market transactions that also inject the market with liquidity or absorb additional funds, directly affecting the level of price rises. To boost the amount of money in passage and decrease the interest rate (cost) for borrowing, the central bank can purchase government bonds, bills, or extra government-issued notes. This buying can, yet, also lead to higher inflation. When it needs to sop up money to reduce inflation, the central bank will sell government bonds on the open market, which increases the interest rate and discourages borrowing. Open marketplace operations are the key process by which a central bank controls inflation, money supply, and price permanence.

#### 1.1.2 Microeconomic Influences

The establishment of central banks as lender of last resort has pressed the need for their autonomy from commercial banking. A commercial bank offers funds to customers on a first come, first serve basis. If the commercial bank does not have enough liquidity to meet its clients' demands (commercial banks typically do not hold reserves balanced to the needs of the entire market), the commercial bank can turn to the central bank to

borrow additional funds. This provides the system with stability in an objective way; central banks cannot favor any particular commercial bank. As such, many central banks will hold commercial-bank reserves that are based on a ratio of each commercial bank's deposits. Thus, a central bank may necessitate all commercial banks to keep, for example, a 1:10 reserve/deposit ratio. Enforcing a policy of commercial bank reserves functions as another means to control money supply in the market. Not all central banks, however, require commercial banks to deposit treasury.

### **1.2 Transitional Economies and Banking Sector**

Today developing economies are faced with issues such as the conversion from managed to free market economies. The main concern is often controlling inflation. This can lead to the establishment of an independent central bank but can take some time, certain that many developing nations maintain control over their economies in an endeavor to retain control of their power. But government intrusion, whether direct or indirect through fiscal policy, can stunt central bank development. Unfortunately, many mounting nations are faced with civil disorder or war, which can force a government to reroute funds away from the development of the economy as a whole. Nonetheless, one factor that seems to be inveterate is that, for a market economy to develop, a stable currency (whether achieved through a fixed or floating exchange rate) is needed. However, the central banks in both industrial and up-and-coming economies are dynamic because there is no guaranteed way to run an economy despite of its stage of development.

### **1.3 Monetary Policy**

Monetary policy is the process by which the government, central bank, or monetary authority of a country controls (i) the supply of money, (ii) availability of money, and (iii) cost of money or rate of interest, in order to attain a set of objectives oriented towards the growth and stability of the economy. Monetary policy is generally referred to as either being an expansionary policy, or a contractionary policy, where an expansionary policy increases the total supply of money in the economy, and a contractionary policy decreases the total money supply. Expansionary policy is traditionally used to combat unemployment in a recession by lowering interest rates, while contractionary policy involves raising interest rates in order to combat inflation.

The growing importance of monetary policy and the diminishing role played by fiscal policing economic stabilization efforts may reflect both political and economic realities. Fighting inflation requires government to take unpopular actions like reducing spending or raising taxes, while traditional fiscal policy solutions to fighting unemployment tend to be more popular since they require increasing spending or cutting taxes. Political realities, in short, may favor a bigger role for monetary policy during times of inflation. One other reason suggests why fiscal policy may be more suited to fighting unemployment, while monetary policy may be more effective in fighting inflation. There is a limit to how much monetary policy can do to help the economy during a period of severe economic decline, such as the States encountered during the 1930s. The monetary policy remedy to economic decline is to increase the amount of money in circulation, thereby cutting interest rates. Thus to see how much this money circulation through credit creation should be done by Pakistani Central Bank, this study tries to forecast proper estimates through suitable selection of econometric technique.

## **2: Objective:**

The objective of this study is:

- To develop a suitable model for banking sector of Pakistan for credit generation.

## **3: Methodology**

To fulfill the objective of the study, choice of Time Series models has been made. Auto-Regressive Integrated Moving Average (ARIMA) methodology is used for univariate time series in which we have tried to develop a forecast model for credit data. If the estimated ARIMA models with show ARCH effect then we will use ARCH/GARCH models. Given below are some of the details of ARIMA models, ARCH/GARCH models. But the start is taken from the concept of forecasting.

### **3.1 Forecasting**

The aim of forecasting in time series is to find out the future values of an observed time series. Forecasting is widely used in econometric models, business, stock price, weather etc. Suppose that an observed time series is of the form  $y_1, y_2, \dots, y_t$  then we have to find out the future values such as  $y_{t+k}$  where 'k' is known as the lead time (horizon) for which the forecast is being done. A number of methods are available for the forecasting purpose but it should be kept in mind that no single method is applicable in all conditions. A person has to make decision about using a particular forecasting method by seeing that whether that particular forecasting method satisfies the existing condition or not. Forecasting has different categories such as subjective forecasting, univariate forecasting and multivariate forecasting. In the subjective forecasting the forecasting is done purely by the

judgment and expertise of a person as well as his past experience. The univariate forecasting is done by the extrapolation of trend curves, exponential smoothing and the Box-Jenkins procedure whereas the multivariate forecasting is done using the Box-Jenkins VAR procedure.

### 3.1.1 Univariate Time Series

A univariate time series is such a time series in which we study a single time series for example the time series of annual GDP, the time series of monthly exchange rate, time series of monthly foreign exchange reserves, a time series of yearly foreign direct investment in Pakistan, a time series of daily stock prices etc. In the univariate time series we develop a model for forecasting for a single variable.

Following univariate models are used commonly:

- i). Auto-Regressive (AR) Process
- ii). Moving Averages (MA) Process
- iii). Auto-regressive Moving Average (ARMA) Process
- iv). Auto-regressive Integrated moving Averages (ARIMA) Process

### 3.1.2. Auto-Regressive (AR) Process

The "AR" models were firstly introduced by G.U. Yule in 1920. Let  $\epsilon_t$  be a white-Noise process which has zero mean and a constant variance  $\sigma^2_{\epsilon}$ . Then the process  $y_t$  is an autoregressive process having an order "p" if:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \epsilon_t$$

### 3.1.3. Moving Averages (MA) Process

Let  $\epsilon_t$  be a white-Noise process which has zero mean and a constant variance  $\sigma^2_{\epsilon}$ . Then the process  $y_t$  is a moving averages process of order "q" if:

$$y_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

### 3.1.4. Auto-regressive Moving Average ARMA Process

In the ARMA process the lags of " $\epsilon_t$ " and " $y_t$ " are included in the model. In other words we can say that the ARMA (p, q) process is a combination of AR (p) and MA (q) process and that is why these models are also known as the mixed models.

Let  $\epsilon_t$  be a white-Noise process which has zero mean and a constant variance  $\sigma^2_{\epsilon}$ . Then  $y_t$  is an ARMA process having an order of (p, q) if:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

Using the backward shift operator "B" we obtain:

$$(y_t - \phi_1 y_{t-1} - \phi_2 y_{t-2} - \dots - \phi_p y_{t-p}) = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

$$y_t - \phi_1 y_{t-1} - \phi_2 y_{t-2} - \dots - \phi_p y_{t-p} = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q}$$

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

Where  $\phi(B)$  and  $\theta(B)$  are the polynomials of order p and q respectively.

### 3.1.5. Auto-regressive Integrated moving Averages (ARIMA) Process

Before applying the ARIMA methodology, we have to find that at which difference the data becomes stationary and the difference at which the time series data is stationary is denoted by "d". For example if the data are stationary at level, then  $d = 0$  and it is denoted by I(0). If the data are stationary at the first difference, then  $d = 1$  and it is denoted by I(1). And in general notations if the data becomes stationary after taking dth difference, then it is written as I(d) which means that the data are integrated of order "d" and becomes stationary at the dth difference. If the mean of a time series has a reverting property and a finite variance, then it is integrated. It is out of equilibrium for a temporary time period and is stationary at level i.e. I(0). However, a time series that has to be differenced to make it stationary has an infinite variance. The series becomes stationary at the dth difference i.e. I(d) e.g. I(2) series is stationary at the second difference. It has been observed that most of the time series are non-stationary in nature. And at the first the data has to be made stationary before applying AR, MA or ARMA process. The ARIMA(p, d, q) process is represented as:

$$\phi(B) w_t = \theta(B) \epsilon_t$$

$$(1 - B)^d y_t = w_t$$

Where "d" roots are inside the unit circle. And the differenced series is denoted by  $w_t$

For example ARIMA(1, 1, 1) means that an ARMA(1, 1) process is applied to the series which is stationary at the first difference. Stationarity of the series is important because the future forecasting can not be done on non-stationary time series.

### 3.1.6. The Unit Root Test

The unit root test is used to test the stationarity of the data and has become very popular over the past several years. In the unit-root test we start with:

$$y_t = \rho y_{t-1} + \epsilon_t \dots (3.1) \quad -1 < \rho < 1$$

Where the white noise error term is denoted by  $\epsilon_t$ . If  $\rho = 1$ , then above model contains a unit root and is a random-walk model without drift which becomes a non-stationary stochastic process.

Therefore why should not we simply regress  $y_t$  on its lagged value  $y_{t-1}$  and find out whether the

estimated  $\rho$  is statistically equal to 1 or not. If it is equal to 1, then  $y_t$  is non-stationary.

Now we subtract  $y_{t-1}$  from both sides of the (3.1) as follows:

$$y_t - y_{t-1} = \rho y_{t-1} - y_{t-1} + \epsilon_t$$

$$y_t - y_{t-1} = (\rho - 1) y_{t-1} + \epsilon_t$$

The above expression can be written as:

$$y_t = (\rho - 1) y_{t-1} + \epsilon_t \quad (3.2)$$

Where  $\Delta$  is known as the first difference operator.

Now instead of estimating (3.1) we estimate (3.2) to check whether  $\rho=1$  or not. If  $\rho = 1$ , then there is a problem of non-stationarity and the model (3.2) becomes:

$$y_t = y_{t-1} + \epsilon_t$$

Since  $\epsilon_t$  is a white-noise error term and it is stationary. It means that a random-walk time series are stationary at the first difference.

Dickey and Fuller have shown that while testing the null hypothesis for  $\rho = 1$ , tau-statistic is followed by the estimated "t" value of  $y_{t-1}$ . The tau-statistic has critical values which are based on the Monte Carlo simulations. The usual t-test can be used if the null hypothesis that  $\rho = 1$  is rejected which means that the time series is stationary.

Several decisions are involved in implementing the actual procedure of Dickey–Fuller test. The estimation of Dickey Fuller test is done in three different forms which are as under:

1. If  $y_t$  is a random-walk process, then;

$$y_t = y_{t-1} + \epsilon_t \quad (3.3)$$

2. If  $y_t$  is a random-walk with drift, then :

$$y_t = \alpha + y_{t-1} + \epsilon_t \quad (3.4)$$

And if  $y_t$  is a random-walk process with drift around a stochastic trend, then:

$$y_t = \alpha_1 + \alpha_2 t + y_{t-1} + \epsilon_t \quad (3.5)$$

Where "t" represents the time or the trend variable. And  $\rho = \rho - 1$

If  $\rho = 0$  i.e.  $\rho = 1$  and unit root in this case, then the time series is non-stationary. If  $\rho < 0$ , i.e.  $\rho < 1$ , then there is no unit root in the data and the null hypothesis is rejected which means that the time series  $y_t$  is stationary with zero mean in case of (3.2).

### 3.1.7. The Box-Jenkins Methodology

The Box-Jenkins methodology is used to model a univariate time series as well as the multivariate time series. The Box-Jenkins methodology is applied on the stationary time series. If the time series are not stationary, then it is made stationary after one or more differencing. Why stationary is mandatory can be explained as follows:

The main objective of the Box-Jenkins methodology is to do identification and estimation of a best statistical model which can be interpreted as having generated the sample data. The features of the model should be constant through time especially for the future time periods if it is used for forecasting. Thus stationarity of time series is important so that the estimated model gives valid and reliable forecasting results.

There are four steps in the Box-Jenkins methodology which are as follows:

- i). Identification
- ii). Estimation
- iii). Diagnostic Checking
- iv). Forecasting

### 3.1.8. Identification

In the Identification stage first of all we find out the appropriate values of p (autoregressive terms), d (no. of differences to be taken to make the data stationary) and q (moving average terms). And for this purpose the correlograms of autocorrelation function (ACF) and partial auto-correlation function (PACF) are used. In the model identification we examine a wide variety of possible models which may include only autoregressive terms, only moving averages terms or both autoregressive and moving averages terms to capture the past data patterns for the purpose of potential forecasting model. And for this purpose the "best" model for a given set of data is obtained by a systematic approach. In the systematic approach the data is differenced to make it stationary in order to determine the autoregressive and moving average terms. The model identification commences by determining whether the data are stationary or not by the examination of the ACF function of the original data. If the positive values of ACF function trail off slowly, then differencing should be done in order to remove trend present in the data. The ACF and PACF of the stationary series are used in determining the best Box-Jenkins model according to the following rules;

- (a) If the ACF is trailing off and PACF is showing spikes, then the model is an AR(p) model where "p" is equal to the number of significant PACF spikes in the best model.
- (b) If the PACF is trailing off and ACF is showing spikes, then the model is an MA(q) model where "q" is equal to the number of significant ACF spikes in the best model.

(c) If both the ACF and PACF are trailing off, then ARMA model is suitable with  $p = 1$  and  $q = 1$ .

### 3.2 Diagnostics

After the identification of the most appropriate  $p$ ,  $d$  and  $q$  values, the next step is to find out the parameters of the autoregressive and moving average terms included in the model.

The selected model should fulfill the following criteria:

- i. Parsimony
- ii. Stationarity and Invertibility
- iii. Goodness-of-fit

**3.2.1 Parsimony:** Principle of parsimony is the fundamental idea in the Box-Jenkins approach. The selected model should be parsimonious. A Parsimonious model is that which uses the minimum number of coefficients. Because by incorporating additional coefficients, the value of  $R^2$  will increase at the cost of reducing degree of freedom. In the opinion of Box and Jenkins the parsimonious models generally produce better results than the models that are over-parameterized.

**3.2.2 Stationarity and Invertibility:** The selected model should fulfill the conditions of stationarity and invertibility. The t-statistic and Ljung - Box Q-statistic also presume that the time series is stationary. The model should also be invertible. Also “ $y_t$ ” is invertible if its representation can be made by a finite order or convergent autoregressive process.

**3.2.3 Goodness-of-fit:** A good estimated model will obviously fit the data well. In ordinary least squares  $R^2$  and the average of the residual sum of squares are the common goodness-of-fit measures. The main problem with these measures is this that the fit improves as the number of parameters increase. And for this purpose of goodness-of-fit Akaike Information Criteria (AIC) and Schwartz Bayesian Criteria (SBC) are used. While selecting a model the following terms and techniques are used:

#### 3.2.3a Sum of squared Residuals

$$\sum e_i^2 = \sum (y - \hat{y})^2 \quad (3.6)$$

#### 3.2.3b Durbin-Watson Statistic

The Durbin-Watson statistic is used to measure auto-correlation in the residuals. It is computed as

$$DW = \frac{\sum_{t=2}^n (\epsilon_t - \epsilon_{t-1})^2}{\sum_{t=1}^n \epsilon_t^2} \quad (3.7)$$

If DW is less than 2, then there is an evidence of positive serial correlation.

#### 3.2.4 Q-Statistics

In the diagnostic checking stage the residual plots are checked in order to find out outliers in the data and to see that when the model do not fit well. And in the diagnostic checking we also see the correlogram of residuals to see that whether the errors have zero mean i.e. white noise or not. Also the correlogram of the squared residuals is constructed to see the ARCH/GARCH effect in the data. The Q-statistic is used for this purpose. The Q-statistic suggested by Box and Pierce (1970) in which sample autocorrelations are used to form the statistic is

$$Q = n \sum_{j=1}^k r_j^2 \quad (3.8)$$

Which tests the null hypothesis that  $\rho_k = 0$ . And if it is not rejected, then the residuals are white noise.

The “Q” statistic follows a  $\chi^2$  distribution with “k” degrees of freedom. To check the normality of the fitted residuals, the Kolmogorov Smirnov test, Shapiro Wilk test and Jerque Bera test are used. Moreover, t-test can also be used to check whether the residuals are white noise or not.

**3.3. Forecasting:** After the first three steps when the final model has been estimated, it is used for forecasting purpose. ARIMA modeling is famous because of its success and greater acceptability in the forecasting. The in-sample forecasts are done to detect the turning points to control the adequacy of the model. And the out-of-sample forecasts are done only to make short-term forecasts.

#### 3.3.1 ARCH and GARCH Models

Time series model has initially introduced either for descriptive purposes like prediction and seasonal corrections for dynamic control. In 1970's, the research focused on specific class of time series models, the so-called Autoregressive Moving Average (ARMA), which were easy to implement. However this approach has two major drawbacks:

- (I). It is essentially a linear setup, which automatically restricts the type of dynamic to be approximated;

(ii) It is generally applied without imposing a priori constraints on the AR (Autoregressive and MA (Moving Average) parameters, which is inadequate for structural interpretations.

Due to these drawbacks, the applications of standard ARMA models to financial and monetary yield poor fit. Specifically, not only the data generating process of financial time series exhibits various forms of non-linear dynamics (the crucial one is the dependent of variability of the series of its own past) but the financial theories based on concepts such as equilibrium risks, certainty, rational behavior of the investors, etc. Would naturally impose some structural constraints on the parameters. Therefore, the testing of the financial models has necessitated the development of new econometrics time series techniques that allows for the modeling of time varying variances and co variances. In this context, Engle (1982) developed ARCH (Autoregressive Conditional Heteroskedasticity) models, which address aforementioned problems properly arising while studying financial time series. Autoregressive conditional heteroskedastic(ARCH) model is developed by Robert F. Engle (1982) in his seminal paper “ Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation” . This model started a whole new era with lots of ARCH extensions that are in practice now-a-days.

Consider a first order Autoregressive model AR(1)

$$y_t = \mu + \phi y_{t-1} + \varepsilon_t \quad |\phi| < 1$$

Normally, we assume that  $\varepsilon_t \sim i.i.d(0, \sigma^2)$ . While the Engle idea starts from the fact that the residuals' variance depends upon the past history, in other words heteroskedasticity because the variance will change over time. i.e.

$$\varepsilon_t \sim i.i.d(0, h_t)$$

It is quite clear from this discussion that we have to model the variance of the residuals along with the mean's modeling. One way to model is as

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2$$

Which is the basic ARCH(1) model.

This model describes that when  $\varepsilon_{t-1}^2$  is large or small; the variance of the next innovation  $\varepsilon_t$  is also small or large respectively. In fact the conditional variance can depend not only on one lagged value of the residuals but more than one. In general the ARCH(q) process will be given by:

$$y_t = \mu + \phi y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim i.i.d(0, h_t)$$

$$h_t = \gamma_0 + \sum_{j=1}^q \gamma_j \varepsilon_{t-j}^2$$

It is important to note that the estimated coefficients of the  $\gamma^s$  have to be positive for positive variance.

### 3.3.2 GARCH Specification

The main problem with the ARCH specification is that it looks more like a moving average specification than an autoregressive terms. The other problem associated with the ARCH model is a difficulty in estimating it because

it often yield negative estimates of the  $\gamma_j^s$ . To overcome these problems, Bollerslev in 1986 gave the idea of GARCH model family in this paper entitled ‘Generalized Autoregressive conditional Heteroskedasticity’. These models are widely used in various branches of econometrics, especially in financial time series analysis. Consider first order autoregressive model is as

$$y_t = \mu + \phi y_{t-1} + \varepsilon_t \quad |\phi| < 1$$

Where

$$\varepsilon_t \sim i.i.d(0, h_t)$$

The General GARCH (1,1) may be of the following form:

$$h_t = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \beta h_{t-1}$$

The  $h_t$  is called conditional variance because it provide one period ahead forecast based on past information and it is a function of three terms.

- A constant term denoted by  $\gamma_0$
- Lag values of the squared residual from the mean equation that provide the information about the

volatility from the previous period, denoted by  $\epsilon_{t-1}^2$ .

- The GARCH term which is the last period forecast variance term denoted by  $h_{t-1}$ .

It is quite clear that GARCH(1,1) model is parsimonious to an infinite ARCH(q) process because GARCH(1,1) can be converted as

$$h_t = \frac{\gamma_0}{1-\delta} + \gamma_1 \sum_{j=1}^{\infty} \delta^{j-1} \epsilon_{t-1}^2$$

Due to this parsimonious property of GARCH model it is often suggested to estimate lower order GARCH model instead of higher-order ARCH model.

The General GARCH (p,q) model has the following form:

$$h_t = \gamma_0 + \sum_{j=1}^p \beta_j h_{t-j} + \sum_{j=1}^q \gamma_j \epsilon_{t-j}^2$$

This model tells us that the forecast variance of current period depends both on the past values of shocks, captured by the lagged squared residual terms and on past values of it which are captured by lagged terms of variances itself.

### 3.3.2.1. Estimation Problem in GRACH Models

Sometimes convergence problems arise, because, the more parameters in GRACH model the flatter the likelihood function becomes which makes it more difficult to maximize the likelihood function and render into only a local optimum. In order to ensure that the estimates correspond to a global optimum of the likelihood function and the renders into only a local optimum of the likelihood function one would have to run the models with any starting values and each time record the likelihood of the optima. If this type of convergence problem is encountered one should use a more parsimonious parameterization of the GRACH model, if possible. Convergence problem with GRACH models may also arise because the gradient algorithm used to maximize the likelihood function has hit a boundary. If there are obvious outliers in the data then is very likely that the iteration will return the value 0 or 1 for either alpha or beta parameters (or both). Therefore, it may be safe to remove a single outlier if the circumstances that produced the outlier are thought to be unlikely to happen in future. A sure sign of using the wrong GRACH model is when the iteration refuses to converge at all, even after you have checked the data for outliers, changed the starting values or chosen a different data period. The normal GRACH models that have been described in this section are commonly used for modeling the volatility of daily returns, exchange rates, valuing path- dependent options or volatility options, measuring risk capital requirements, calibration, of binomial trees, etc.

### 3.3.2.2. Post-Estimation Diagnostic Tests for selecting the Best GRACH Model

The estimated GRACH model is correctly specified if:

- The residual from the model should be nearly white noise (i.e. there should be no serial correlation left in the residuals);
- There should be no ARCH effect left in the variance equation; and
- Residual to some extent exhibits normality.
- In addition, the sum of ARCH and GRACH coefficient should satisfy the stability condition i.e.  $a + b$  should be  $< 1$ .

Now, we will briefly discuss these post- estimation diagnostic tests.

### 3.3.2.3. Correlogram and Q-statistics

The first condition, which the mean equation of the GRACH model should satisfy, is that the residuals generated from the mean equation should be white-noise i.e. there should be no autocorrelation in the residual. Correlogram (autocorrelations and the partial autocorrelations) of the standardized residuals and Q-statistics can be used to test the serial correlation and specification of the mean equation. If the mean equation is correctly specified, all q-statistics should not be significant. The Ljung-Box Q-statistics at lag k is a test statistics for the null hypothesis that there is no autocorrelation up to order k.

### 3.3.2.4. Correlogram of Squared Residual and ARCH-LM Test

The second and the foremost question to answer for a chosen GRACH model is how well it models the conditional volatility of the process. If a GRACH model is capturing volatility clustering adequately, residuals should have no significant autoregressive conditional heteroskedasticity (ARCH) once they have been standardized by their conditional volatility. The standard tests for ARCH are:

- To test the autocorrelation in the squared residuals; and
- To use the ARCH-LM.

Correlogram of squared residuals displays the correlogram (autocorrelations and partial autocorrelations) of squared standardized residuals. This view can be used for remaining ARCH in the variance equation and to

check the specification of the variance equation. Such tests may be based on autocorrelation test statistic such as the Ljung-Box statistics described equation 3.7. If the variance equation is correctly specified, all Q-statistics should not be significant.

### 3.3.2.5. Histogram-Normality test

Histogram-Normality test displays descriptive statistics and a histogram of the standardized residuals. You can use the Jarque-Bera statistic to test whether the standardized residuals are normally distributed, the Jarque-Bera statistic not be significant.

### 3.3.2.6. Stability of Estimated GRACH Model

The other important post estimation diagnostic test is to check the stability of the GARCH model by looking at the sum of ARCH and GRACH coefficients. If sum of these two coefficients are equal to or less than one it indicates that the estimate GRACH model is stable. On the other hand, if the sum of these two coefficients is greater than one it means that estimated GRACH model is unstable.

### 3.3.2.7. Forecasting within GRACH Framework

Once the stable and well specified GRACH model is estimated, it is subsequently used to perform static and dynamics within-sample and out-of-sample forecast of mean and variance of the variable of interest (for instance, exchange rate in our case). Once the forecast either within sample or out-of-sample forecast is obtained, the same can be evaluated on the basis of following sets of evaluations.

Suppose the forecast sample is  $j=T+1, T+2, T+h$  and denote the actual forecasted value in period  $t$  as  $Y_t$  and  $Y_1$ , respectively. The reported forecasted error statistics are computed as follows:

- Root means Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error (MAPE)
- Theil Inequality Coefficient

The first two forecast error statistics depend on the scale of the dependent variable. These should be used as a relative measures to compare forecasts for the same series across different measures to compare forecasts for the same series across different models; the smaller the error, better the forecasting ability of that model according to that criterion. The remaining two statistics are scale invariant. Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit. The further decomposition of mean square yields following forecast evaluation indicators:

- The bias proportion tells us how far the forecast is from the mean of the actual series;
- The variance proportion tells us how far the variation of the forecast is from the variation of the actual series; and
- The covariance proportion measures the remaining unsystematic forecasting errors.
- Note that the bias, variance, and covariance proportions add up to one. If your forecast is good, the bias and variance proportion should be small so that most of the bias should be concentrated on the covariance proportions.

## 4: Data Source and Description:

Our aim is to model the amount of credit to private sector in Pakistan. The data of credit to private sector (denoted by CREDIT) is taken from the publications of State Bank of Pakistan (SBP) that is available on the website of SBP. The format of data is monthly from July 1990 to June 2010. To make the forecasting more precise dummy variables are introduced in order to capture the month's effect. M1 represents the effect of January, M2 represents the effect of February and so on up till M11, which represents November. Here December is taken as a reference category.

## 5: Result Estimation and Data Analysis

The first and the foremost thing while analyzing a time series data, is to plot it on a graph paper and check for the presence of either secular trend or seasonal variation. By looking at the time plot of the credit to private sector data, it shows that the credit increases over time, which indicates the presence of secular trend. The rising secular trend means that the credit data is not stationary at level. In order to forecast the future values of the credit to private sector, we must make the credit series non-stationary. We will use Augmented Dickey-Fuller (ADF) test for achieving this task. In the following Table, some summary statistics for the credit data are presented.

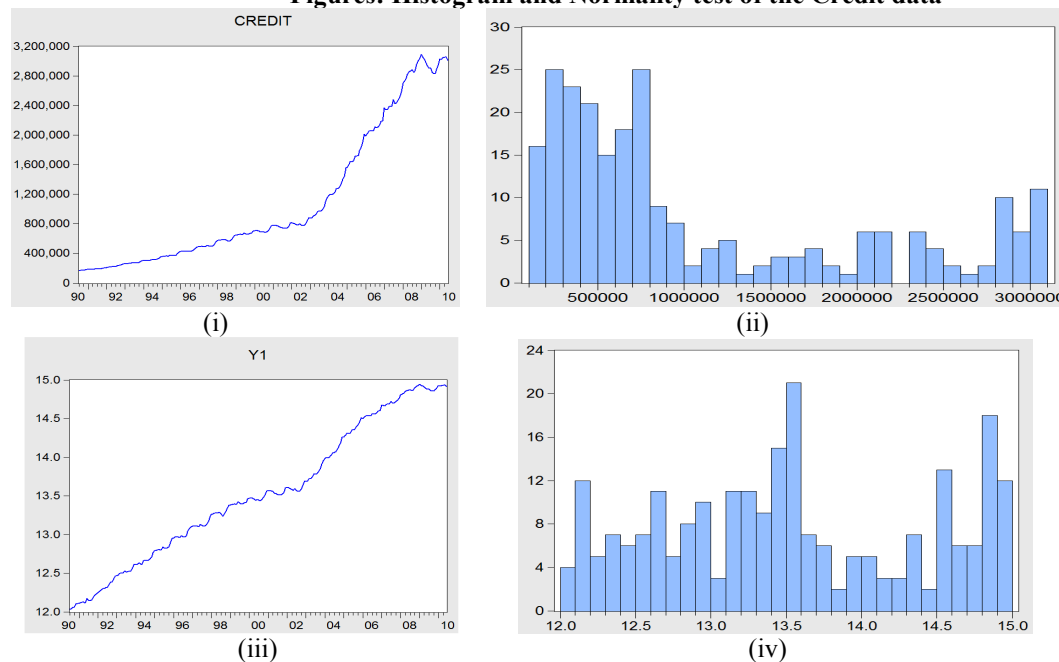


**Table 1: Summary Statistics of the data from July 1990 to June 2010**

Table 1: Summary Statistics		
	Credit	Log (Credit)
Mean	1088851	13.5332
Median	704263.5	13.4649
Maximum	3091176	14.94406
Minimum	168058	12.03206
S. D	924486.4	0.876506
Skewness	0.983542	0.106381
Kurtosis	2.517767	1.884216
Jarque-Bera	41.01968	12.90242
P-value	0.0000	0.001579

In the above Table, the average credit to private sector is 1088851 rupees that shows, on the average 1088851 rupees are given every month from July 1990 to June 2010. Minimum amount of credit given was 168058 rupees and maximum amount of credit was 3091176 rupees in this period. The Standard Deviation of credit between July 1990 and June 2010 is 924486.4 rupees and as the p-value is rejecting the null hypothesis so it means that the data is not normal. Given below is the histogram of the data. Moreover the average log(credit) to private sector is 13.5332 with minimum amount of log(credit) given was 12.032 and maximum amount of log(credit) was 14.944 in this period. The Standard Deviation of log (credit) between July 1990 and June 2010 is 0.876 and as the p-value is rejecting the null hypothesis so it means that the transformed data is not normal. Time plot and the histogram of the both variables Credit and Log of Credit data from July 1990 to June 2010 are given below:

**Figures: Histogram and Normality test of the Credit data**



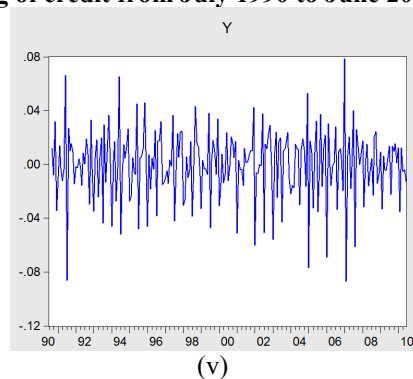
Due to high variation in the data, as evident from the histogram and from the high values of the standard deviation in the summary statistics Table, we will apply the log transformation to the credit data in order to reduce the high variation in the data. Let the variable Y1 denote the log of credit. Given below are the time plot and the summary statistics of Y1. From the transformed data now, there is a reduction in the variation of credit data after applying the Log transformation. Now we will use the correlogram for the Log of Credit data at level, which will be utilized for the purpose of the assessment of the stationarity of the variable under study. There are various ways for assessing the stationarity of a given time series. Some of the methods use subjective approach (like time plot and correlogram) while others use objective approach of parametric and non-parametric tests (like Augmented Dickey-Fuller ADF test or Philips-Perron PP test). We will adopt both of them. The correlogram showed that the log credit series is not stationary at the level as all the spikes of the Autocorrelation are outside with significant Q statistics. We will now apply the Augmented Dickey-Fuller test on this series at level for the sake of checking stationarity. Results are reported below:

**Table 2: Augmented Dickey-Fuller test applied to Log Credit data at Level**

		LEVEL		FIRST DIFFERENCE		SECOND DIFFERENCE	
		t-stat.	Sig.	t-stat.	Sig.	t-stat.	Sig.
ADF test Statistic		-3.07	0.1165	-1.95	0.6252	-14.60	0.0000
Test Critical Values:	1%	-3.99		-3.99		-3.99	
	5%	-3.43		-3.43		-3.43	
	10%	-3.14		-3.1384		-3.1384	

The null hypothesis of unit root of log credit data is not being rejected at 1%, 5% or even at 10% level of significance. So, we conclude that Y1 (log of Credit) contains the unit root i.e., it is not stationary at level. Then we have applied the unit root test to Y1 but at first difference. Again, the log credit data suffers with the problem of non-stationarity at first difference as the p-value of 0.6252 didn't reject the null hypothesis of unit root in the series. Then we applied the correlogram at first difference. Then Augmented Dickey-Fuller test applied to Y1 at Second Difference which showed that Y1 is stationary at second difference meaning that log credit data was I(2). The time plot of the differenced data is given as follows.

**Figure v: Time plot of log of credit from July 1990 to June 2010 at second difference**



Now all the variation is around zero which is the one of sign of stationarity.

## 5.1: ARIMA Modelling

### Step-1 Identification

Since the log credit data is stationary at second difference, so, in order to identify the possible Auto-Regressive (AR) terms and Moving-Average (MA) terms, we'll use the correlogram of Y (second difference of log of credit data) at second difference. From the close investigation of the applied correlogram, we can say that the AR terms of order 1,2,4,5,8,9,10,11 while MA terms of order 1, 6,7,12 should be utilized along with the dummy variables for month's effect in the ARIMA model.

Figure 4.12 Estimated ARIMA model—I

The general specification of ARIMA models with p auto-regressive terms and q moving average terms along with d differences is given as follows:

$$\Delta^d Y_t = \mu + \sum_{i=1}^p \Delta^d Y_{t-i} + \sum_{j=1}^q \varepsilon_{t-j} + \varepsilon_t$$

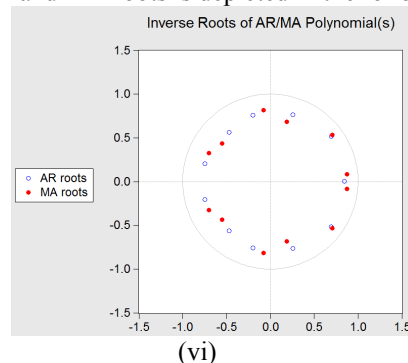
**Table 3: ARIMA Models**

Variable	Coefficient	t-Statistic	P-Value
<b>Constant</b>	0.00725	1.449229	0.1489
<b>January</b>	-0.034018	-3.889878	0.0001
<b>February</b>	-0.016723	-2.338337	0.0204
<b>March</b>	-0.005519	-0.829981	0.4076
<b>April</b>	-0.013165	-1.851512	0.0656
<b>May</b>	-0.01078	-1.323276	0.1873
<b>June</b>	0.0142	3.015512	0.0029
<b>July</b>	-0.029706	-3.627645	0.0004
<b>August</b>	-0.008509	-1.188732	0.236
<b>September</b>	0.00874	1.314647	0.1902
<b>October</b>	0.003086	0.431894	0.6663
<b>November</b>	0.004457	0.509853	0.3107
<b>AR-1</b>	-0.10183	0.091745	0.2763
<b>AR-2</b>	-0.074483	-0.86868	0.3861
<b>AR-5</b>	-0.085078	-1.098326	0.2734
<b>AR-8</b>	0.007092	0.082054	0.9347
<b>AR-9</b>	0.084059	0.97552	0.3305
<b>AR-10</b>	0.087189	1.010359	0.3136
<b>AR-11</b>	0.082533	1.063821	0.2887
<b>MA-1</b>	-0.867704	-14.43068	0.0000
<b>MA-6</b>	0.230293	2.888189	0.0043
<b>MA-7</b>	-0.286779	-3.197367	0.0016
<b>MA-12</b>	0.060157	1.21782	0.2248
<b>R-Squared</b>	0.70		
<b>Adjusted R-Squared</b>	0.66		
<b>Durbin-Watson</b>	1.9768		
<b>F-Statistic</b>	20.5436		
<b>P-Value</b>	0.0000		

From the above Table, the effect of January ,February ,April ,june ,july is significant while the effect Of March ,May ,August , September ,October ,November is insignificant. The AR lags are insignificant and at the lags of 1,6,7 of MA is significant. All the variables explains 70% variation in the model and the overall model is significant. Now to check the reliability of the model certain diagnostic checks have to be performed so that we could reach to the final model after doing some amendments. The diagnostic checks are as following:

### 5.2: ARMA Structure

The graph of the inverted AR and MA roots is depicted in the following figure.



Showing that all the inverse roots of AR and MA terms are inside the unit circle, meaning that the estimated AR model is stationary and the estimated MA model is invertible. To check the correlation of different lags we checked Correlogram of Residuals: From correlogram we came to know that At lags lower than 17, the standardized residuals are correlated. At higher lags the serial correlation among standardized residuals is insignificant. Now we will check the Correlogram of Squared Residuals: In correlogram of squared residuals all the AC and PAC of the squared standardized residuals are highly correlated at higher lags, indicating the possibility of ARCH effect in the data.

### 5.2.1. Serial Correlation LM test

For the possible presence of serial correlation in the mean equation, we apply the serial correlation Langrage Multiplier (LM) test.

#### Serial Correlation Lm Test

##### Breush-Godfrey Serial Correlation Lm Test

F-STATISTIC	1.2060	Prob.	0.2818
-------------	--------	-------	--------

The output of the Breusch-Godfrey serial correlation LM test suggests that there is no serial correlation in the standardized residuals as the p-value 0.2818 is higher than 0.05.

Heteroskedasticity LM test. Another diagnostic check is to check for the possible presence of heteroskedasticity in the mean equation. We have applied this test and results are as follows:

#### Heteroskedasticity LM Test

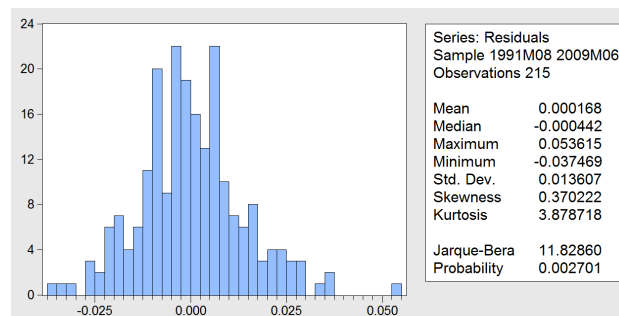
F-STATISTIC	2.6471	Prob.	0.0027
-------------	--------	-------	--------

We applied the ARCH-LM test to the standardized residuals, and we conclude on behalf of p-value 0.0027, that our ARIMA model contains the ARCH effect, as the squared residuals are serially correlated. We should use a suiTable ARCH/GARCH model.

### 5.2.2. Histogram Normality test

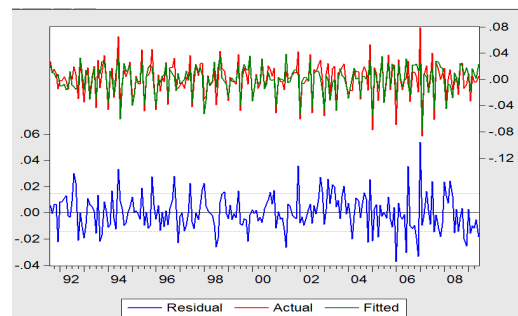
One of the assumption was the white noise residuals having zero mean and normal distribution. The following output gives us the histogram normality test of the residuals.

#### Histogram Normality test



(vi)

#### Examination of Residuals



(vii)

Residuals are not normal so our model is poor.

### 5.2.3. Examination of Residuals:

The graph of the actual and fitted residuals given above on the very right side gives us the picture of the model adequacy. Residuals plot suggests that our fitted residuals are capturing the effect of actual residuals. But due to the presence of ARCH effect in the estimated model, we cannot recommend to use ARIMA model for forecasting. So we have to build ARCH/GARCH Models to find the suiTable model for forecasting.

### 5.3: ARCH/GARCH Models:

When the ARCH effect is present in the estimated ARIMA models and is being detected either by ARCH-LM test or by the correlogram of the squared error terms. It is then become necessary not to rely solely upon the ARIMA models. Rather, we can utilize the more sophisticated class of ARCH and GARCH models. The GARCH(p,q) model with ARIMA(p,d,q) is given as follows:

$$\Delta^d Y_t = \mu + \sum_{i=1}^p \alpha_i \Delta^d Y_{t-i} + \sum_{j=1}^q \beta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\sigma_t^2 = \mu + \sum_{i=1}^p \varphi_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \omega_i \sigma_{t-i} + \nu_t$$

Mean Equation With ARIMA (p,d,q)

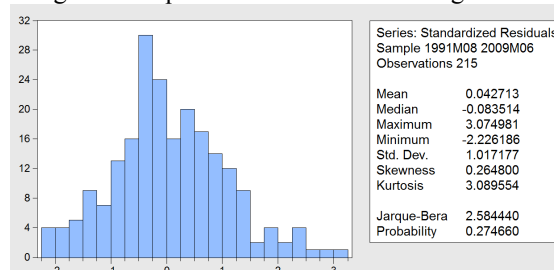
Variance Equation with GARCH (p,q)

**Table 4: ARCH/GARCH I Model**

Variable	Coefficient	t-Statistic	P-Value
Constant	0.011903	1.898697	0.0576
January	-0.049677	-4.958193	0.000
February	-0.017525	-2.011256	0.0443
March	-0.011737	-1.747065	0.0806
April	-0.017575	-0.171399	0.0098
May	-0.016301	2.318806	0.0299
June	0.015054	-4.481823	0.0204
July	-0.042015	-1.055961	0.000
August	-0.008613	0.426685	0.291
September	0.002913	-0.040787	0.6696
October	-0.000321	-0.077871	0.9675
November	-0.000736	-0.077871	0.9675
AR-1	-0.159511	1.426399	0.9379
AR-2	-0.081668	-0.882798	0.1538
AR-5	-0.051753	-0.956299	0.3773
AR-8	0.003929	0.057261	0.3389
AR-9	0.089416	1.251057	0.9543
AR-10	0.064898	1.0792	0.2098
AR-11	0.046043	0.581197	0.2805
MA-1	-0.712961	-8.576505	0.5611
MA-6	0.130725	2.220937	0.000
MA-7	-0.163115	-2.338184	0.0264
MA-12	0.138624	3.127789	0.0018
R-Squared	0.67		
Adjusted R-Squared	0.60		
Durbin-Watson	2.0880		
F-Statistic	10.1799		
P-Value	0.000		

**Explanation**

From the results given above, we can see that in mean equation, out of twelve months, only January, February, April, May, June and July are showing significant effect on the amount of credit and interestingly all of them are the first half of the year except July while the rest are not significant. As far as the auto-regressive and moving average terms are concerned, only moving average terms are significant (i.e., moving average terms of order 6, 7 and 12) while the auto-regressive terms are not of significant effect. Some diagnostics are also checked by Correlogram of Residuals, Correlogram of Squared Residuals and Histogram Normality test.



(viii)  
**ARCH-LM test**

Hetreoskadasticity Test			
F-Statistcs	1.4155	Probability	0.1615

**ARCH/GARCH Model—II**

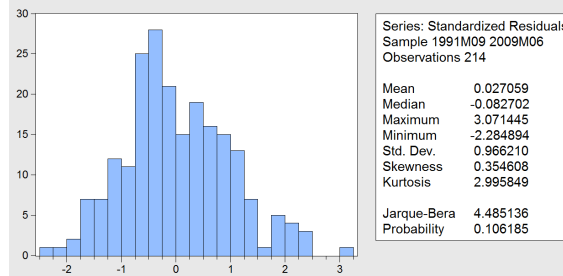
In the previous GARCH model, we have excluded the insignificant terms and come up with this new model. Here the number of parameters to be estimated are somewhat less than the previous model giving us a parsimonious model.

**Table 5: ARCH/GARCH II Model**

Variable	Coefficient	t-Statistic	P-Value
Constant	0.009392	5.70636	0.000
January	-0.046125	-6.705124	0.000
February	-0.012386	-2.063912	0.039
March	-0.009966	-1.630656	0.103
April	-0.0137	-2.604319	0.0092
May	-0.013431	-2.12613	0.0335
June	0.014239	1.967615	0.0491
July	-0.036254	-4.526387	0.000
August	-0.008498	-0.866334	0.3863
September	0.005072	0.621854	0.534
October	0.003932	0.500158	0.617
November	0.001588	0.230435	0.8178
AR-12	0.148652	2.157041	0.031
MA-1	-0.816278	-14.32838	0.000
MA-7	-0.06001	-1.119036	0.2631
<b>R-Squared</b>	0.657482		
<b>Adjusted R-Squared</b>	0.605641		
<b>Durbin-Watson</b>	2.21458		
<b>F-Statistic</b>	12.68276		
<b>P-Value</b>	0.000		

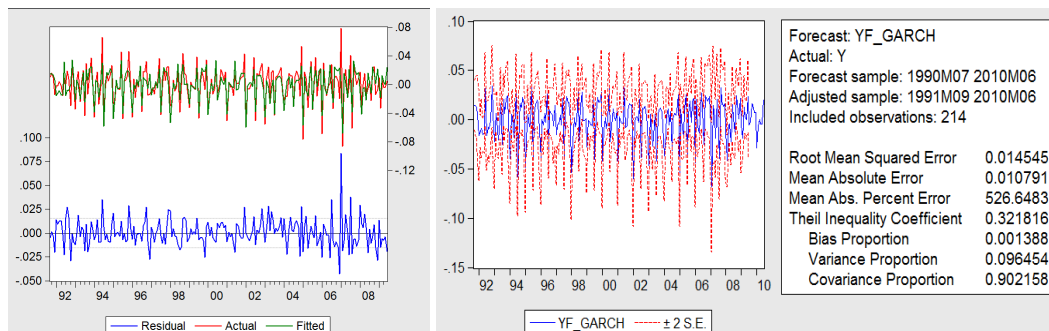
**Explanation**

With this new model of GARCH type, the months of January, February, April, May, June and July are showing significant impact on the average credit. While auto-regressive term of order 12 and moving average term of order 1 has also a significant effect on the average credit. There is also improvement in the R-squared and adjusted R-squared values and a decline in the residual sum of squares, which indicates that this model is far better than the previous model. Again same diagnostic checks are being performed.



(ix)

Hetreoskadasticity Test			
F-Statistics	1.4865	Probability	0.1320

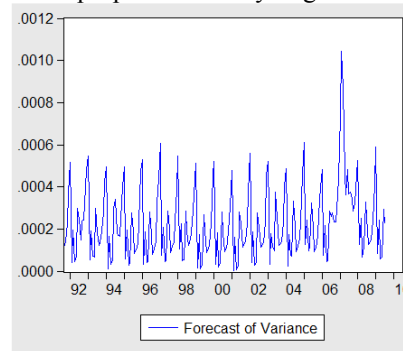


(x)

(xi)

As the blue lines are inside the boundaries of red lines (confidence interval) so the model is good. And the combined value of Bias Proportion, Variance Proportion and Covariance Proportion is approximately 1 which is

required for best fit and also the covariance proportion is very large indicating a good fit.



(xii)

The above Table gives us the forecast of the variance term in the estimated GARCH model.

## 6: Conclusion

As in this study an attempt has been made to develop a suitable time series econometric model for the forecasting of the credit to private sector data, in Pakistan. The relevant data has been obtained from the website of State Bank of Pakistan (SBP) regarding the amount of credit given to the private sector for the sake of economic activity and its development. The data thus obtained was of time series type in months starting from July 1990 to June 2010. Keeping in mind, the influence of months' effect, we have also introduced eleven dummy variables in our analysis, to address this issue. In order to develop a suitable forecast model for credit to private sector, we have firstly applied the famous Augmented Dickey-Fuller (ADF) test to check the level of integration as the data contains a secular trend. It has been observed through ADF test that the credit to private sector data has two unit roots (i.e., it is integrated of order 2). So, we have to take two differences, in order to eliminate I(2) process to I(0) level and making the data stationary for further analysis. As far as the choice of forecast models are concerned, we have started procedure from the simplest forecast models of ARIMA type proposed by Box and Jenkins. After estimating three to four ARIMA models, we come to know, that the ARIMA models contains ARCH effect, meaning the standardized squared error terms are correlated to each other. Thus, making room for the sophisticated ARCH and GARCH econometric models for the purpose of forecasting. Next, we have compared two GARCH(1,1) models on the basis of various diagnostic checks discussed briefly in chapter four, and come up with a final model. In the final model, we have some significant AR and MA terms of specific order along with influential months of the year that describe the possible patterns in the credit to private sector data. Some forecasts have been generated and from forecast evaluation criterions, the choice of final model has been justified. It has been found that the months of January, February, April, May, June and July are the significant months explaining the variation in the credit data along with AR term of order 12 and MA terms of order 1 being significant.

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