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Modeling and Forecast of Stock Prices for Several Banks in ISE

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FEN – EDEBİYAT FAKÜLTESİ

BİTİRME TEZİ

BİST'teki Bazı Bankalar için Hisse Senedi Fiyatı Modellemesi ve Tahmini

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Cenan KARALİ

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SUMMARY

In recent years, forecasting is becoming more and more important for investment strategies. Before doing forecast, data must be prepared for forecasting by analyzing and modeling with suitable models. While volatility is seen mostly in financial data, the model used for forecasting must calculate the volatility factor. Academic researches show that ARCH/GARCH models with ARMA calculations give better results for volatility modeling.

In [1], volatility is modeled with different types of ARCH/GACH models for XU100 daily data and GARCH model gives better results. On the other side, Switching ARCH (SWARCH) is found more suitable for weekly closing of XU100 index in [2]. And in [3], while EGARCH is used for US Dollar, TARCH is a better model for Euro currencies.

In this thesis, we concentrate to make an application of forecast of stock prices for one month, by using 2003-2012 daily closing of stock price of four banks, AKBNK (AK BANK), GARAN (GARANTİ BANK), ISCTR (İŞ BANK) and YKBNK (YAPI – KREDİ BANK). Firstly, theoretical background was given according to academic literature. After that, application part was started. A demo version of E-views, which is a statistical package, was used. Data of four banks were analyzed and modeled separately. Akaike Information Criteria (AIC) and Bayesian (Schwarz) Information Criteria (BIC) were considered while deciding to the model. AR(1) and EGARCH(1,1,1) models had the smallest Akaike Information Criteria and Bayesian Information Criteria values. So, these models were used for modeling the data.

Forecast was done after best model had been reached. At first, last five days were selected as forecast sample and five forecast values were obtained. These five forecast value were added to the end of the modeled data and then all data was modeled and forecasted again. This process was repeated three times and 20 forecast values were obtained for January 2013. Finally, these obtained forecast values were compared with real data of January 2013. All these applications were showed with graphs and tables.

ÖZET

Son yıllarda, yatırım stratejileri için, öngörü giderek daha önemli olmaktadır. Öngörü yapmadan önce, veriler analiz edilerek ve modellenerek öngörü için hazırlanmalıdır. Volatilite en çok finansal verilerde görüldüğünden, öngörü için kullanılan model öngörü faktörünü hesaba katmalıdır. Akademik araştırmalar ARMA hesaplamalı ARCH/GARCH modellerinin volatiliteyi modellemede daha iyi sonuçlar verdiğini göstermektedir.

[1]'de volatilite, İMKB100 günlük verileri için farklı türdeki ARCH/GARCH modelleriyle modellenmiş ve GARCH modeli daha iyi sonuç vermiştir. Diğer yandan, [2]'de Switching ARCH (SWARCH) modeli İMKB100 endeks haftalık kapanış verileri için daha uygun bulunmuştur. [3]'de, EGARCH modeli ABD Doları için kullanılırken, TARCH Euro için daha iyi bir model olmuştur.

Biz bu tezde, dört bankanın, AKBNK (AK BANK), GARAN (GARANTİ BANKASI), ISCTR (İŞ BANKASI) ve YKBNK (YAPI – KREDİ BANKASI), 2003 – 2012 günlük kapanış hisse senedi fiyatlarını kullanarak, bir aylık öngörü uygulaması yaptık. Öncelikle, akademik literature gore teorik altyapı verildi. Daha sonra uygulama kısmı başladı. Bir istatistiksel paket olan E-views'un demo versiyonu kullanıldı. Dört bankanın verileri ayrı ayrı analiz edildi ve modellendi. Modele karar verirken Akaike Bilgi Kriteri (AIC) ve Bayezyen (Schwarz) Bilgi Kriteri (BIC) göz önüne alındı. AR(1) ve EGARCH(1,1,1) modelleri en küçük Akaike Bilgi Kriteri ve Bayezyen Bilgi Kriteri değerlerine sahiptir. Bu yüzden verileri modellemek için bu modeller kullanıldı.

En iyi model elde edildikten sonra öngörü yapıldı. Öncelikle son beş gün öngörü aralığı olarak seçildi ve beş öngörü değeri elde edildi. Bu beş öngörü değeri, modellenmiş verilerin altına eklendi ve bütün veriler tekrar modellendi ve öngör yapıldı. Bu süreç üç kez tekrar edildi ve Ocak 2013 için 20 öngörü değeri elde edildi. Sonuçta, elde edilen bu değerler Ocak 2013'ün gerçek değerleriyle karşılaştırıldıç Bütün bu uygulamalar grafikler ve tablolarla gösterildi.

INTRODUCTION

Forecasting for stock prices is the process of estimation about future values of stock certificates. Making Forecasting by using suitable mathematical models is very important for investment strategies. Good forecast depends on a good model. Stochastic and deterministic parts of data must be analyzed as good as possible while trying to define a good model.

Forecasting can be done according to model that used when modeling the data. These models, called Autoregressive (AR) Model, Moving Average (MA) Model and the combination of these two models, Autoregressive Moving Average (ARMA) Model, utilized according to the correlogram of the data. If the data has volatility, AR models gives better results when forecasted.

There are many academical researchs about forecasting of financial and stock price data. According to many researchs, most of financial data (financial data include stock price data.) have volatility. In literature financial data with volatility are forecasted by using ARCH, GARCH, EGARCH, TARCH models.

In [1], it can be seen a large application of ARCH, GARCH, EGARCH, TARCH models with ARMA calculations to XU100 daily data. This application is used to analyzed valuation and forecast capacity of ARCH model and its types. This article shows that GARCH and ARMA models are successful for modeling volatility.

Volatility of XU100 index weekly closing data is forecasted with ARCH, GARCH and Switching ARCH (SWARCH) models in [2]. According to empirical results of the application, performance of alternative forecast models are compared and this search says that SWARCH model gives better results than ARCH and GARCH models for this data.

In [3], return series of foreign currencies are forecasted with ARCH models. In this article, US Dollar and Euro prices are used for the application part. After applying different types of ARCH models to the data, the best solution for US Dollar is found at AR and EGARCH models and Euro has the best result at AR and TARCH models.

The objective of this thesis is to evaluate future stock price of AK BANK (AKBNK), GARANTI BANK (GARAN), IS BANK (ISCTR), YAPI-KREDI BANK (YKBNK) in ISE by modeling historical data with GARCH models. Historical daily closing stock price values of these four banks for ten years are used for the application part. If there will be a good and clear result then successful investment can be attained about the four Banks in ISE.

In second section, we give fundamental information about theoretical background of volatility and modeling. In third section, forecast methods are introduced. In fourth section, our data is presented, compared, modeled and forecasted and the graphs of these applications are given. In fifth section, we give the conclusion of the thesis.

2. THEORITICAL BACKGROUND

2.1. Volatility

Volatility means the spread of all probably results of an uncertain variable. Especially, in financial markets, we are often faced with the spread of entity returns. Statistically, volatility is often calculated like standard deviation

$$\sigma' = \sqrt{\frac{1}{T-1}\sum_{T=1}^{T}(r_t - \mu)^2}$$

where r_t is the return on day t, and μ is the average return over the T –day period.

Sometimes, variance, σ^2, is used to calculate volatility. Since variance is the square of standard deviation, it does not matter which one is used for comparing the volatility of two assets. However, variance is much less stable and less admirable than standard deviation and it is not good for using computer prediction and volatility forecast evaluation. Furthermore, standard deviation is expressed in the same unit of measure like mean, so variance is expressed in the square of that unit. Therefore, standard deviation is more suitable and intuitive for volatility measuring. [4]

2.1.1. Historical Volatility

The historical volatility is the volatility of a stock prices obtained from the historical prices of a special stock. As it said above, the mostly used way is standard deviation. Therefore, the historical volatility is estimated as

$$\sigma = \sqrt{1/(n-1)\sum_{i=1}^{n}(u_i - \bar{u})^2}$$

where $\bar{u}$ is defined by

$$\bar{u} = 1/n \sum_{j=1}^{n} u_j$$

σ gives the estimated volatility per interval. Volatility is generally expressed in annual terms to do it independent from the interval lengths. To do this, estimation is measured with an annualization factor (make normal constant) *h*, the number of intervals per annum such that

$$\sigma_{an} = \sigma * \sqrt{h}$$

2.1.2. Implied Volatility

An option pricing model (like the *Black & Scholes* model) gives a theoretical price for an option as a function of the exact parameters — constant volatility being one. However, if the option is traded, the market price might be different from the model price. In that case it may be asked that, which volatility estimate should be used in the model so that the model price and the market price are the same? This is the implied volatility. In a constant volatility construction, implied volatility is the volatility of the underlying asset price that is definite in the market price of an option according to a specific model. [5]

2.2. Augmented Dickey-Fuller Unit Root Tests

Augmented Dickey-Fuller t-statistic is used for deciding to difference time series to make it stationary.

If the time series is stationary (i.e. doesn't have a trend) and tends to slow-turning around zero, the following test equation can be used:

$$\Delta z_t = \theta z_{t-1} + \alpha_1 \Delta z_{t-1} + \alpha_2 \Delta z_{t-2} + \cdots + \alpha_p \Delta z_{t-p} + a_t$$

where the number of augmenting lags (p)is determined by minimizing the Schwartz Bayesian information criterion or minimizing the Akaike information criterion or lags are dismissed until the last lag is statistically meaningful. The t-statistic combined with the ordinary least squares estimate of θ, is used for the test and it is called the Dickey-Fuller t-statistics. The Dickey-Fuller t-statistic does not follow a standard t-distribution as the sampling distribution of this test statistic is skewed to the left with a long, left-hand-tail. The test is left-tailed. The null hypothesis of the Augmented Dickey-Fuller t-test is

$H_0 : \theta = 0$ (i.e. the data must be differenced to be stationary)

versus the alternative hypothesis of

$H_1 : \theta < 0$ (i.e. the data is trend stationary and does not need to be differenced)

If the time series is stationary and tends to slow-turning around a non-zero value, the following test equation can be used:

$$\Delta z_t = \alpha_0 + \theta z_{t-1} + \alpha_1 \Delta z_{t-1} + \alpha_2 \Delta z_{t-2} + \cdots + \alpha_p \Delta z_{t-p} + a_t$$

This equation is suitable for time series which has an intercept term but no time trend. Again the number of augmenting laps (p) is determined by minimizing the Schwartz Bayesian information criterion or minimizing the Akaike information criterion or lags are dismissed until the last lag is statistically meaningful. The t-statistic may be used on the θ coefficient to decide whether data should be differenced to be stationary or not. The test is left-tailed. The null hypothesis of the Augmented Dickey-Fuller t-test is

$H_0 : \theta = 0$ (i.e. the data should be differenced to be stationary)

versus the alternative hypothesis of

$H_1 : \theta < 0$ (i.e. the data is trend stationary and does not need to be differenced)

If the time series has an upward or downword trend in it and tends to slow-turning around a trend line you would draw throgh the data, the following test equation can be used :

$$\Delta z_t = \alpha_0 + \theta z_{t-1} + \gamma t + \alpha_1 \Delta z_{t-1} + \alpha_2 \Delta z_{t-2} + \cdots + \alpha_p \Delta z_{t-p} + a_t$$

This equation has an intercept term and a time trend. Again, the number of augmenting laps (p) is determined by minimizing the Schwartz Bayesian information criterion or minimizing the Akaike information criterion or lags are dismissed until the last lag is statistically meaningful. The t-statistic may be used on the θ coefficient to decide whether data should be differenced to be stationary or a time trend is needed to put in the regression model to correct for the variables deterministic trend. The test is left-tailed.

The null hypothesis of the Augmented Dickey-Fuller t-test is

$H_0 : \theta = 0$ (i.e. the data should be differenced to be stationary)

versus the alternative hypothesis of

$H_1 : \theta < 0$ (i.e. the data is trend stationary and needs to be analyzed by means of using a time trend in the regression model instead of differencing the data) [6]

2.3. AR & MA Models

2.3.1. Autoregressive Model

One of the most commonly used way for modeling time series is the AR model. The background of this model is that the observed time series X_t depends on a weighted linear sum of the past values, *p*, of X_t and a random shock ε_t, Therefore, the name "autoregressive" comes from this idea.

Technically, AR(p) model can be formulated by the following equation:

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \varepsilon_t,$$

where X_t shows the time-series and ε_t implies a white-noise process. The value of *p* is called the order of the AR model. If $p = \infty$ then the process is called infinite AR process.

So, an autoregressive model means a linear regression of the current value of the series against one or more previous values of the series. Therefore the model might be compared with other methods with the standard linear least squares technique, where the resulting estimation of the parameters, Φ_p, has a straight forward interpretation.

Often in the literature, AR(p) model is expressed with the lag operator, *L*, which is defined as

$$LX_t = X_{t-1}$$

Consequently $L(LX_t) = L^2 X_t = X_{t-2}$ and therefore in general $L^s X_t = X_{t-s}$ and $L^0 X_t = X_t$ this means operating *L* on a constant leaves the constant unaffected. With the lag operator, an AR(1) model $X_t = \Phi X_{t-1} + \varepsilon_t$ can be showed in the following way:

$X_t = \Phi X_{t-1} + \varepsilon_t \Leftrightarrow X_t(1 - \Phi L) = \varepsilon_t$

Similarly, a general form of the AR(p) model is

$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \varepsilon_t,$

or, with the lag operator:

$X_t = \Phi_1 LX_t + \Phi_2 L^2 X_t + \cdots + \Phi_p L^p X_t + \varepsilon_t$

$X_t = X_t(\Phi_1 L + \Phi_2 L^2 + \cdots + \Phi_p L^p) + \varepsilon_t$

$X_t\left(1 - \Phi_1 L + \Phi_2 L^2 + \cdots + \Phi_p L^p\right) = \varepsilon_t$

in the brief form: $X_t \Phi(L) = \varepsilon_t$, where $\Phi(L)$ is a polynomial of order p in the lag operator:

$\Phi(L) = 1 - \Phi_1 L + \Phi_2 L^2 + \cdots + \Phi_p L^p$

2.3.2. Moving Average Model

Another most commonly used way for modeling time-series is the MA model. The background of this model is that the observed time-series X_t depends on a weighted linear sum of past, *q*, random shocks. This means that at period *t* a random shock ε_t is activated and this random shock is independent of random shocks of other periods. The observed time-series X_t is then generated by a weighted average of current past shocks – so the name of model is "moving average".

Technically, MA(q) model can be expressed with the following equation:

$X_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q},$

where X_t is the time–series and ε_{t-q} implies to a white-noise process. The value of *q* is called the order of the MA model. If q=∞ then the process is called infinite MA process.

So a MA model means a linear regression of the current value of the series against the random shocks of one or more previous values of the series. Since moving average model is based on the unobservable error terms, fitting a moving average model is more complicated than fitting an autoregressive model. Therefore in opposite to an AR model, itterate non-linear fitting process has to be utilized and the resulting estimation of the parameters has a less obvious comment than in the case of AR models.

As before, MA model is also can be expressed with the lag operator in the following way:

$X_t = \theta(L)\varepsilon_t,$

where $\theta(L)$ is a polynomial of order q in the lag operator

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q.$$

2.3.3. Autoregressive Moving Average (ARMA) Model

Box and Jenkins (1970) developed a systematic methodology for combining two processes which were given below and originally investigated by Yule. An ARMA model occur from his name of two components: the weighted sum of past values (autoregressive component) and the weighted sum of past errors (moving average component). An ARMA model of order (p,q) can be expressed as in the following equation:

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

Since both AR and MA models are stationary, the ARMA process is also stationary, if the roots of the polynomial $\Phi(z) = 0$ lie outside unit circle. This is the only condition, as every MA(q) process is stationary. In contrast, an ARMA process is called invertible, if the roots of $\theta(z) = 0$ lie outside the unit circle, this is the only condition as every AR(p) process is invertible. [7]

2.4. ARCH, GARCH & EGARCH Models

2.4.1. Autoregressive Conditional Heteroscedasticity Model

The autoregressive conditional heteroscedasticity is utilized for modeling financial time series. It is presented by Robert F. Engle in 1982.

Consider the following simple scalar model

$$y_t = \mu + e^t, t = 1, \ldots, T$$

$$e^t = z_t \sigma_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i e_{t-i}^2 = \omega + a(L) e_t^2$$

where $\alpha_1, \ldots, \alpha_q, \mu$ and ω are scalar parameters to be predicted. z_t is thought to have mean zero and variance one, and is often (but not always) supposed to be normally distributed. ω and α_i have to be assumed all positive for obtaining positive values for the estimate of the condition variance.

2.4.2. Generalized Autoregressive Conditional Heteroscedasticity Model

Generalized autoregressive conditional heteroscedasticity model is presented by Tim Bollerslev (1986). It is an upper version of autoregressive conditional heteroscedasticity model.

Let the $e_{t=}\sigma_t$ as before, but now let

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2$$

which is a natural generalization corresponding to an ARMA model for the variance. This model is called a GARCH(p,q) model. Also in the GARCH model, parameters must be restricted to be positive, which guarantees a positive prediction of the conditional variance. More compactly;

$$\sigma_t^2 = \omega + b(L)\sigma_t^2 + a(L)e_t^2$$

If the variance process follows the equivalent of an ARIMA model, allowing for unit roots in the lag polynomials, in that case where

$$\alpha_1 + \ldots + \alpha_q + \beta_1 + \ldots + \beta_p = 1$$

they refer to the model as an IGARCH(p,q) model.

2.4.3. Exponential Autoregressive Conditional Heteroscedasticity Model

A constraint of the GARCH models is that it limits the shocks to the model to have the same effect on the conditional variance whether the shocks are negative or positive. This may or may not be a reasonable assumption but it is testable. Since it rules out cyclic attitude in the conditional variance, the positivity constraints on the parameters can also be considered restrictive. For those reasons Nelson (1991) suggests the EGARCH(p,q) model:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \log(\sigma_{t-i}^2) \sum_{i=1}^{q} \alpha_i(\varphi z_{t-i} + \gamma[|z_{t-i}| - E|z_{t-i}|])$$

In the EGARCH the parameters do not have to be not positive. The term $|z_{t-i}| - E|z_{t-i}|$ is positive if the error term is larger than its expected value and negative otherwise. For $\log(\sigma_t^2)$, other models can also be used but for the specific model suggested by Nelson, he shows that the model seems to behave well asymptotically. [8]

3. FORECAST

According to Chatfield (2001), a forecasting method is described as in the following way: Let $x_1, x_2, \ldots, x_N$ be observations on a single time series and x_{N+h} values is going to be forecasted for h=1,2,…. Then the process of calculation a point forecast, $\hat{x}_N(h)$, which is based only on past and present values of the given series is called a forecasting method.

3.1. Model-Based Forecasting

Forecast will be calculated after having identified a particular model for the time series and predicted the model parameters, by using the fitted model (M denotes the true model, M_f fitted model). The best way to calculate a forecast is to choose $\hat{x}_N(h)$ to be the expected value of X_{N+h} conditional on the model, M, and on the information available at time N, which will be denoted by I_N :

$$\hat{x}_N(h) = \mathrm{E}(X_{N+h} | \mathrm{M}, I_N),$$

where I_N consists for a procedure of $x_N, x_{N-1}, \ldots$ plus the current value of time, namely N.

3.1.1. Linear Model: Autoregressive (AR) Models

The estimation is done as in the following equation:

<u>One step forecast:</u> $\ddot{X}_{t-1}(1) = \ddot{\Phi}_1 X_{t-1} + \ddot{\Phi}_2 X_{t-2} + \cdots + \ddot{\Phi}_p X_{t-p}$ where the true coefficients are replaced by in-sample estimates Φ’$_j$

<u>Two step forecast:</u> $\ddot{X}_{t-1}(2) = \ddot{\Phi}_1 \ddot{X}_{t-1}(1) + \ddot{\Phi}_2 X_{t-1} + \cdots + \ddot{\Phi}_p X_{t-p+1}$ where the unknown observation X_t is changed with its estimation $\hat{X}_{t-1}(1)$. For longer periods, predictions will converge to the long run mean which must be zero in the end.

Specifying AR models with a constant term:

$$X_t = \mu + \Phi_1 X_{t-1} + \cdots + \Phi_p X_{t-p} + \varepsilon_t$$

And with a mean:

$$EX_t = \frac{\mu}{1 - \Phi_1 - \cdots - \Phi_p} = \frac{\mu}{\Phi(1)}$$

(Case of $\Phi(1) = 0$ has been excluded)

3.1.2. Linear Model: Moving Average (MA) Models

Forecasting an MA model needs the prediction of the coefficients θ_j from the sample after having defined the lag order q. The visual inspection of correlograms or information criterias can be used for defining the lag order q. By maximizing the likelihood or by approximating computer algorithm predictions for coefficients θ_j can be obtained, but also predictions of the error terms ε_t have to be calculated with some computer algorithm.

One step forecast(if $\hat{\theta}_j$ and $\hat{\varepsilon}_t$ are available):

$$\hat{X}_{t-1}(1) = \hat{\theta}_1 \hat{\varepsilon}_{t-1} + \hat{\theta}_2 \hat{\varepsilon}_{t-2} + \cdots + \hat{\theta}_q \hat{\varepsilon}_{t-q}$$

Two step forecast:

$$\hat{X}_{t-1}(2) = \hat{\theta}_2 \hat{\varepsilon}_{t-1} + \hat{\theta}_3 \hat{\varepsilon}_{t-2} + \cdots + \hat{\theta}_q \hat{\varepsilon}_{t-q+1},$$

This means that some steps later, forecast values will be trivially zero.

3.1.3. Linear Model: Autoregressive Moving Average (ARMA) Models

Forecasting with parsimonious (parsimonious: representation with minimum number of free parameters) ARMA models could be exciting if it the sample is a small sample and some parameters set to zero while normally different from zero could lead to better predictions than models correctly including all parameters. Autocorrelation function and partial autocorrelation functions result is determined zero at a geometric rate for ARMA processes. To decide the lag orders p and q is difficult by looking to the visual inspection of correlograms and partial correlograms; therefore in the literature it is sometimes said to decide by considering the extended versions of the correlogram (extended ACF, extended sample ACF) and most set lag order by information criteria.

One step forecast (if $\hat{\theta}_j$ and $\hat{\Phi}_j$ are estimated, maximum likelihood approximated and approximate errors $\hat{\varepsilon}_t$ calculated):

$$\hat{X}_{t-1}(1) = \hat{\Phi}_1 X_{t-1} + \cdots + \hat{\Phi}_p X_{t-p} + \hat{\theta}_1 \hat{\varepsilon}_{t-1} + \hat{\theta}_2 \hat{\varepsilon}_{t-2} + \cdots + \hat{\theta}_q \hat{\varepsilon}_{t-q}$$

Two step forecasts:

$$\hat{X}_{t-2}(2) = \hat{\Phi}_1 \hat{X}_t(1) + \hat{\Phi}_2 X_{t-1} + \cdots + \hat{\Phi}_p X_{t-p} + \hat{\theta}_2 \hat{\varepsilon}_{t-1} + \cdots + \hat{\theta}_q \hat{\varepsilon}_{t-q+1}$$

[7]

3.2 Static vs. Dynamic Forecasting

While doing forecasting, two different way can be used:

Dynamic version calculates forecasts for the periods after the first period by using the values which are the previously forecasted results of the lagged left-hand. These are also called n-step ahead forecasts.

Static version do the forecast with actual values rather than forecasted values (it can only be used when actual data are available). These are also called 1-step ahead or rolling forecasts. [12]

4. APPLICATION

4.1 DATA

For the application part, daily closing stock prices of four banks in ISE, which are AKBNK, GARAN, ISCTR and YKBNK are used. Stock prices graphs are drawn for each bank separately year by year.

Firstly, AKBNK' s daily closing stock prices are analyzed yearly and their graphs are given below.

AKBNK (AK BANK)

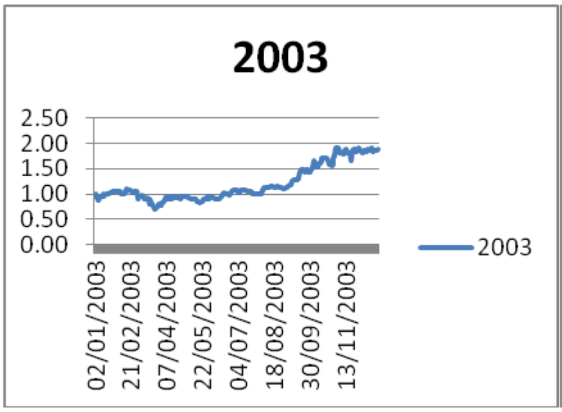


Figure 3.1 : AKBNK 2003 Stock Prices

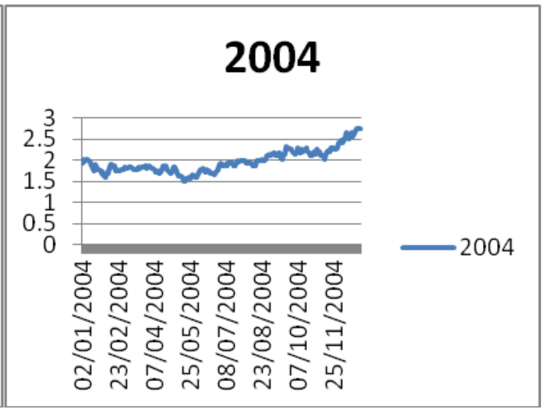
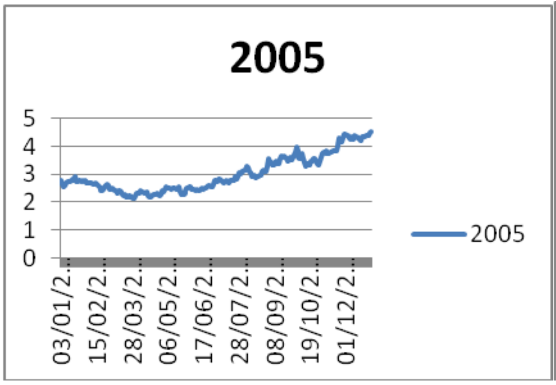


Figure 3.2: AKBNK 2004 Stock Prices

When we look at the first two years, we can see the increase of stock prices. A trend would be seen at both years' graphs.



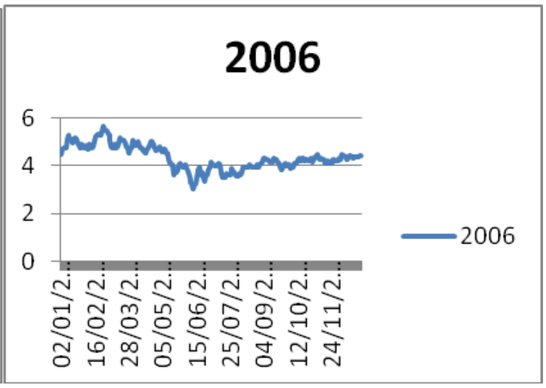
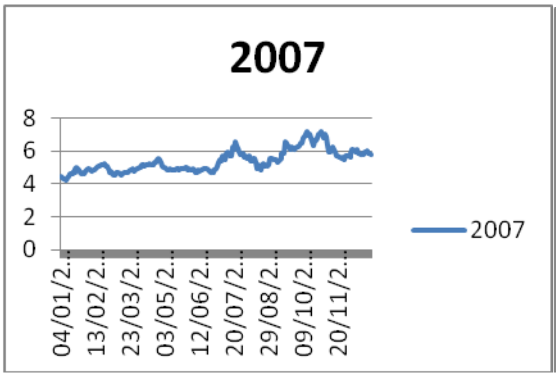


Figure 3.3 : AKBNK 2005 Stock Prices

Figure 3.4: AKBNK 2006 Stock Prices

At 2005's graph stock prices continue to rise. But in 2006 they are said to be decreased.



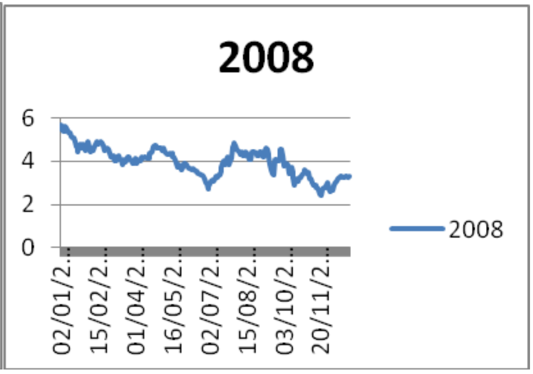
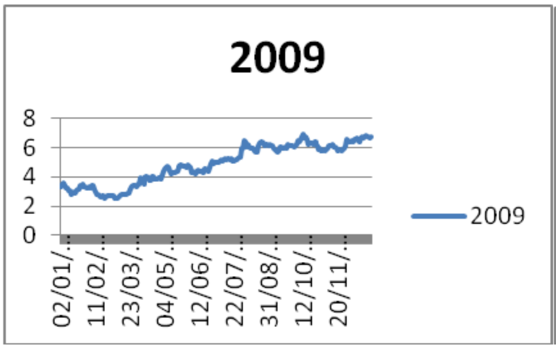


Figure 3.5 : AKBNK 2007 Stock Prices

Figure 3.6 : AKBNK 2008 Stock Prices

In 2007, prices again start to increase. But in 2008, they are seen to decrease again. This decrease may be caused by the economical crises which occurred in this year and affected nearly all the countries.



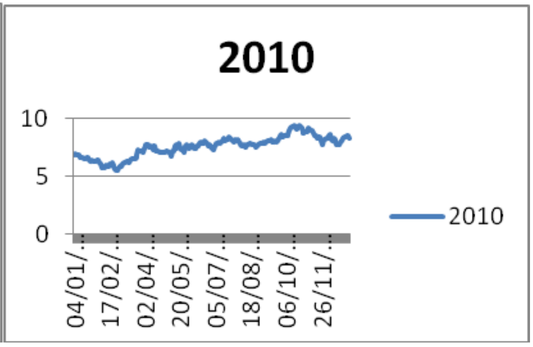


Figure 3.7 : AKBNK 2009 Stock Prices

Figure 3.8 : AKBNK 2010 Stock Prices

Effects of economical crises are seen to be eliminated in 2009. Prices increase after the first quarter of the year. The rise also can be seen in 2010 but increment range is not so wide.

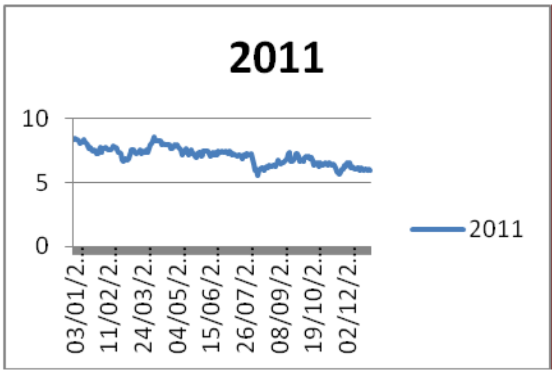


Figure 3.9 : AKBNK 2011 Stock Prices

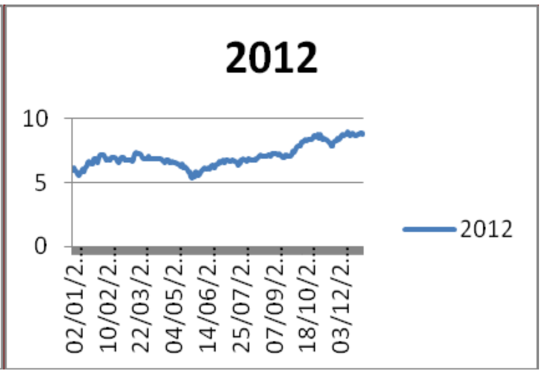


Figure 3.10 : AKBNK 2012 Stock Prices

From the 2011's graph a slow decrease is seen. But in the last year the graph caught the trend again and the values rise nearly up to 2011's beginning values.

Figure 3.41: AKBNK 2003 – 2012 Stock Prices

When we look at the whole values, in some ranges a decline of stock prices can be seen. In a small part of 2006, in 2008 and in 2011 prices decrease more sharply than the other years. But in the whole perspective AKBNK' s stock prices show upward trend and in 10 years prices become nine times larger than the beginning value.

GARAN (GARANTI BANK)

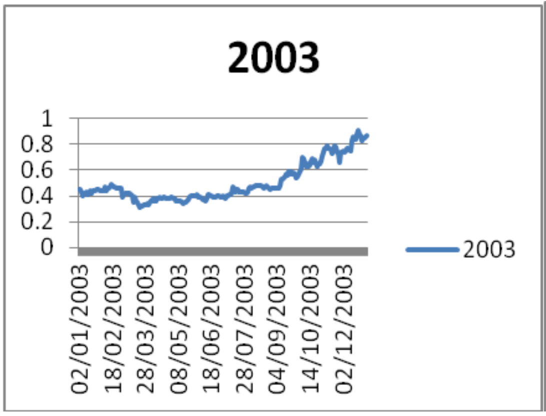


Figure 3.11: GARAN 2003 Stock Prices

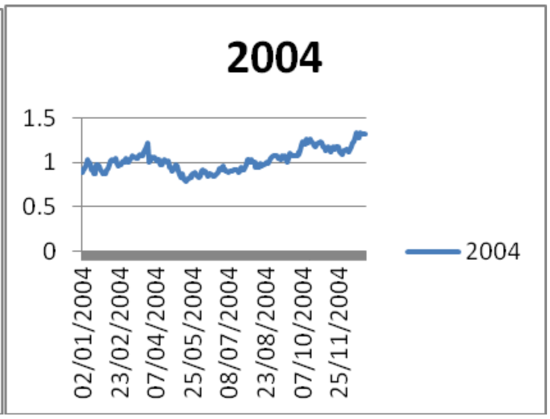


Figure 3.12: GARAN 2004 Stock Prices

GARAN' s stock prices show a visible increase in the first year. But in the second year its increase become slower.

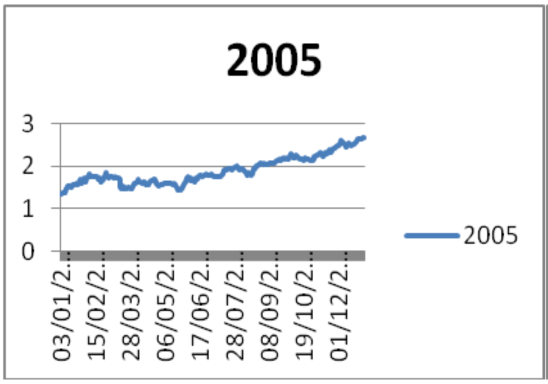


Figure 3.13: GARAN 2005 Stock Prices

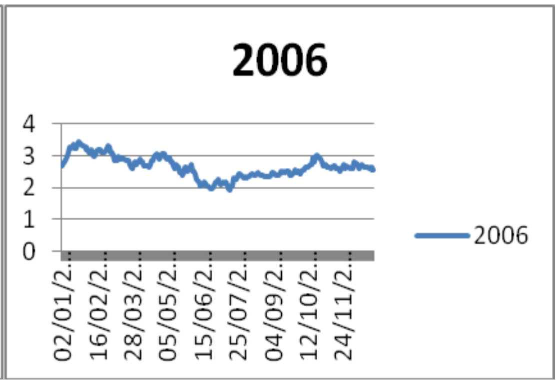


Figure 3.14: GARAN 2006 Stock Prices

The rise also continues in 2005. But it turns down in 2006 and prices start to decrease.

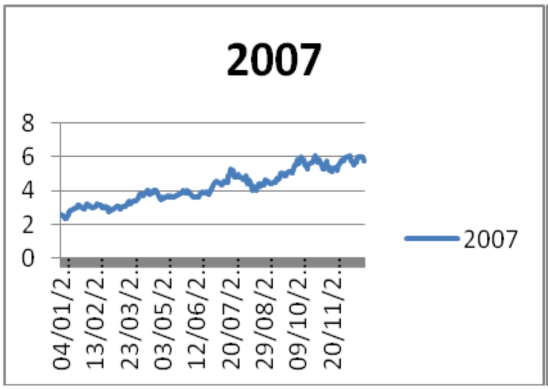


Figure 3.15: GARAN 2007 Stock Prices

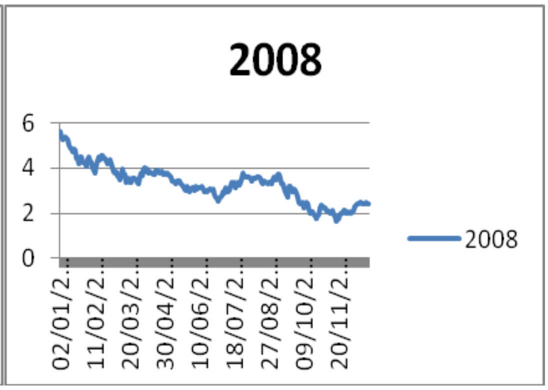


Figure 3.16: GARAN 2008 Stock Prices

Although stock prices increase in 2007, the economical crise's negative effect is seen again in 2008's values.

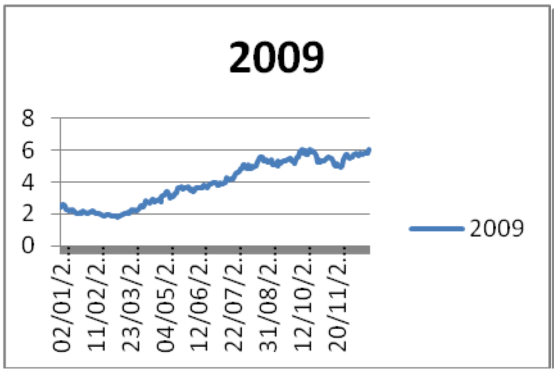


Figure 3.17: GARAN 2009 Graph

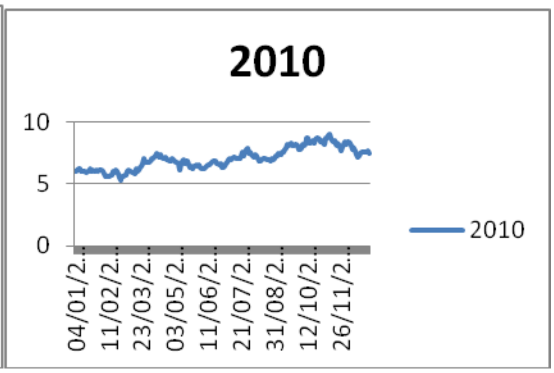


Figure 3.18: GARAN 2010 Graph

After 2008, GARAN gets over the effect of crises and its stock prices increase again along the 2009 and 2010.

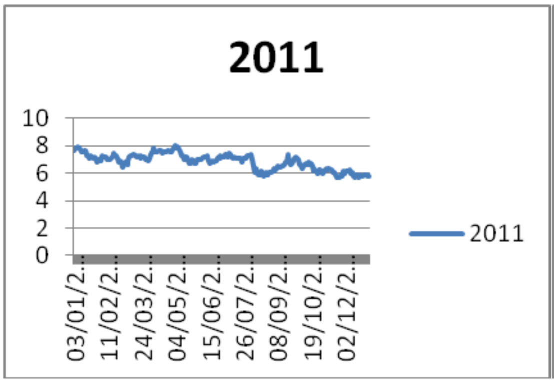


Figure 3.19: GARAN 2011 Stock Prices

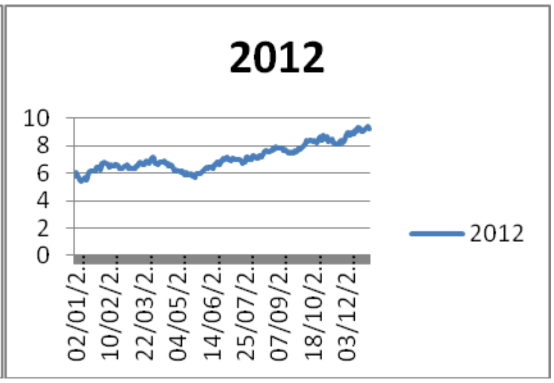


Figure 3.20: GARAN 2012 Stock Prices

Though we see a slow decline in prices in 2011, in the last year GARAN also catch the upward trend as AKBNK.

Figure 3.42: GARAN 2003 - 2012 Stock Prices

The whole behavior of GARAN' s stock prices seems like have an upward trend. In a part of 2006, in 2008 and in 2011 sharp declines can be seen. But GARAN increase its stock prices nearly ten times larger in 10 years.

ISCTR (IS BANK)

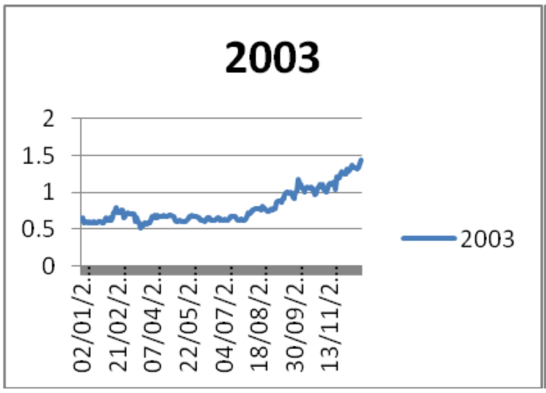


Figure 3.21: ISCTR 2003 Stock Prices

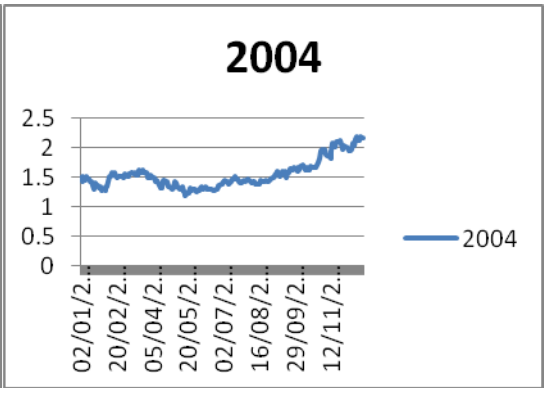
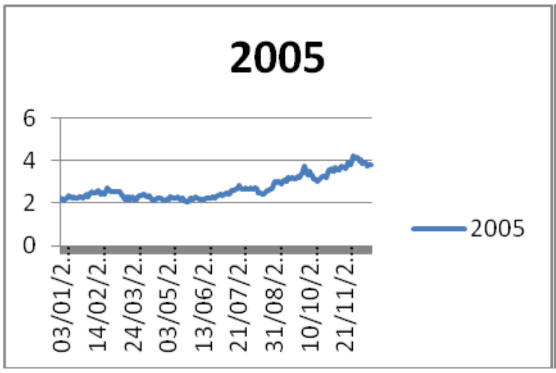


Figure 3.22: ISCTR 2004 Stock Prices

At the end of the first year, ISCTR stock prices become three times larger than the beginning of the year. The second year this increase continues slowly.



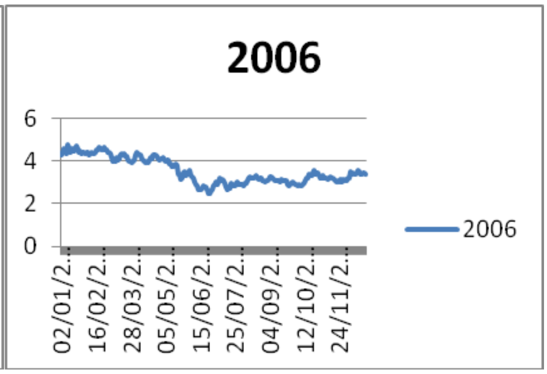
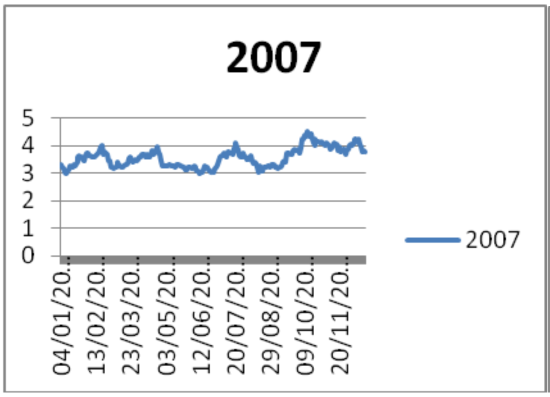


Figure 3.23: ISCTR 2005 Stock Prices

Figure 3.24: ISCTR 2006 Stock Prices

In 2005, prices also increase. But after the first quarter of the 2006, this increase turns down and at the end of the year, prices seem like the beginning of the year's values.



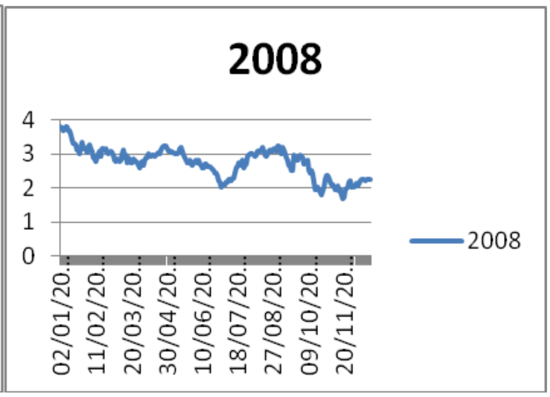
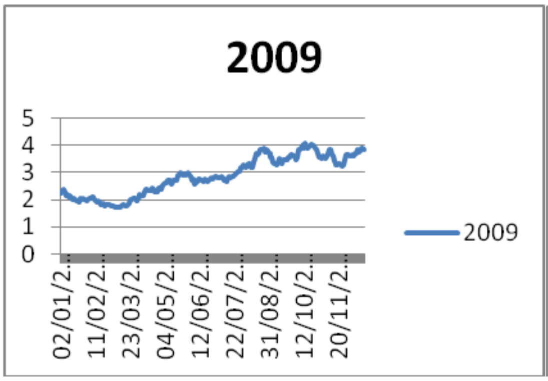


Figure 3.25: ISCTR 2007 Stock Prices

Figure 3.26: ISCTR 2008 Stock Prices

In 2007, stock prices rise up seasonally. After that year, in 2008, we again see the effect of economical crises. Along the year, stock prices lose their values nearly 50%.



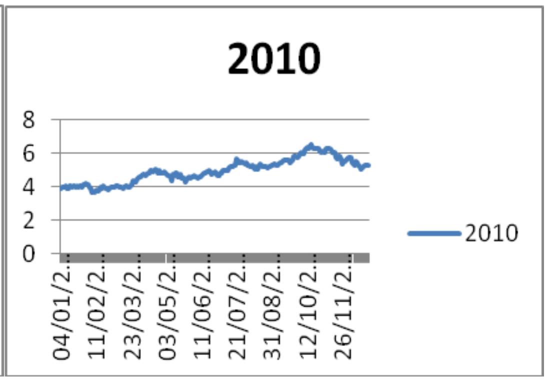


Figure 3.27: ISCTR 2009 Stock Prices

Figure 3.28: ISCTR 2010 Stock Prices

At the end of 2009, prices gain their 2008 beginning values and increase continues in 2010.

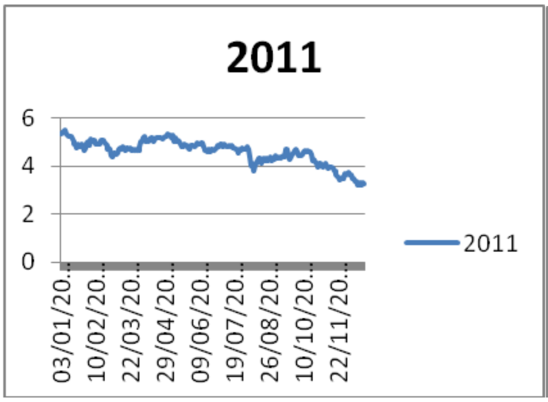


Figure 3.29: ISCTR 2011 Stock Prices

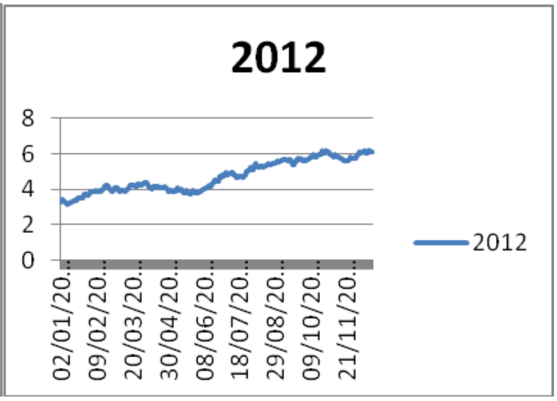


Figure 3.30: ISCTR 2012 Stock Prices

A slow decrease can be seen in 2011.However, in 2012 we see the top values İş Bank has ever had.

Figure 3.43: ISCTR 2003 - 2012 Stock Prices

In general perspective, except a part of 2006, all 2008 and 2011, ISCTR stock prices have a visible increase. Last values are six times larger than the beginning prices.

YKBNK (YAPIKREDI BANK)

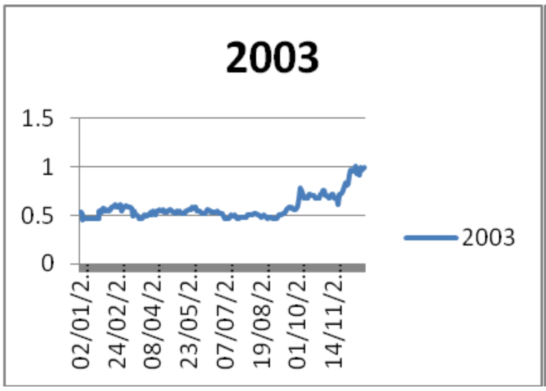


Figure 3.31: YKBNK 2003 Stock Prices

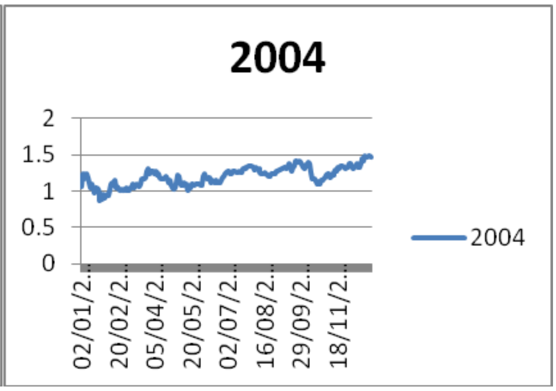


Figure 3.32: YKBNK 2004 Stock Prices

In the last quarter of 2003 YKBNK has a sharp increase, while in the first three quarter prices are nearly stabile. In 2004, increase also continues but not as sharp as in 2003' last quarter.

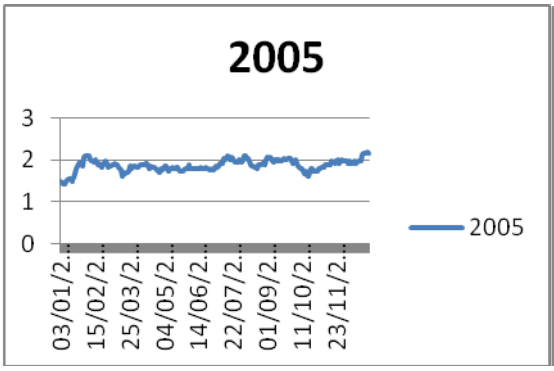


Figure 3.33: YKBNK 2005 Stock Prices

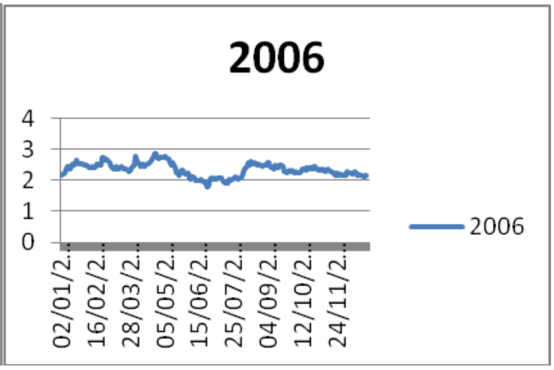
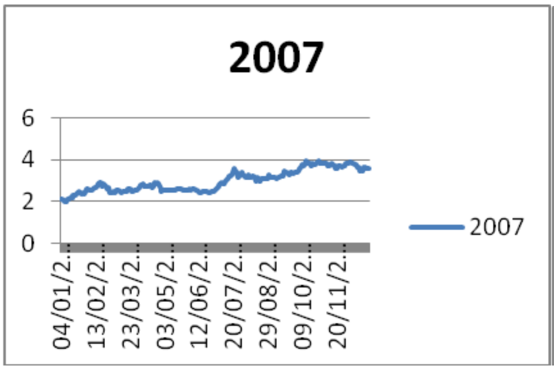


Figure 3.34: YKBNK 2006 Stock Prices

In 2005, prices increase in first month and then continues at the same level. In the first semi-year of 2006, prices also increase but in the second semi-year they decline to the 2006's beginning values.



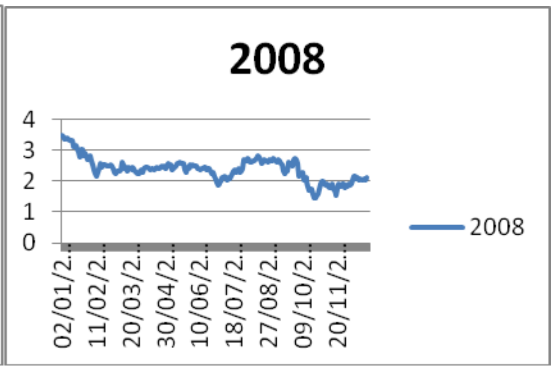
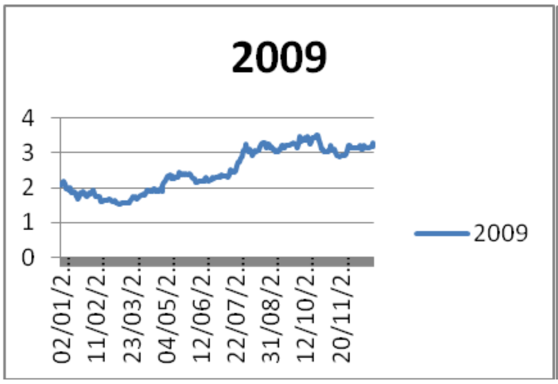


Figure 3.35: YKBNK 2007 Stock Prices

Figure 3.36: YKBNK 2008 Stock Prices

In 2007, prices has an upward trend and nearly 100% increase. After this year, we see the economical crise's effects on the stock prices and prices decrease.



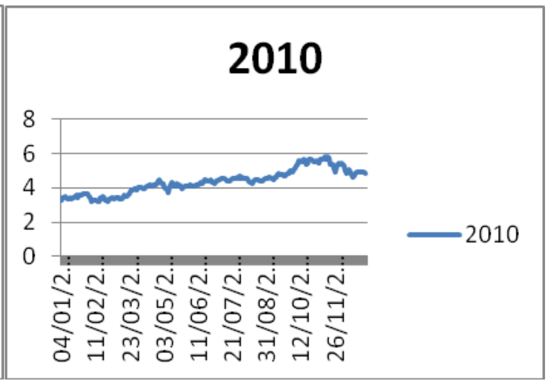
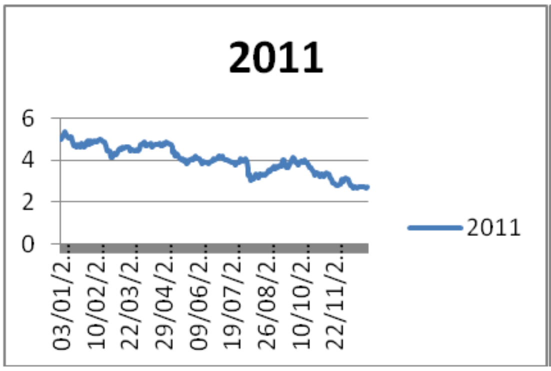


Figure 3.37: YKBNK 2009 Graph

Figure 3.38: YKBNK 2010 Graph

After crises year, we again see the upward trend in 2009 and 2010.



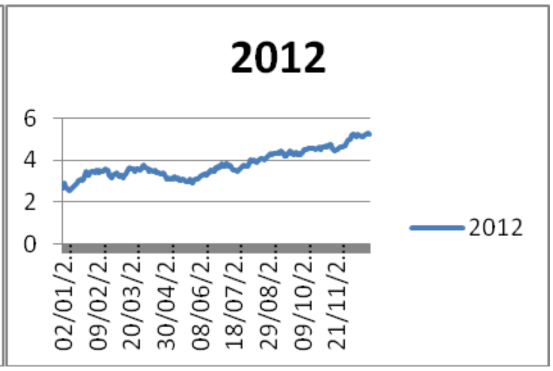


Figure 3.39: YKBNK 2011 Stock Prices

Figure 3.40: YKBNK 2012 Stock Prices

Upward trend turns down in 2011. But YKBNK stock prices catch an increase in the last year.

Figure 3.44: YKBNK 2003 – 2012 Stock Prices

Although we see decreases in a part of 2006, in 2008 and in 2011, in general YKBNK' s stock prices has an upward trend through the past ten years. Prices have their top values in 2010 and in ten years, get nearly six times larger.

4.2 COMPARISON of BANKS BY YEARS FROM 2003 to 2012

2003

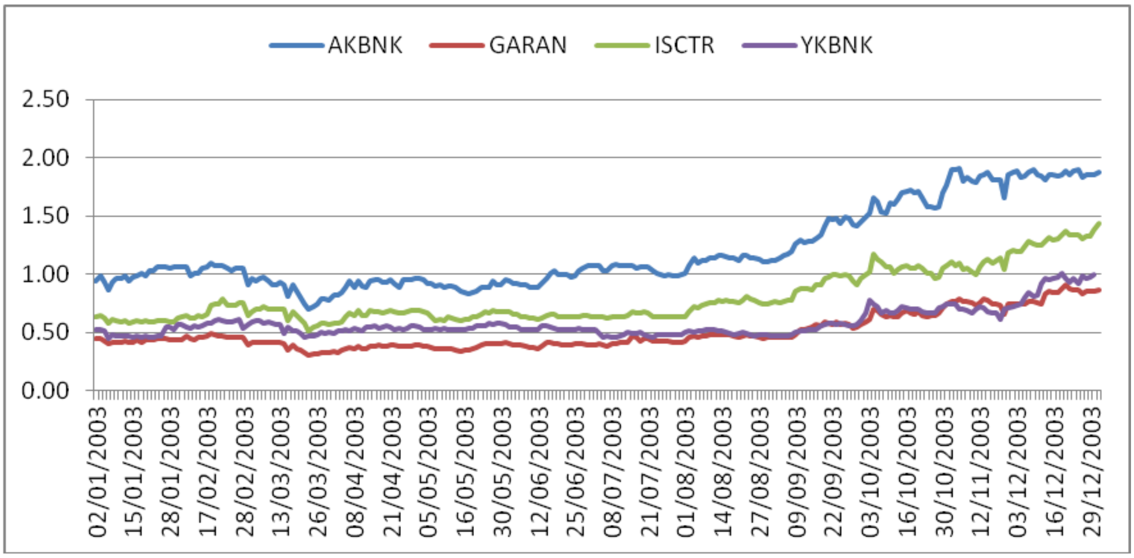


Figure 3.45: 2003 Stock Prices of Four Banks

At the first year, although all banks' stock prices are near, AKBNK seems more expensive than the others.

2004

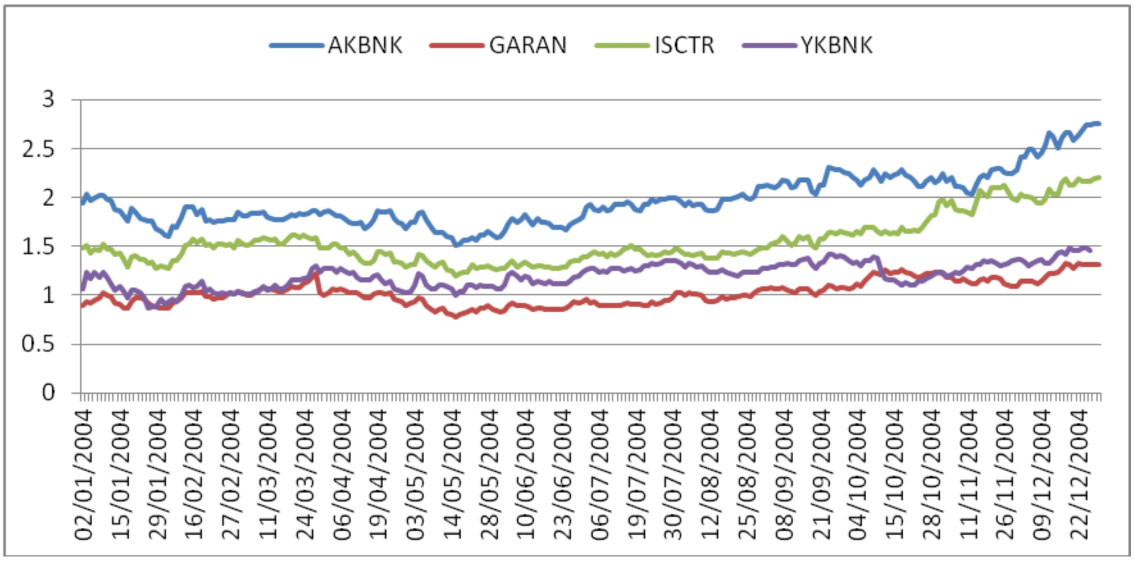


Figure 3.46: 2004 Stock Prices of Four Banks

ISBNK's stock prices come nearer to AKBNK. But AKBNK is still the most important stock price.

2005

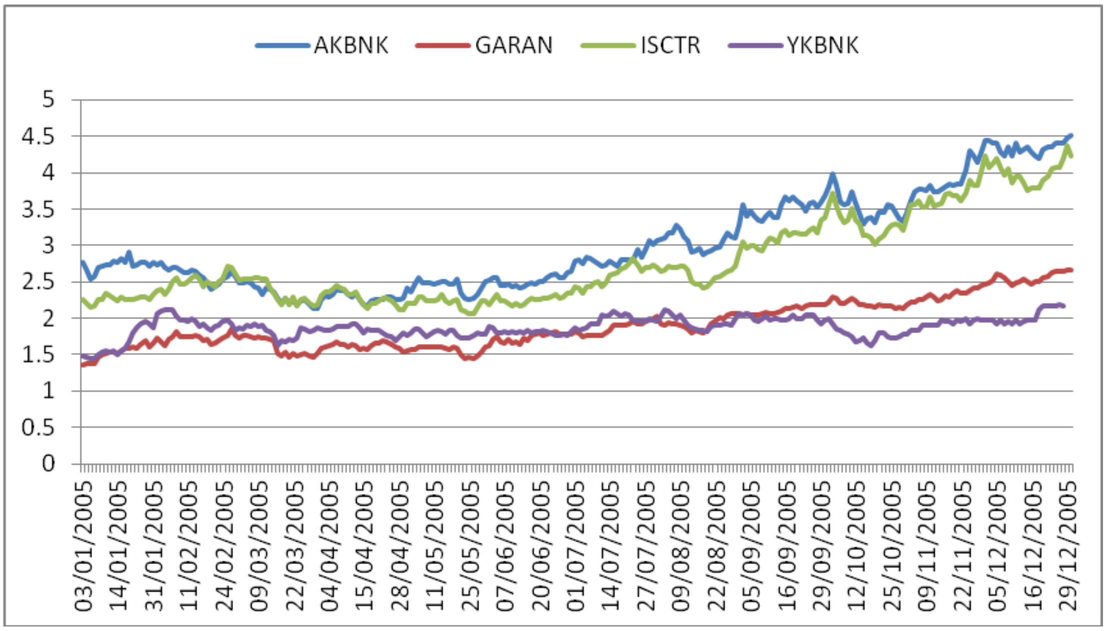


Figure 3.47: 2005 Stock Prices of Four Banks

In 2005, AKBNK and ISBNK behave nearly the same. On the other hand, GARAN and YKBNK go together.

2006

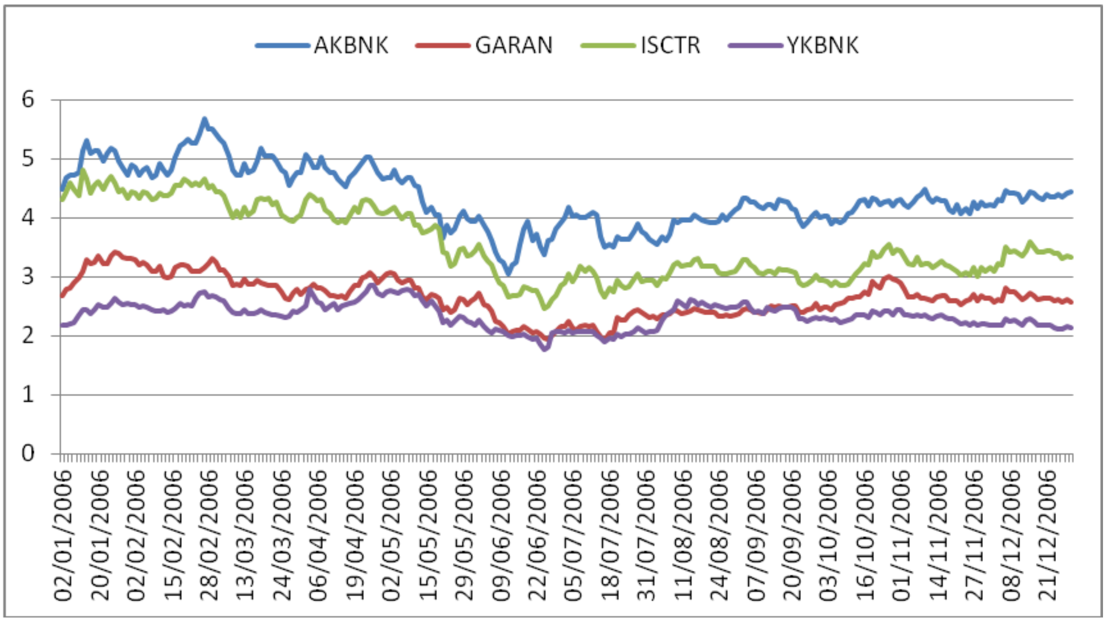


Figure 3.48: 2006 Stock Prices of Four Banks

The difference between AKBNK – ISCTR and GARAN - YKBNK is getting more.

2007

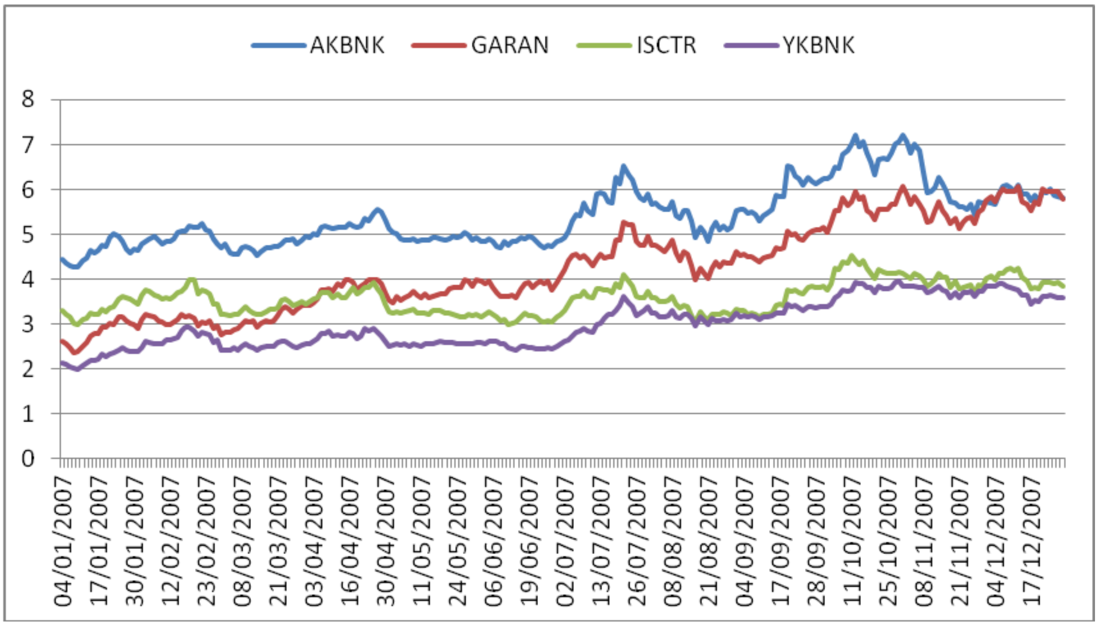


Figure 3.49: 2007 Stock Prices of Four Banks

In 2007, all stock prices behave the same, but they have differences between stock prices. AKBNK is still the most expensive stock price.

2008

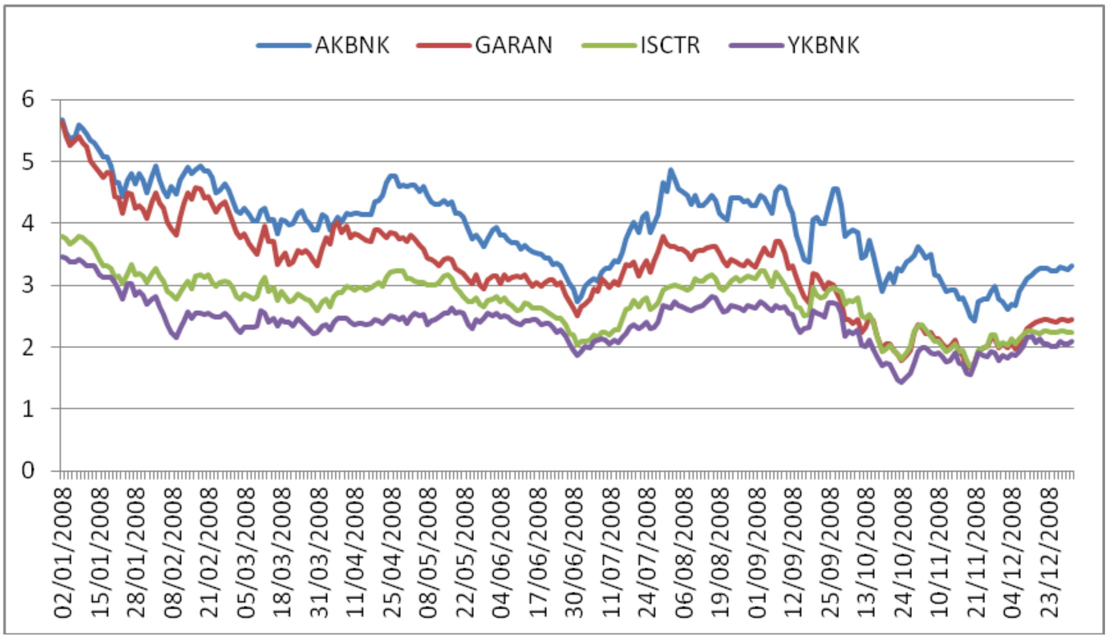


Figure 3.50: 2008 Stock Prices of Four Banks

GARAN's stock prices become more expensive than ISCTR. ISCTR behave like YKBNK. But in whole year, we see the crise's negative effect on each bank.

2009

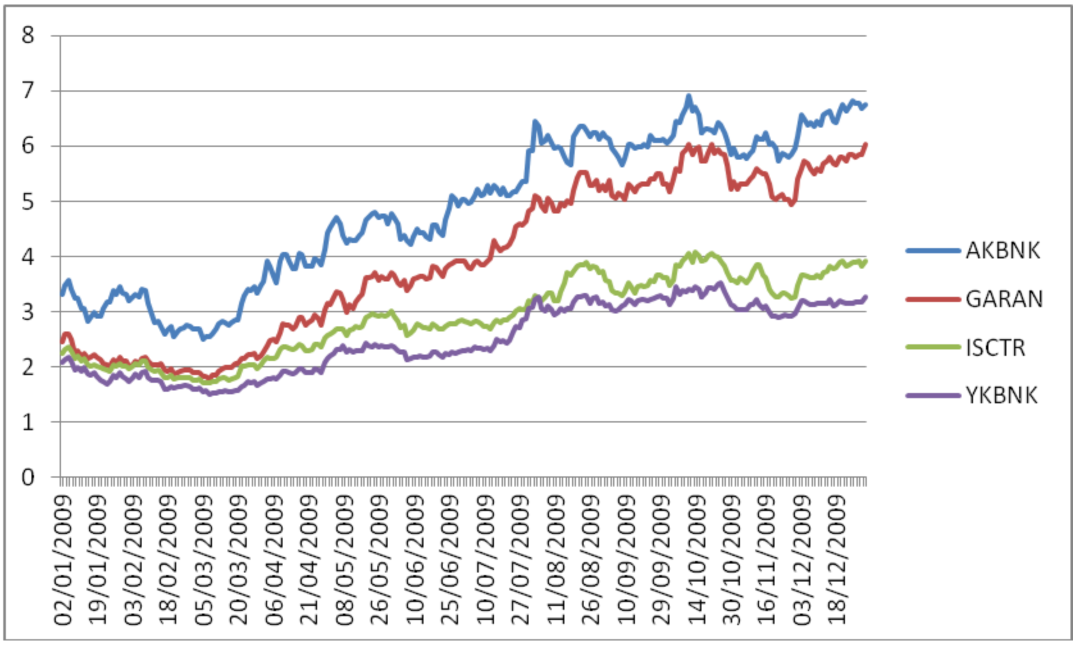


Figure 3.51: 2009 Stock Prices of Four Banks

At the beginning of the year, AKBNK is more expensive than the others. But GARAN's stock prices increase during the year and at the end, GARAN and AKBNK come closer.

2010

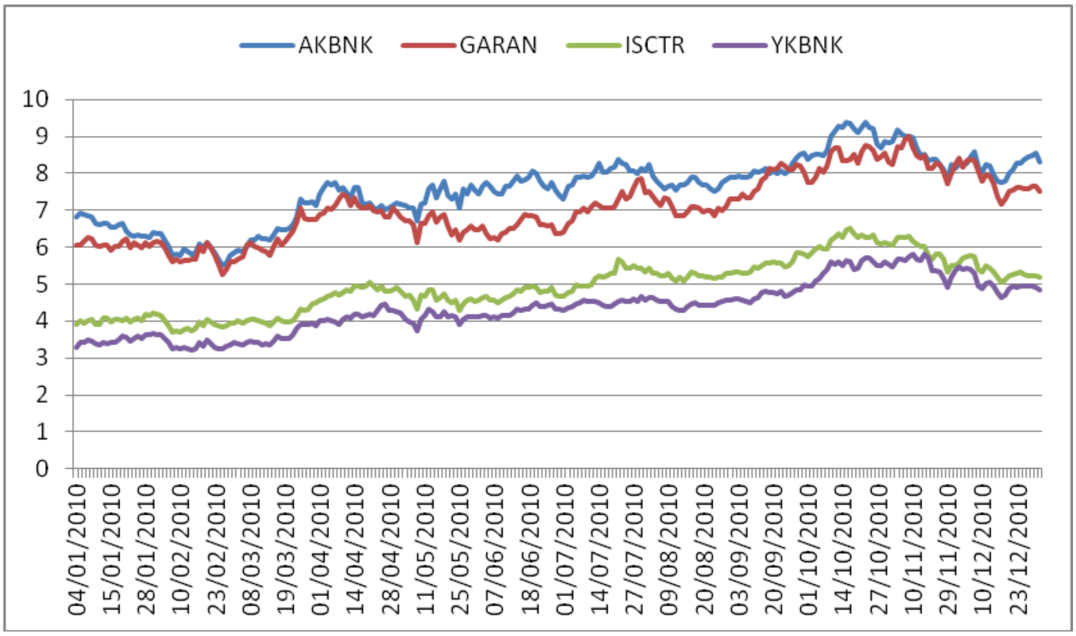


Figure 3.52: 2010 Stock Prices of Four Banks

In 2010, AKBNK – GARAN and ISCTR – YKBNK behave nearly the same again.

2011

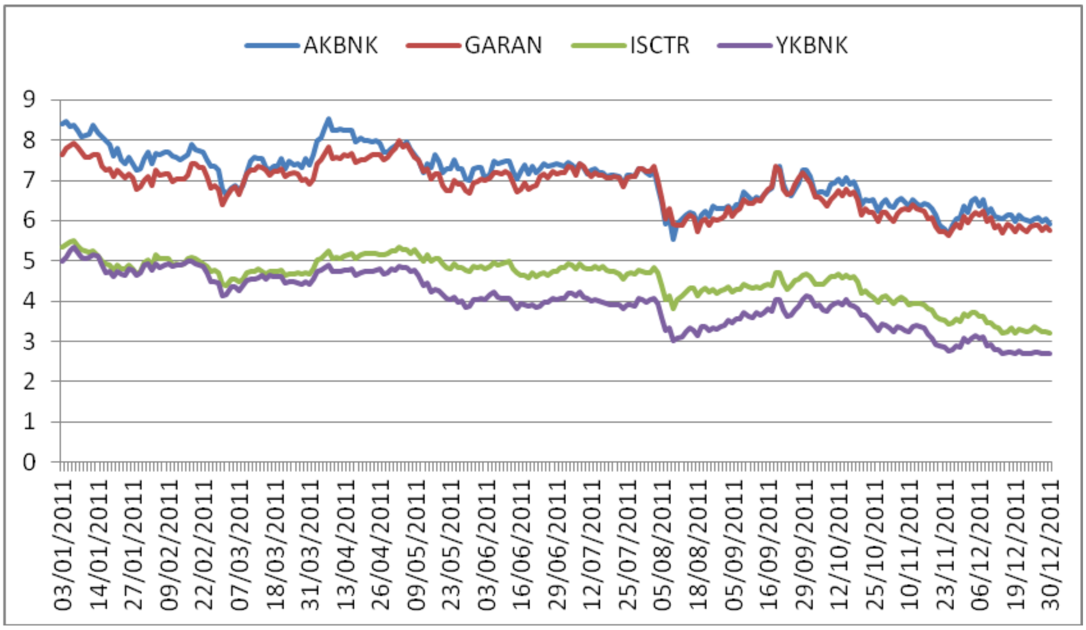


Figure 3.53: 2011 Stock Prices of Four Banks

Although the difference between stock prices of AKBNK-GARAN and ISCTR-YKBNK is getting more, all the prices have a downward trend in 2011

2012

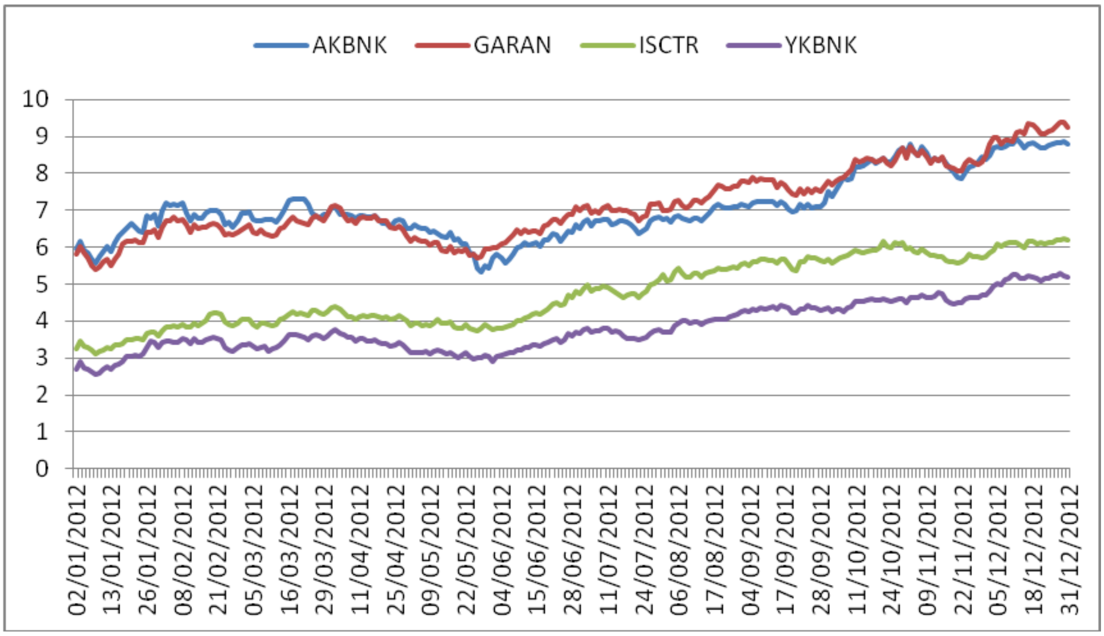


Figure 3.54: 2012 Stock Prices of Four Banks

All the banks have an upward trend and see the top value in this year.

4.3 MODELLING

4.3.1. Model Testing

4.3.1.1. White Noise

A stationary time series ε_t is said to be white noise if

$$Corr(\varepsilon_t, \varepsilon_s) = 0 \text{ for all } t \neq s$$

Thus ε_t is a sequence of uncorrelated random variables with constant variance and constant mean. This constant mean value is assumed zero. Plots of white noise series exhibit a very erratic, jumpy, unpredictable behavior. Since the ε_t are uncorrelated, previous values do not help us to forecast future values White noise series themselves are quite uninteresting from a forecasting standpoint (they are not linearly forecastable),but they form the building blocks for more general models. [9]

4.3.1.2. Akaike Information Criteria (AIC)

One of the most commonly used information criteria is AIC. The idea of AIC (Akaike, 1973) is to select the model that minimizes the negative likelihood penalized by the number of parameters as specified in the equation (1).

$$\text{AIC}= -2\log p(L) + 2p \qquad (1)$$

where L refers to the likelihood under the fitted model and p is the number of parameters in the model.

Specifically, AIC is aimed at finding the best approximating model to the unknown true data generating process and its applications draws from.

4.3.1.3. Bayesian (Schwarz) Information Criteria (BIC)

Another widely used information criteria is the BIC or Schwarz Criteria. Unlike Akaike Information Criteria, BIC is derived within a Bayesian framework as an estimate of the Bayes factor for two competing models (Schwarz, 1978; Kass and Rafftery, 1995).BIC is defined as:

$$\text{BIC}= -2\log p(L) + p\log(n)$$

Superficially, BIC differs from AIC only in the second term which now depends on sample size n. Models that minimize the Bayesian Information Criteria are selected. From a Bayesian perspective, BIC is designed to find the most probable model given the data.

Performance of the model selection criteria in selecting good models for the observed data is examined using simulation studies. Such a comparison is not straight forward and its relevance could be questioned, given that the two criteria are based on different theoretical motivations and objectives. However, for application purpose, the Akaike Information Criteria and the Bayesian Information Criteria do have the same aim of identifying good models even if they differ in their exact definition of a “good model”. Comparing them is thus justified, at least to examine how each criterion performs according to recovery of the correct model or how they behave when both should prefer the same model. [10]

4.3.2 Application of Model On Data

4.3.2.1. Model of AKBNK

Correlogram of AKBNK_CLOSING

Date: 04/17/13 Time: 22:55
Sample: 1 2509
Included observations: 2509

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.997	0.997	2497.6	0.000
		2	0.994	-0.008	4981.6	0.000
		3	0.991	0.001	7452.1	0.000
		4	0.988	0.006	9909.3	0.000
		5	0.986	0.020	12354.	0.000
		6	0.983	0.004	14786.	0.000
		7	0.980	0.022	17207.	0.000
		8	0.978	0.014	19616.	0.000
		9	0.976	0.010	22014.	0.000
		10	0.973	0.002	24402.	0.000
		11	0.971	-0.006	26778.	0.000
		12	0.968	-0.004	29144.	0.000
		13	0.966	-0.020	31498.	0.000
		14	0.963	-0.017	33840.	0.000
		15	0.960	0.003	36170.	0.000
		16	0.958	0.005	38488.	0.000
		17	0.955	-0.008	40794.	0.000
		18	0.952	-0.002	43089.	0.000
		19	0.950	-0.004	45372.	0.000
		20	0.947	-0.005	47643.	0.000
		21	0.945	0.055	49903.	0.000
		22	0.943	0.034	52154.	0.000
		23	0.940	-0.026	54396.	0.000
		24	0.938	0.013	56627.	0.000
		25	0.936	0.014	58850.	0.000
		26	0.934	0.005	61063.	0.000
		27	0.932	0.008	63268.	0.000
		28	0.930	0.016	65464.	0.000
		29	0.928	0.008	67652.	0.000

Firstly Correlogram of AKBNK have to be analyzed. When we look at the correlogram, we see that AR(1) model have to apply on data.

Table 4.1: Correlogram of AKBNK

Equation: AKBNK_EGARCH Workfile: BITIRME::Untitl...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: AKBNK_CLOSING
Method: ML - ARCH
Date: 04/08/13 Time: 20:10
Sample (adjusted): 2 2509
Included observations: 2508 after adjustments
Convergence achieved after 23 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.001136	0.000473	2116.069	0.0000
		Variance Equation		
C(2)	-0.141465	0.012090	-11.70124	0.0000
C(3)	0.147835	0.010604	13.94147	0.0000
C(4)	0.014874	0.007149	2.080640	0.0375
C(5)	0.993495	0.001392	713.6746	0.0000

R-squared	0.996775	Mean dependent var	4.661280
Adjusted R-squared	0.996775	S.D. dependent var	2.207321
S.E. of regression	0.125345	Akaike info criterion	-1.690956
Sum squared resid	39.38848	Schwarz criterion	-1.679339
Log likelihood	2125.459	Hannan-Quinn criter.	-1.686739
Durbin-Watson stat	1.982685		

Inverted AR Roots	1.00	
	Estimated AR process is nonstationary	

Table 4.2: Equation of EGARCH Model of AKBNK

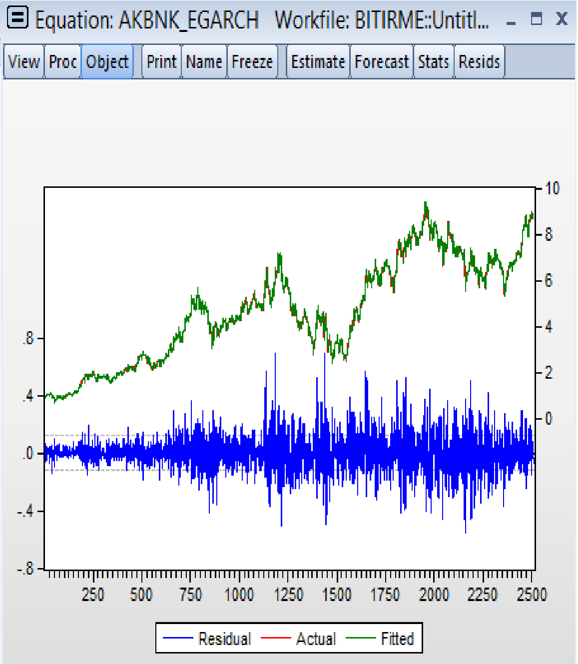


Table 4.3: Actual-Fitted-Residual of EGARCH Model of AKBNK

Correlogram of Standardized Residuals

Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

Lag	AC	PAC	Q-Stat	Prob
1	0.032	0.032	2.5118	
2	0.010	0.009	2.7454	0.098
3	-0.007	-0.007	2.8611	0.239
4	-0.026	-0.025	4.5087	0.212
5	-0.011	-0.009	4.8118	0.307
6	-0.030	-0.029	7.1374	0.211
7	-0.000	0.002	7.1374	0.308
8	-0.030	-0.030	9.4036	0.225
9	-0.011	-0.010	9.7043	0.286
10	0.047	0.046	15.191	0.086
11	0.018	0.014	16.005	0.099
12	0.024	0.020	17.482	0.094
13	0.010	0.008	17.746	0.124
14	-0.006	-0.007	17.840	0.164
15	-0.011	-0.009	18.135	0.201
16	0.013	0.017	18.576	0.234
17	0.002	0.002	18.590	0.290
18	0.009	0.013	18.816	0.339
19	-0.000	0.001	18.816	0.403
20	-0.065	-0.066	29.394	0.060
21	-0.035	-0.032	32.517	0.038
22	0.021	0.023	33.619	0.040
23	-0.010	-0.014	33.895	0.050
24	0.006	0.004	34.001	0.065
25	0.007	0.006	34.129	0.082
26	0.040	0.036	38.107	0.045
27	-0.009	-0.013	38.295	0.057
28	-0.015	-0.020	38.900	0.065
29	0.003	0.000	38.928	0.082
30	-0.038	-0.029	42.531	0.050
31	-0.026	-0.019	44.260	0.045
32	0.013	0.018	44.698	0.053
33	-0.022	-0.020	45.910	0.053
34	-0.026	-0.028	47.669	0.047
35	0.013	0.012	48.122	0.055
36	-0.012	-0.018	48.482	0.064

Table 4.4: Residual Cor. of EGARCH Model of AKBNK

Correlogram of Standardized Residuals Squared

Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

Lag	AC	PAC	Q-Stat	Prob
1	0.026	0.026	1.6646	
2	0.069	0.068	13.538	0.000
3	-0.004	-0.007	13.578	0.001
4	0.036	0.032	16.829	0.001
5	0.010	0.009	17.085	0.002
6	-0.018	-0.023	17.910	0.003
7	-0.006	-0.006	17.995	0.006
8	-0.006	-0.004	18.098	0.012
9	-0.025	-0.025	19.626	0.012
10	0.014	0.018	20.153	0.017
11	-0.006	-0.003	20.255	0.027
12	0.027	0.025	22.117	0.023
13	-0.007	-0.006	22.253	0.035
14	0.027	0.023	24.106	0.030
15	-0.033	-0.034	26.837	0.020
16	-0.038	-0.041	30.470	0.010
17	-0.001	0.006	30.472	0.016
18	-0.037	-0.034	33.949	0.009
19	0.001	0.005	33.952	0.013
20	0.005	0.015	34.028	0.018
21	-0.041	-0.042	38.274	0.008
22	-0.021	-0.021	39.431	0.009
23	-0.017	-0.009	40.207	0.010
24	0.002	-0.001	40.222	0.015
25	-0.015	-0.011	40.768	0.018
26	0.036	0.039	44.077	0.011
27	-0.027	-0.028	45.911	0.009
28	0.011	0.008	46.200	0.012
29	-0.013	-0.008	46.635	0.015
30	0.016	0.013	47.284	0.017
31	0.005	0.004	47.360	0.023
32	0.014	0.013	47.873	0.027
33	0.007	0.006	48.006	0.034
34	-0.014	-0.020	48.512	0.040
35	0.001	0.007	48.515	0.051
36	-0.008	-0.011	48.685	0.062

Table 4.5: Residual Squared Cor. of EGARCH Model of AKBNK

When we apply AR model with EGARCH method, R- Squared is nearly 1. Our Actual and Fitted graphs are acting like each other also our correlogram of q-statics and correlogram of squared residuals have no lag.

Equation: AKBNK_GARCH Workfile: BITIRME::Untitle...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: AKBNK_CLOSING
Method: ML - ARCH
Date: 04/17/13 Time: 21:34
Sample (adjusted): 2 2509
Included observations: 2508 after adjustments
Failure to improve Likelihood after 13 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.990073	0.006576	150.5695	0.0000
Variance Equation				
C	0.517981	0.051600	10.03846	0.0000
RESID(-1)^2	-0.554343	0.080702	-6.869048	0.0000
GARCH(-1)	-0.647833	0.146763	-4.414128	0.0000

R-squared	0.996211	Mean dependent var	4.661280
Adjusted R-squared	0.996211	S.D. dependent var	2.207321
S.E. of regression	0.135870	Akaike info criterion	0.718263
Sum squared resid	46.28057	Schwarz criterion	0.727557
Log likelihood	-896.7017	Hannan-Quinn criter.	0.721636
Durbin-Watson stat	1.668861		

Inverted AR Roots .99

Table 4.6: Equation of GARCH Model of AKBNK

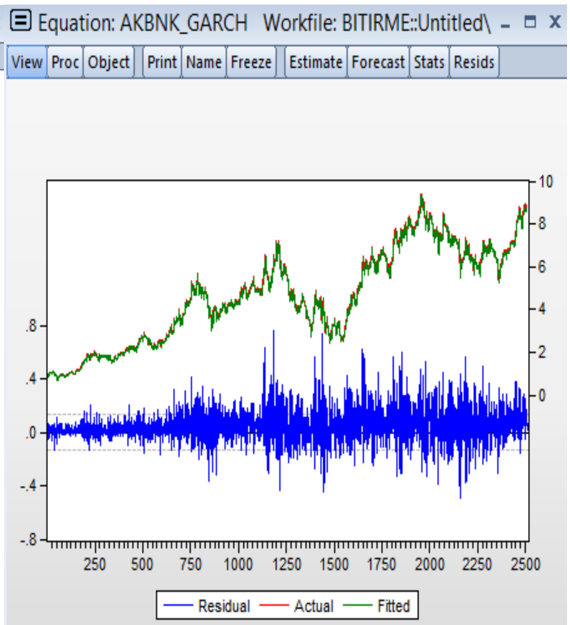


Table 4.7: Actual-Fitted-Residual of GARCH Model of AKBNK

Correlogram of Standardized Residuals

Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.052	0.052	6.8130	
		2	0.024	0.021	8.2468	0.004
		3	0.007	0.005	8.3702	0.015
		4	0.005	0.004	8.4311	0.038
		5	0.025	0.024	10.018	0.040
		6	-0.006	-0.008	10.098	0.073
		7	-0.009	-0.010	10.316	0.112
		8	0.001	0.002	10.319	0.171
		9	0.021	0.021	11.440	0.178
		10	0.048	0.046	17.303	0.044
		11	0.038	0.033	20.879	0.022
		12	0.046	0.041	26.149	0.006
		13	0.055	0.049	33.785	0.001
		14	0.038	0.030	37.500	0.000
		15	0.015	0.007	38.059	0.001
		16	0.040	0.037	42.113	0.000
		17	0.037	0.033	45.626	0.000
		18	0.029	0.023	47.701	0.000
		19	0.035	0.030	50.813	0.000
		20	-0.045	-0.052	56.023	0.000
		21	-0.019	-0.021	56.912	0.000
		22	0.065	0.062	67.727	0.000
		23	0.014	0.001	68.254	0.000
		24	0.014	0.003	68.753	0.000
		25	0.032	0.027	71.402	0.000
		26	0.034	0.022	74.397	0.000
		27	0.020	0.002	75.428	0.000
		28	0.013	0.000	75.832	0.000
		29	0.023	0.014	77.217	0.000
		30	0.009	0.001	77.403	0.000
		31	0.014	0.008	77.886	0.000
		32	0.059	0.052	86.673	0.000
		33	-0.015	-0.023	87.208	0.000
		34	-0.020	-0.026	88.189	0.000
		35	0.027	0.018	90.018	0.000
		36	0.023	0.014	91.330	0.000

Table 4.8: Residual Cor. Of GARCH Model of AKBNK

Correlogram of Standardized Residuals Squared

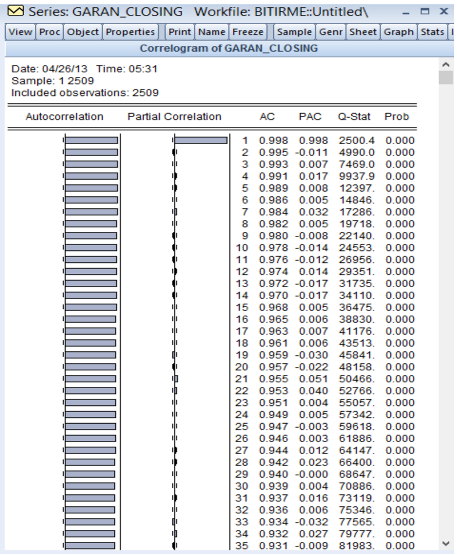
Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.174	0.174	76.239	
		2	0.135	0.108	122.24	0.000
		3	0.139	0.104	170.85	0.000
		4	0.117	0.070	205.28	0.000
		5	0.178	0.132	284.74	0.000
		6	0.085	0.014	303.10	0.000
		7	0.118	0.062	338.16	0.000
		8	0.102	0.037	364.55	0.000
		9	0.107	0.047	393.40	0.000
		10	0.094	0.023	415.67	0.000
		11	0.093	0.036	437.57	0.000
		12	0.098	0.033	462.03	0.000
		13	0.083	0.020	479.30	0.000
		14	0.112	0.051	511.23	0.000
		15	0.071	0.003	523.84	0.000
		16	0.063	-0.000	533.86	0.000
		17	0.123	0.068	571.99	0.000
		18	0.066	-0.002	583.14	0.000
		19	0.074	0.010	597.11	0.000
		20	0.087	0.031	616.18	0.000
		21	0.074	0.013	629.88	0.000
		22	0.061	-0.008	639.34	0.000
		23	0.075	0.025	653.41	0.000
		24	0.070	0.011	665.93	0.000
		25	0.088	0.032	685.60	0.000
		26	0.097	0.038	709.31	0.000
		27	0.082	0.022	726.21	0.000
		28	0.095	0.030	748.92	0.000
		29	0.064	-0.002	759.23	0.000
		30	0.093	0.033	780.99	0.000
		31	0.096	0.026	804.26	0.000
		32	0.080	0.015	820.44	0.000
		33	0.052	-0.018	827.31	0.000
		34	0.076	0.016	842.09	0.000
		35	0.134	0.075	887.63	0.000
		36	0.089	0.016	907.59	0.000

Table 4.9: Residual Squared Cor. Of GARCH Model of AKBNK

When we apply AR model with GARCH method, R- Squared is nearly 1 but smaller than EGARCH R-Squared. On the other hand GARCH method's absolute Akaike Criterion is smaller than EGARCH method. This means that we should use GARCH Method. Actual and Fitted graphs are also acting like each other and our correlogram of q-statics has no lag. But our correlogram of squared residuals has lags This means that GARCH method is not suitable for our data. We must use EGARCH method for AKBNK and the other banks (GARAN, ISCTR, YKBNK).

4.3.2.2. Model of GARAN



Series: GARAN_CLOSING Workfile: BITIRME::Untitled\

View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stats

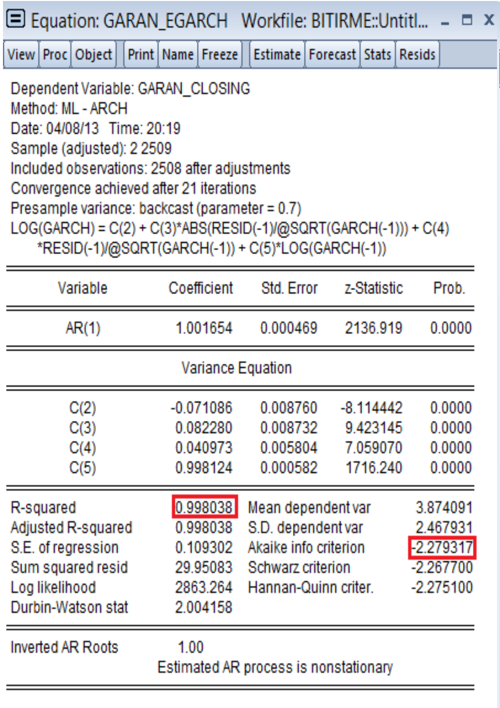
Correlogram of GARAN_CLOSING

Date: 04/26/13 Time: 05:31
Sample: 1 2509
Included observations: 2509

	AC	PAC	Q-Stat	Prob
1	0.998	0.998	2500.4	0.000
2	0.995	-0.011	4990.0	0.000
3	0.993	0.007	7469.0	0.000
4	0.991	0.017	9937.9	0.000
5	0.989	0.008	12397.	0.000
6	0.986	0.005	14846.	0.000
7	0.984	0.032	17286.	0.000
8	0.982	0.005	19718.	0.000
9	0.980	-0.008	22140.	0.000
10	0.978	-0.014	24553.	0.000
11	0.976	-0.012	26956.	0.000
12	0.974	0.014	29351.	0.000
13	0.972	-0.017	31735.	0.000
14	0.970	-0.017	34110.	0.000
15	0.968	0.005	36475.	0.000
16	0.965	0.006	38830.	0.000
17	0.963	0.007	41176.	0.000
18	0.961	0.006	43513.	0.000
19	0.959	-0.030	45841.	0.000
20	0.957	-0.022	48158.	0.000
21	0.955	0.051	50466.	0.000
22	0.953	0.040	52766.	0.000
23	0.951	0.004	55057.	0.000
24	0.949	0.005	57342.	0.000
25	0.947	-0.003	59618.	0.000
26	0.946	0.003	61886.	0.000
27	0.944	0.012	64147.	0.000
28	0.942	0.023	66400.	0.000
29	0.940	-0.000	68647.	0.000
30	0.939	0.004	70886.	0.000
31	0.937	0.016	73119.	0.000
32	0.936	0.006	75346.	0.000
33	0.934	-0.032	77565.	0.000
34	0.932	0.027	79777.	0.000
35	0.931	-0.009	81983.	0.000

Firstly Correlogram of GARAN have to be analyzed. When we look at the correlogram, we see that AR(1) model have to apply on data.

Table 4.10: Correlogram of GARAN



Equation: GARAN_EGARCH Workfile: BITIRME::Untitl...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: GARAN_CLOSING
Method: ML - ARCH
Date: 04/08/13 Time: 20:19
Sample (adjusted): 2 2509
Included observations: 2508 after adjustments
Convergence achieved after 21 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.001654	0.000469	2136.919	0.0000
Variance Equation				
C(2)	-0.071086	0.008760	-8.114442	0.0000
C(3)	0.082280	0.008732	9.423145	0.0000
C(4)	0.040973	0.005804	7.059070	0.0000
C(5)	0.998124	0.000582	1716.240	0.0000

R-squared	0.998038	Mean dependent var	3.874091
Adjusted R-squared	0.998038	S.D. dependent var	2.467931
S.E. of regression	0.109302	Akaike info criterion	-2.279317
Sum squared resid	29.95083	Schwarz criterion	-2.267700
Log likelihood	2863.264	Hannan-Quinn criter.	-2.275100
Durbin-Watson stat	2.004158		

Inverted AR Roots 1.00
Estimated AR process is nonstationary

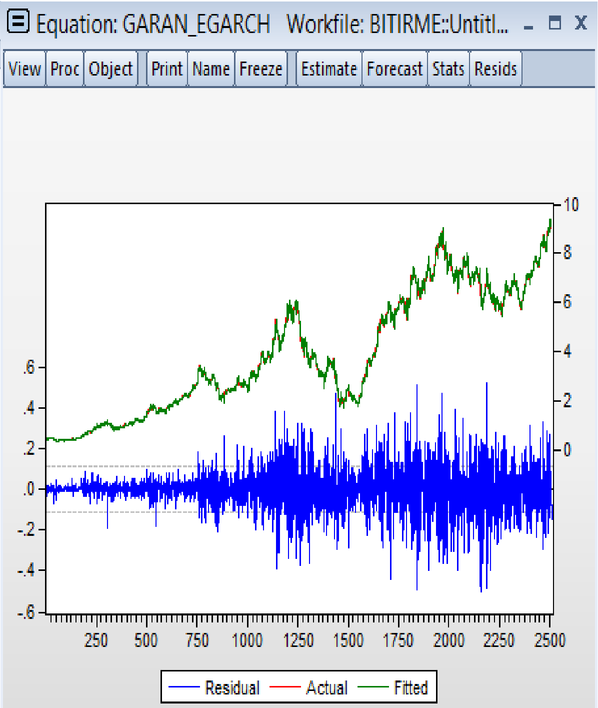


Table 4.11: Equation of EGARCH Model of GARAN

Table 4.12: Actual-Fitted-Residual of EGARCH Model of GARAN

Equation: GARAN_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals

Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.011	0.011	0.3076	
		2	-0.013	-0.013	0.7335	0.392
		3	-0.008	-0.008	0.9029	0.637
		4	-0.012	-0.012	1.2527	0.740
		5	-0.013	-0.013	1.6745	0.795
		6	-0.037	-0.037	5.1714	0.395
		7	-0.005	-0.004	5.2239	0.515
		8	-0.019	-0.020	6.1141	0.526
		9	0.000	-0.001	6.1141	0.634
		10	0.032	0.031	8.7709	0.459
		11	0.012	0.010	9.1118	0.522
		12	0.017	0.015	9.8076	0.548
		13	0.010	0.010	10.050	0.612
		14	0.031	0.030	12.413	0.494
		15	-0.021	-0.021	13.556	0.483
		16	-0.004	0.000	13.592	0.557
		17	0.018	0.020	14.440	0.566
		18	0.004	0.007	14.482	0.633
		19	0.042	0.044	18.944	0.395
		20	-0.065	-0.064	29.605	0.057
		21	-0.026	-0.025	31.329	0.051
		22	0.009	0.009	31.545	0.065
		23	0.007	0.005	31.656	0.083
		24	-0.003	-0.005	31.675	0.107
		25	-0.006	-0.003	31.759	0.133
		26	0.026	0.022	33.525	0.118
		27	-0.014	-0.016	33.990	0.135
		28	0.001	-0.001	33.993	0.166
		29	-0.023	-0.027	35.367	0.159
		30	-0.041	-0.038	39.629	0.090
		31	-0.002	-0.001	39.636	0.112
		32	0.015	0.017	40.215	0.124
		33	-0.028	-0.032	42.214	0.107
		34	-0.010	-0.004	42.457	0.125
		35	-0.003	-0.008	42.475	0.151
		36	0.009	0.000	42.668	0.175

Table 4.13: Residual Cor. Of GARCH Model of AKBNK

Equation: GARAN_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals Squared

Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.047	0.047	5.4424	
		2	0.023	0.020	6.7151	0.010
		3	0.034	0.032	9.6557	0.008
		4	-0.004	-0.008	9.7011	0.021
		5	-0.010	-0.011	9.9413	0.041
		6	0.001	0.001	9.9426	0.077
		7	-0.025	-0.025	11.539	0.073
		8	0.004	0.007	11.589	0.115
		9	0.013	0.014	12.041	0.149
		10	0.013	0.014	12.498	0.187
		11	-0.006	-0.009	12.593	0.247
		12	-0.013	-0.014	13.022	0.292
		13	0.014	0.015	13.495	0.334
		14	0.003	0.002	13.511	0.409
		15	-0.009	-0.009	13.733	0.470
		16	-0.028	-0.028	15.749	0.399
		17	-0.002	0.001	15.763	0.470
		18	0.039	0.041	19.677	0.291
		19	0.001	-0.002	19.680	0.351
		20	-0.008	-0.009	19.835	0.405
		21	0.009	0.008	20.062	0.454
		22	-0.012	-0.012	20.405	0.496
		23	-0.036	-0.036	23.680	0.364
		24	-0.030	-0.027	25.942	0.304
		25	-0.018	-0.009	26.732	0.317
		26	0.004	0.009	26.764	0.368
		27	0.002	0.001	26.776	0.421
		28	-0.005	-0.006	26.828	0.473
		29	-0.028	-0.028	28.783	0.424
		30	0.007	0.009	28.913	0.470
		31	0.004	0.003	28.963	0.520
		32	-0.012	-0.011	29.311	0.553
		33	0.028	0.032	31.371	0.498
		34	-0.026	-0.027	33.115	0.462
		35	-0.006	-0.005	33.206	0.506
		36	0.005	0.001	33.263	0.552

Table 4.14: Residual Squared Cor. Of GARCH Model of AKBNK

When we apply AR model with EGARCH method, R- Squared is nearly 1. Our Actual and Fitted graphs are acting like each other also our correlogram of q-statics and correlogram of squared residuals have no lag.

4.3.2.3. Model of ISCTR

Series: ISCTR_CLOSING Workfile: BITIRME::Untitled\

View | Proc | Object | Properties | Print | Name | Freeze | Sample | Genr | Sheet | Graph | Stat

Correlogram of ISCTR_CLOSING

Sample: 1 2509
Included observations: 2509

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.997	0.997	2495.3	0.000
		2	0.993	0.002	4975.0	0.000
		3	0.990	0.009	7439.6	0.000
		4	0.987	-0.010	9888.8	0.000
		5	0.984	0.006	12323.	0.000
		6	0.980	0.003	14742.	0.000
		7	0.977	0.009	17147.	0.000
		8	0.974	0.002	19537.	0.000
		9	0.971	0.015	21914.	0.000
		10	0.968	-0.006	24276.	0.000
		11	0.965	-0.013	26624.	0.000
		12	0.962	0.018	28959.	0.000
		13	0.959	-0.016	31280.	0.000
		14	0.956	-0.027	33586.	0.000
		15	0.952	-0.002	35877.	0.000
		16	0.949	0.007	38154.	0.000
		17	0.946	-0.001	40416.	0.000
		18	0.943	0.003	42665.	0.000
		19	0.940	-0.007	44898.	0.000
		20	0.936	-0.016	47118.	0.000
		21	0.933	0.031	49323.	0.000
		22	0.930	0.026	51516.	0.000
		23	0.927	-0.013	53696.	0.000
		24	0.924	-0.022	55862.	0.000
		25	0.921	0.007	58015.	0.000
		26	0.918	-0.007	60154.	0.000
		27	0.915	0.007	62280.	0.000
		28	0.912	0.031	64394.	0.000
		29	0.910	0.011	66496.	0.000
		30	0.907	0.000	68586.	0.000
		31	0.904	0.010	70665.	0.000
		32	0.902	0.005	72733.	0.000
		33	0.899	-0.040	74789.	0.000
		34	0.896	0.026	76833.	0.000
		35	0.894	0.014	78866.	0.000
		36	0.891	0.002	80888.	0.000

Table 4.15: Correlogram of ISCTR

Firstly Correlogram of ISCTR have to be analyzed. When we look at the correlogram, we see that AR(1) model have to apply on data.

Equation: ISCTR_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: ISCTR_CLOSING
Method: ML - ARCH
Date: 04/17/13 Time: 21:41
Sample (adjusted): 2 2509
Included observations: 2508 after adjustments
Convergence achieved after 20 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.001262	0.000467	2143.073	0.0000
		Variance Equation		
C(2)	-0.130842	0.012098	-10.81541	0.0000
C(3)	0.129679	0.010903	11.89381	0.0000
C(4)	0.026411	0.007458	3.541313	0.0004
C(5)	0.993715	0.001303	762.7688	0.0000

R-squared	0.996428	Mean dependent var	3.222699
Adjusted R-squared	0.996428	S.D. dependent var	1.406226
S.E. of regression	0.084043	Akaike info criterion	-2.375387
Sum squared resid	17.70758	Schwarz criterion	-2.363770
Log likelihood	2983.735	Hannan-Quinn criter.	-2.371170
Durbin-Watson stat	2.024372		

Inverted AR Roots 1.00
Estimated AR process is nonstationary

Table 4.16: Equation of EGARCH Model of ISCTR

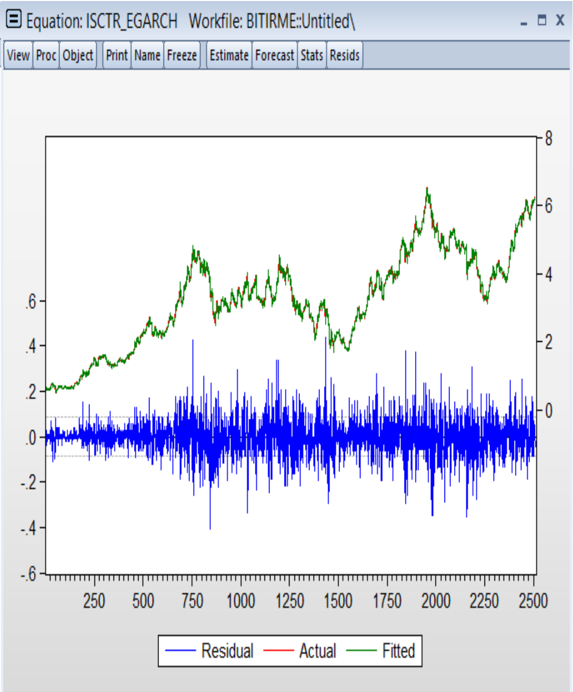


Table 4.17: Actual-Fitted-Residual of EGARCH Model of ISCTR

Equation: ISCTR_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals

Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.006	0.006	0.0828	
		2	-0.010	-0.010	0.3198	0.572
		3	0.007	0.007	0.4390	0.803
		4	-0.015	-0.015	1.0155	0.797
		5	0.013	0.014	1.4701	0.832
		6	-0.019	-0.019	2.3574	0.798
		7	0.000	0.001	2.3574	0.884
		8	-0.027	-0.027	4.1357	0.764
		9	0.010	0.011	4.3682	0.822
		10	0.042	0.041	8.8629	0.450
		11	-0.014	-0.014	9.3657	0.498
		12	0.017	0.016	10.058	0.525
		13	0.025	0.025	11.619	0.477
		14	-0.009	-0.009	11.820	0.542
		15	-0.020	-0.021	12.800	0.542
		16	-0.007	-0.006	12.932	0.608
		17	0.011	0.012	13.264	0.653
		18	-0.000	0.002	13.264	0.718
		19	0.041	0.041	17.548	0.486
		20	-0.027	-0.029	19.407	0.431
		21	-0.019	-0.016	20.325	0.438
		22	0.008	0.004	20.485	0.491
		23	0.012	0.011	20.852	0.530
		24	-0.006	-0.007	20.955	0.584
		25	-0.004	-0.001	20.996	0.639
		26	0.018	0.017	21.801	0.647
		27	-0.043	-0.042	26.483	0.437
		28	-0.003	-0.003	26.503	0.491
		29	0.004	-0.001	26.536	0.544
		30	-0.019	-0.016	27.464	0.547
		31	-0.006	-0.007	27.545	0.595
		32	0.025	0.025	29.188	0.559
		33	-0.034	-0.034	32.179	0.458
		34	-0.030	-0.026	34.429	0.399
		35	0.006	0.002	34.519	0.443
		36	-0.036	-0.040	37.839	0.341

Equation: ISCTR_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals Squared

Q-statistic probabilities adjusted for 1 ARMA term(s)

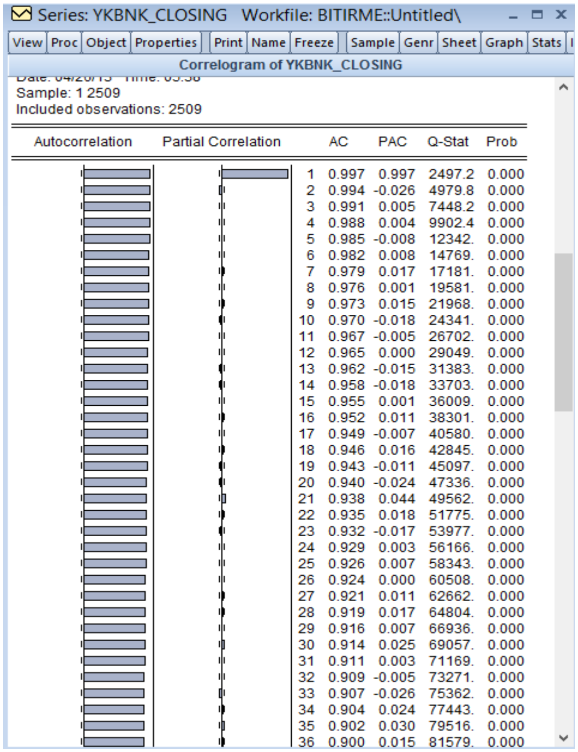
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.020	0.020	0.9558	
		2	0.048	0.047	6.6534	0.010
		3	-0.003	-0.004	6.6696	0.036
		4	0.021	0.019	7.8222	0.050
		5	0.018	0.018	8.6499	0.070
		6	-0.004	-0.007	8.6901	0.122
		7	-0.013	-0.014	9.1057	0.168
		8	-0.029	-0.028	11.186	0.131
		9	0.003	0.004	11.204	0.190
		10	-0.010	-0.008	11.468	0.245
		11	-0.002	-0.001	11.476	0.322
		12	0.013	0.015	11.882	0.373
		13	0.010	0.010	12.123	0.436
		14	-0.011	-0.013	12.412	0.494
		15	-0.040	-0.041	16.414	0.289
		16	-0.033	-0.032	19.115	0.209
		17	-0.014	-0.011	19.630	0.237
		18	-0.043	-0.040	24.274	0.112
		19	0.013	0.018	24.672	0.134
		20	-0.002	0.005	24.683	0.171
		21	0.001	0.001	24.688	0.214
		22	-0.022	-0.022	25.928	0.209
		23	-0.027	-0.029	27.768	0.183
		24	0.016	0.016	28.439	0.200
		25	-0.007	-0.008	28.568	0.237
		26	0.004	0.001	28.618	0.280
		27	0.013	0.019	29.067	0.308
		28	-0.020	-0.020	30.104	0.309
		29	0.030	0.029	32.383	0.259
		30	-0.020	-0.022	33.381	0.263
		31	0.008	0.002	33.537	0.300
		32	-0.014	-0.015	34.039	0.323
		33	0.009	0.003	34.235	0.361
		34	0.018	0.019	35.043	0.371
		35	0.004	0.005	35.092	0.416
		36	0.002	-0.002	35.098	0.464

Table 4.18: Residual Cor. Of GARCH Model of ISCTR

Table 4.19: Residual Squared Cor. Of GARCH Model of ISCTR

When we apply AR model with EGARCH method, R- Squared is nearly 1. Our Actual and Fitted graphs are acting like each other also our correlogram of q-statics and correlogram of squared residuals have no lag.

4.3.2.4. Model of YKBNK



Series: YKBNK_CLOSING Workfile: BITIRME::Untitled\

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats

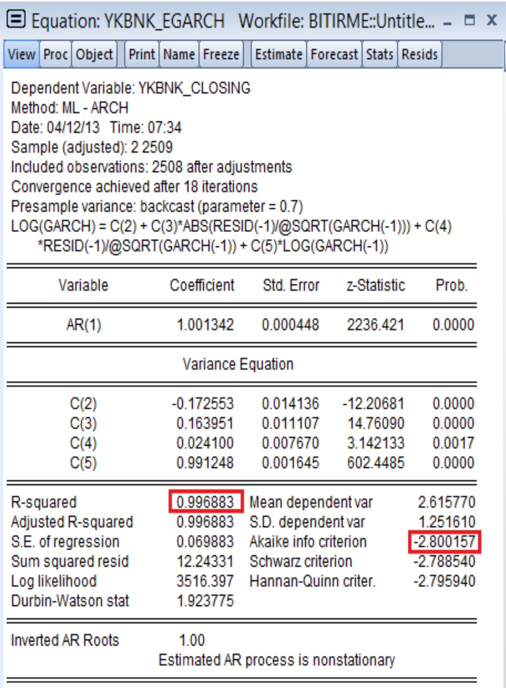
Correlogram of YKBNK_CLOSING

Sample: 1 2509
Included observations: 2509

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.997	0.997	2497.2	0.000
		2	0.994	-0.026	4979.8	0.000
		3	0.991	0.005	7448.2	0.000
		4	0.988	0.004	9902.4	0.000
		5	0.985	-0.008	12342.	0.000
		6	0.982	0.008	14769.	0.000
		7	0.979	0.017	17181.	0.000
		8	0.976	0.001	19581.	0.000
		9	0.973	0.015	21968.	0.000
		10	0.970	-0.018	24341.	0.000
		11	0.967	-0.005	26702.	0.000
		12	0.965	0.000	29049.	0.000
		13	0.962	-0.015	31383.	0.000
		14	0.958	-0.018	33703.	0.000
		15	0.955	0.001	36009.	0.000
		16	0.952	0.011	38301.	0.000
		17	0.949	-0.007	40580.	0.000
		18	0.946	0.016	42845.	0.000
		19	0.943	-0.011	45097.	0.000
		20	0.940	-0.024	47336.	0.000
		21	0.938	0.044	49562.	0.000
		22	0.935	0.018	51775.	0.000
		23	0.932	-0.017	53977.	0.000
		24	0.929	0.003	56166.	0.000
		25	0.926	0.007	58343.	0.000
		26	0.924	0.000	60508.	0.000
		27	0.921	0.011	62662.	0.000
		28	0.919	0.017	64804.	0.000
		29	0.916	0.007	66936.	0.000
		30	0.914	0.025	69057.	0.000
		31	0.911	0.003	71169.	0.000
		32	0.909	-0.005	73271.	0.000
		33	0.907	-0.026	75362.	0.000
		34	0.904	0.024	77443.	0.000
		35	0.902	0.030	79516.	0.000
		36	0.900	0.015	81579.	0.000

Firstly Correlogram of ISCTR have to be analyzed. When we look at the correlogram, we see that AR(1) model have to apply on data.

Table 4.20: Correlogram of YKBNK



Equation: YKBNK_EGARCH Workfile: BITIRME::Untitle...

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: YKBNK_CLOSING
Method: ML - ARCH
Date: 04/12/13 Time: 07:34
Sample (adjusted): 2 2509
Included observations: 2508 after adjustments
Convergence achieved after 18 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	1.001342	0.000448	2236.421	0.0000
Variance Equation				
C(2)	-0.172553	0.014136	-12.20681	0.0000
C(3)	0.163951	0.011107	14.76090	0.0000
C(4)	0.024100	0.007670	3.142133	0.0017
C(5)	0.991248	0.001645	602.4485	0.0000

R-squared	0.996883	Mean dependent var	2.615770
Adjusted R-squared	0.996883	S.D. dependent var	1.251610
S.E. of regression	0.069883	Akaike info criterion	-2.800157
Sum squared resid	12.24331	Schwarz criterion	-2.788540
Log likelihood	3516.397	Hannan-Quinn criter.	-2.795940
Durbin-Watson stat	1.923775		

Inverted AR Roots	1.00
	Estimated AR process is nonstationary

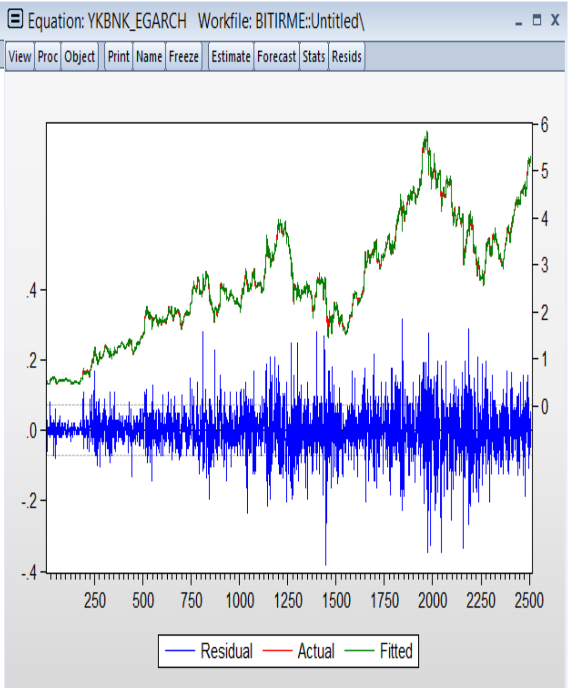


Table 4.21: Equation of EGARCH Model of YKBNK

Table 4.22: Actual-Fitted-Residual of EGARCH Model of YKBNK

Equation: YKBNK_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals

Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	0.039	0.039	3.9042	
2	-0.005	-0.007	3.9703	0.046
3	-0.007	-0.007	4.1046	0.128
4	0.014	0.015	4.5979	0.204
5	0.012	0.011	4.9519	0.292
6	-0.021	-0.022	6.0851	0.298
7	0.004	0.006	6.1334	0.408
8	-0.036	-0.036	9.3406	0.229
9	0.026	0.029	11.092	0.197
10	0.021	0.019	12.238	0.200
11	0.018	0.016	13.047	0.221
12	0.026	0.026	14.772	0.193
13	-0.000	-0.001	14.772	0.254
14	-0.024	-0.026	16.193	0.239
15	-0.015	-0.012	16.750	0.270
16	0.017	0.015	17.445	0.293
17	0.014	0.014	17.917	0.329
18	0.007	0.009	18.051	0.386
19	0.058	0.059	26.467	0.090
20	-0.043	-0.048	31.145	0.039
21	-0.012	-0.011	31.505	0.049
22	0.012	0.011	31.900	0.060
23	-0.022	-0.026	33.073	0.061
24	-0.021	-0.017	34.184	0.063
25	0.001	0.008	34.185	0.081
26	0.004	0.001	34.229	0.103
27	-0.042	-0.039	38.669	0.052
28	-0.018	-0.022	39.501	0.057
29	-0.030	-0.033	41.786	0.045
30	-0.037	-0.035	45.277	0.028
31	-0.006	-0.004	45.357	0.036
32	0.006	0.010	45.463	0.045
33	-0.036	-0.033	48.738	0.029
34	-0.036	-0.032	51.986	0.019
35	-0.004	-0.008	52.037	0.025
36	-0.023	-0.024	53.374	0.024

Equation: YKBNK_EGARCH Workfile: BITIRME::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals Squared

Sample: 2 2509
Included observations: 2508
Q-statistic probabilities adjusted for 1 ARMA term(s)

	AC	PAC	Q-Stat	Prob
1	0.091	0.091	20.676	
2	0.029	0.021	22.760	0.000
3	0.002	-0.003	22.768	0.000
4	0.021	0.020	23.848	0.000
5	-0.021	-0.025	24.952	0.000
6	-0.010	-0.007	25.182	0.000
7	-0.028	-0.026	27.138	0.000
8	-0.003	0.002	27.161	0.000
9	-0.013	-0.010	27.566	0.001
10	0.010	0.012	27.835	0.001
11	-0.002	-0.003	27.847	0.002
12	-0.004	-0.005	27.889	0.003
13	-0.040	-0.039	31.909	0.001
14	-0.033	-0.028	34.650	0.001
15	-0.019	-0.011	35.518	0.001
16	-0.023	-0.020	36.861	0.001
17	-0.008	-0.002	37.031	0.002
18	-0.008	-0.007	37.184	0.003
19	-0.017	-0.017	37.882	0.004
20	0.018	0.019	38.681	0.005
21	-0.040	-0.046	42.772	0.002
22	-0.010	-0.005	43.021	0.003
23	-0.027	-0.025	44.837	0.003
24	0.016	0.019	45.488	0.003
25	0.001	0.001	45.494	0.005
26	0.000	-0.005	45.494	0.007
27	0.014	0.013	45.975	0.009
28	0.031	0.023	48.420	0.007
29	0.013	0.006	48.849	0.009
30	0.014	0.007	49.327	0.011
31	0.008	0.006	49.507	0.014
32	-0.012	-0.017	49.896	0.017
33	0.049	0.054	55.897	0.006
34	0.024	0.014	57.378	0.005
35	-0.010	-0.017	57.608	0.007
36	-0.022	-0.021	58.845	0.007

Table 4.23: Residual Cor. Of GARCH Model of YKBNK   Table 4.24: Residual Squared Cor. Of GARCH Model of YKBNK

When we apply AR model with EGARCH method, R- Squared is nearly 1. Our Actual and Fitted graphs are acting like each other also our correlogram of q-statics and correlogram of squared residuals have no lag.

4.4 FORECAST

4.4.1 Mean Square Error

The mean square error (MSE) of an estimator $\hat{\theta}$ of a parameter θ is the function of θ defined by $E(\hat{\theta} - \theta)^2$ and this is denoted as $MSE_{\hat{\theta}}$.

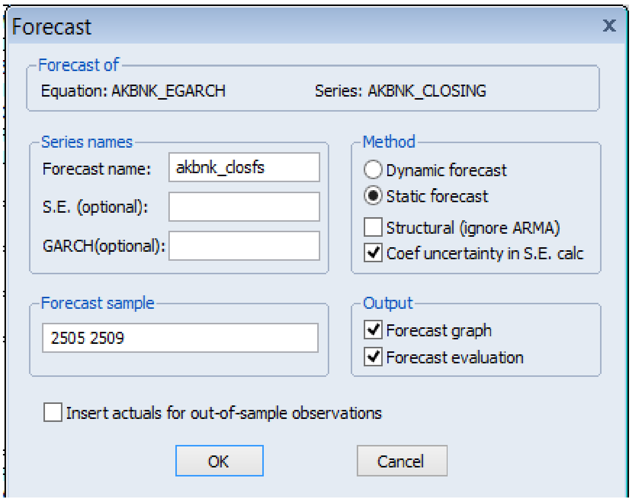
The MSE measures the average squared difference between the estimator $\hat{\theta}$ and the parameter θ ,o somewhat reasonable measure of performance of an estimator.

$$MSE_{\hat{\theta}} = E(\hat{\theta} - \theta)^2 = Var(\hat{\theta}) \quad [11]$$

4.4.2. Forecast of AKBNK

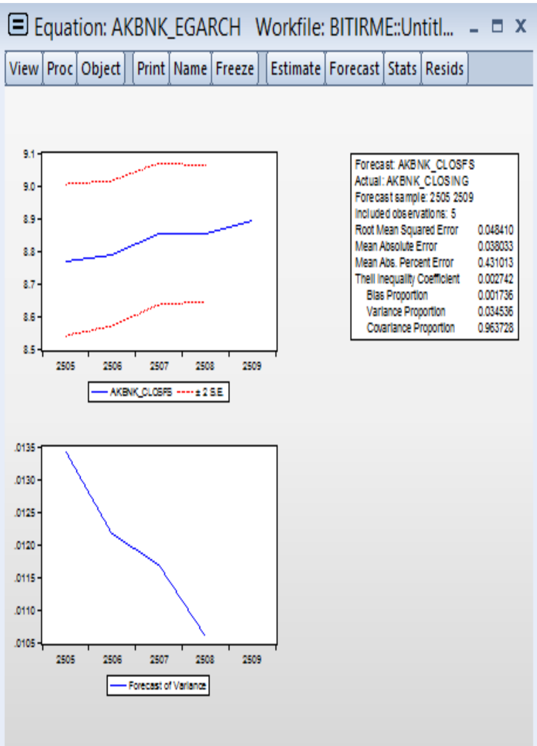
Our data will be forecasted step by step in 4 degree. We mentioned that there are two types of forecast. Static forecast and Dynamic Forecast. We use static forecast at the first step. Dynamic forecast is used for the other steps.

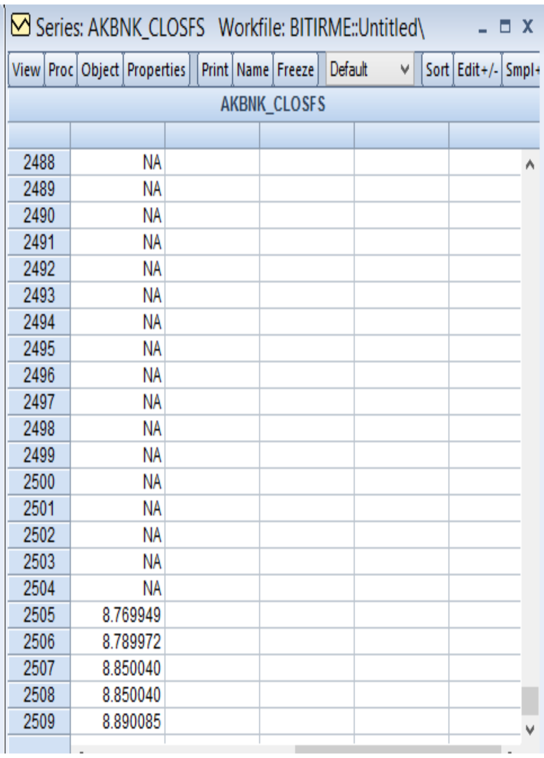
4.4.2.1. First Step



At the first step, we forecast last 5 terms in our data which are modelled by AR with EGARCH and our forecast method is static forecast.

Table 4.25: Forecast of AKBNK at first step



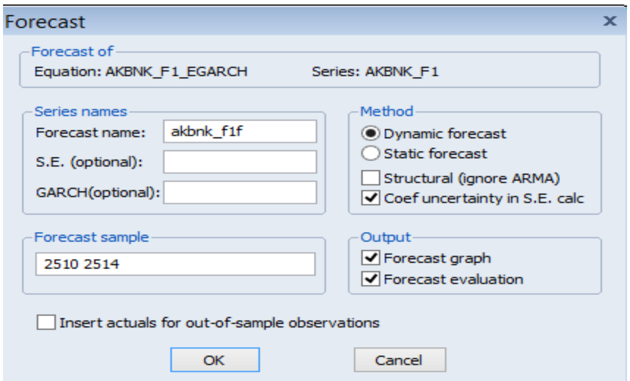


	AKBNK_CLOSFS
2488	NA
2489	NA
2490	NA
2491	NA
2492	NA
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	8.769949
2506	8.789972
2507	8.850040
2508	8.850040
2509	8.890085

Table 4.26: Forecast Graph of Step 1

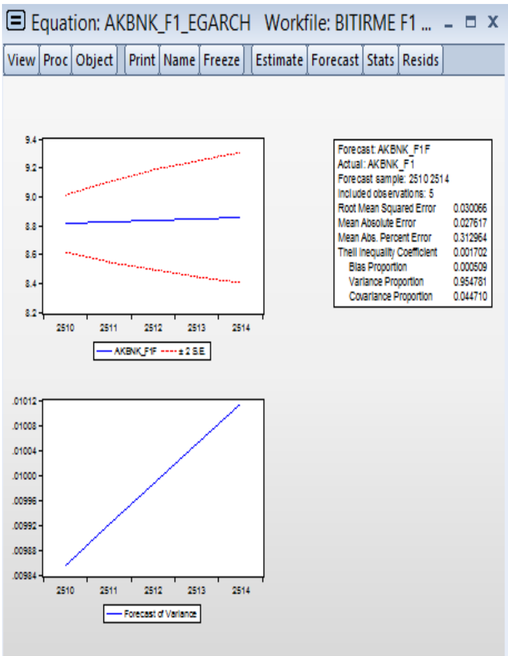
Table 4.27: Forecast Values of Step 1

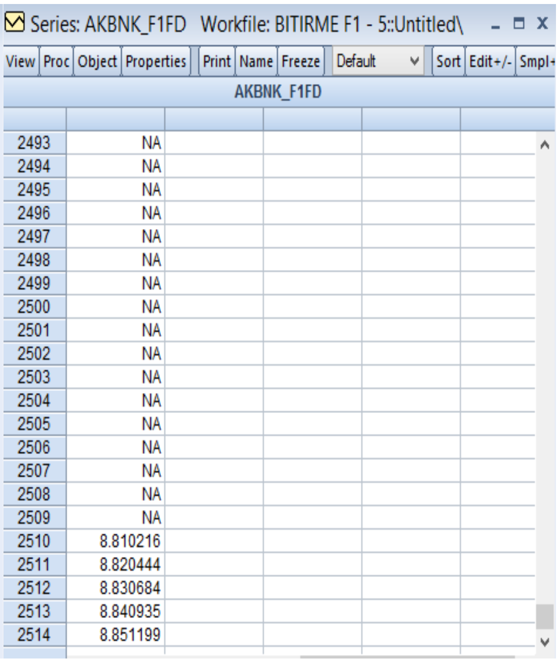
4.4.2.2 Second Step



At the second step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.71: Forecast of AKBNK at second step



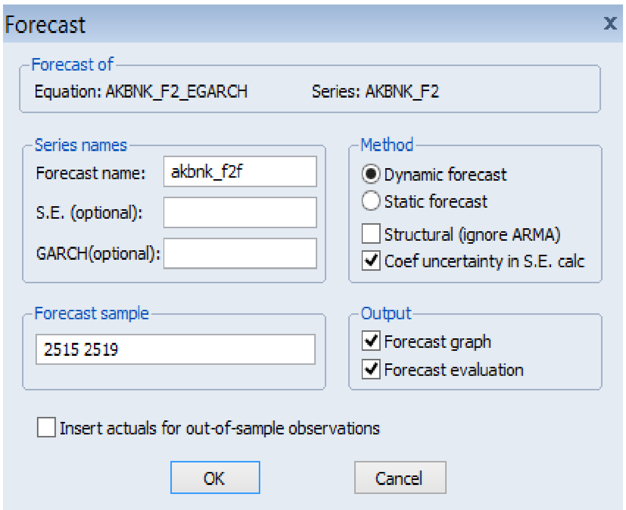


	AKBNK_F1FD
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	8.810216
2511	8.820444
2512	8.830684
2513	8.840935
2514	8.851199

Table 4.28: Forecast Graph of Step 2

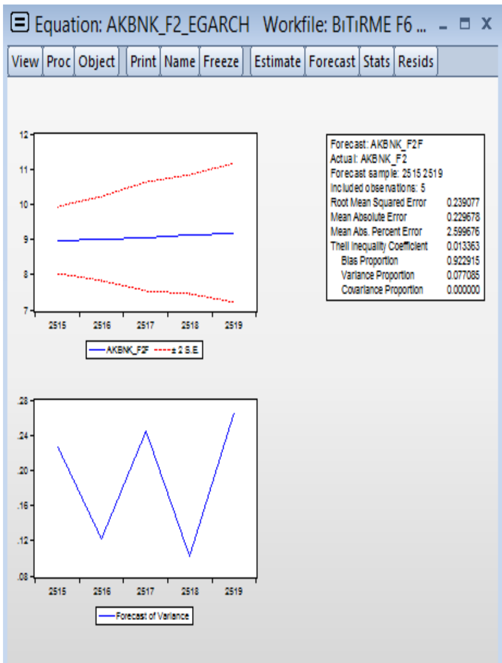
Table 4.29: Forecast Values of Step 2

4.4.2.3. Third Step



At the Third step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.30: Forecast of AKBNK at third step



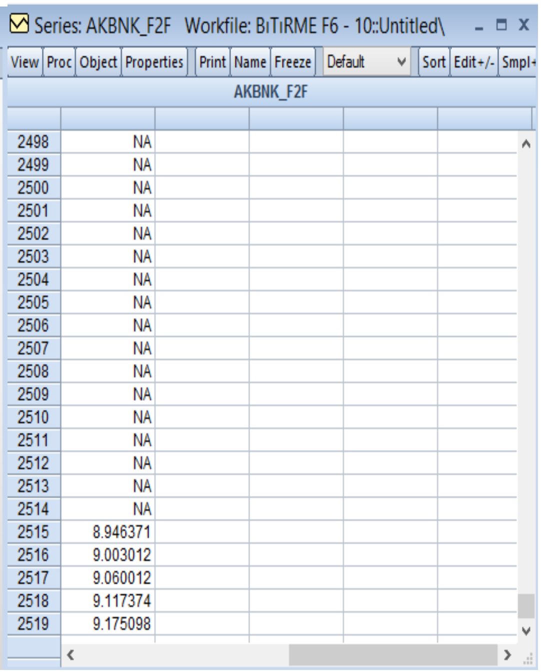
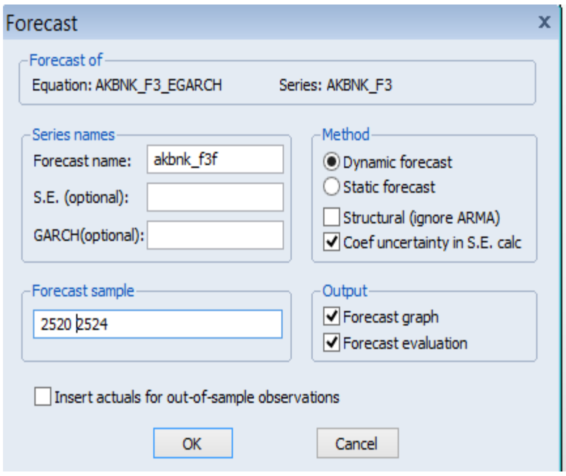


Table 4.31: Forecast Graph of Step 3

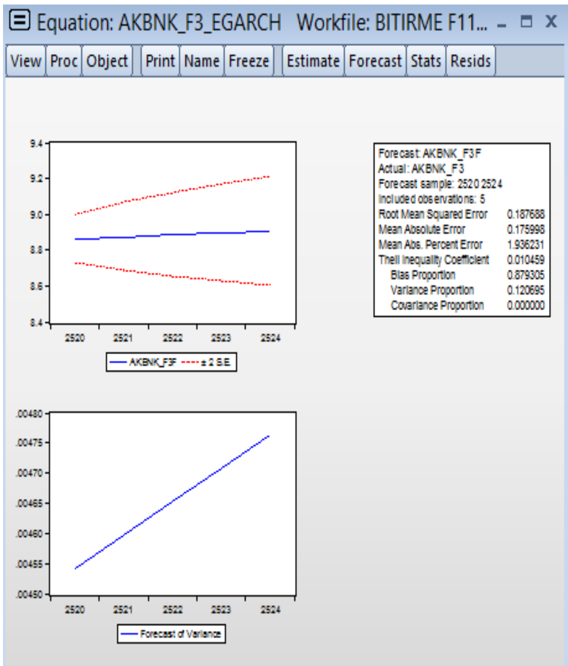
Table 4.32: Forecast Values of Step 3

4.4.2.4 Fourth Step



At the Fourth step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.33: Forecast of AKBNK at fourth step



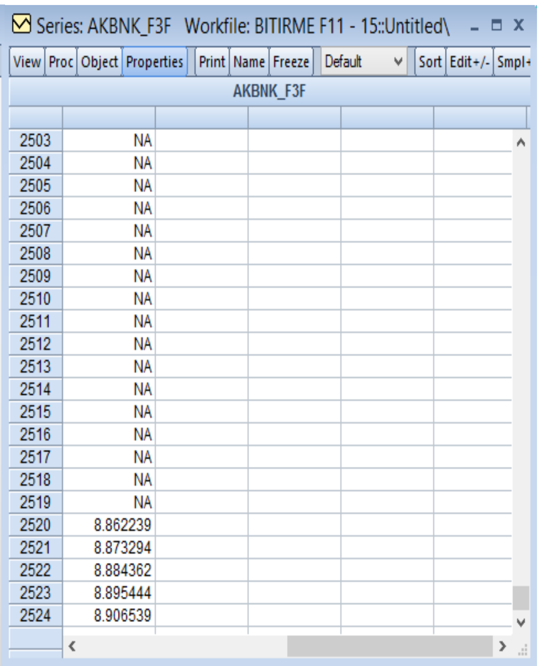


Table 4.34: Forecast Graph of Step 4

Table 4.35: Forecast Values of Step 4

Date	Real Values	Forecasted Values	|RV-FV|	difference %
02/01/2013	8,96	8,769	0,191	2,178127495
03/01/2013	9,04	8,789	0,251	2,85584253
04/01/2013	8,98	8,85	0,13	1,468926554
07/01/2013	9,02	8,85	0,17	1,920903955
08/01/2013	9,04	8,89	0,15	1,687289089
09/01/2013	9,02	8,81	0,21	2,383654938
10/01/2013	9,08	8,82	0,26	2,947845805
11/01/2013	9	8,83	0,17	1,925254813
14/01/2013	9,16	8,84	0,32	3,619909502
15/01/2013	9,2	8,85	0,35	3,95480226
16/01/2013	9,48	8,95	0,53	5,921787709
17/01/2013	9,8	9	0,8	8,888888889
18/01/2013	9,86	9,06	0,8	8,830022075
21/01/2013	9,88	9,12	0,76	8,333333333
22/01/2013	10	9,18	0,82	8,932461874
23/01/2013	10,08	8,86	1,22	13,76975169
24/01/2013	10,25	8,87	1,38	15,55806088
25/01/2013	9,86	8,88	0,98	11,03603604
28/01/2013	9,3	8,9	0,4	4,494382022
29/01/2013	9,42	8,91	0,51	5,723905724

5,821559359 Average Difference

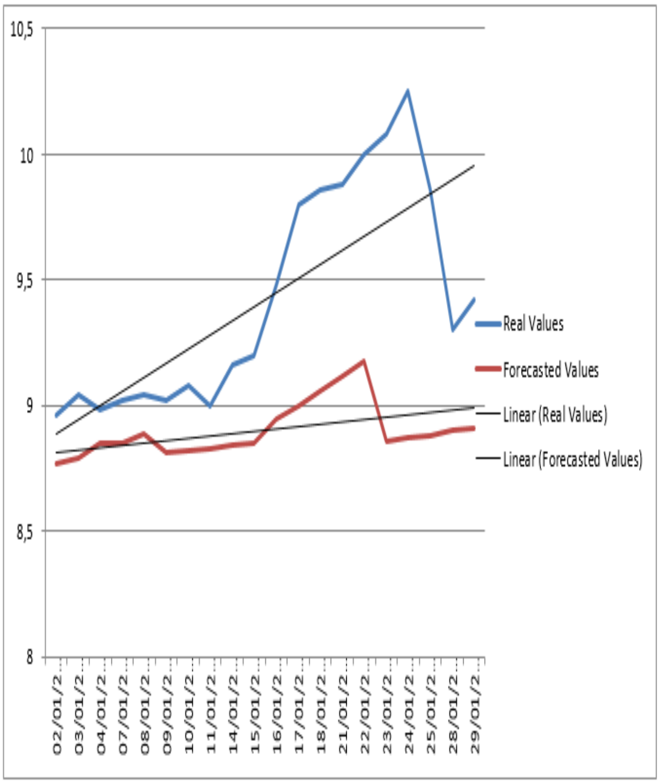


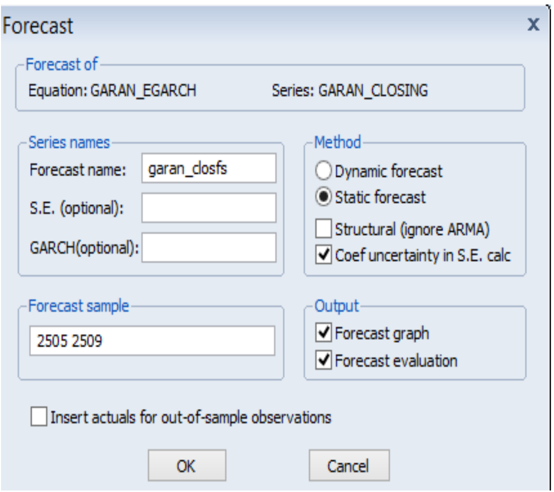
Figure 4.1: Comparison of Real Values and Forecasted Values of AKBNK

Forecast result of AKBNK is successful, because real values and forecasted values are acting like each other. The biggest difference is graph of real values shifted up. This is the result of political choices.

4.4.3 Forecast of GARAN

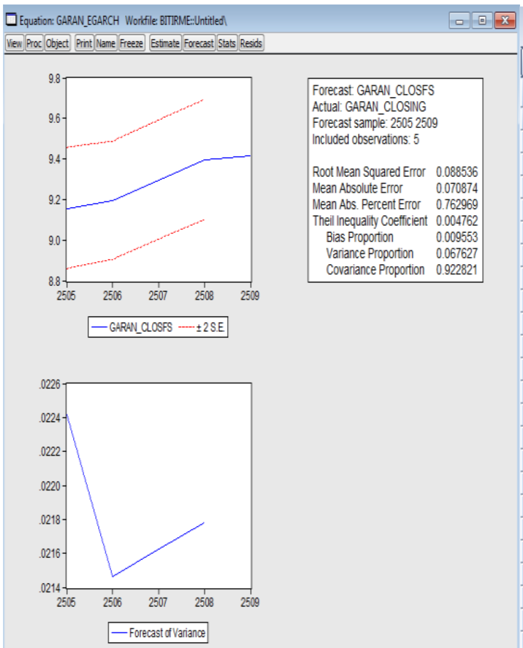
Our data will be forecasted step by step in 4 degree. We mentioned that there are two types of forecast. Static forecast and Dynamic Forecast. We use static forecast at the first step. Dynamic forecast is used for the other steps.

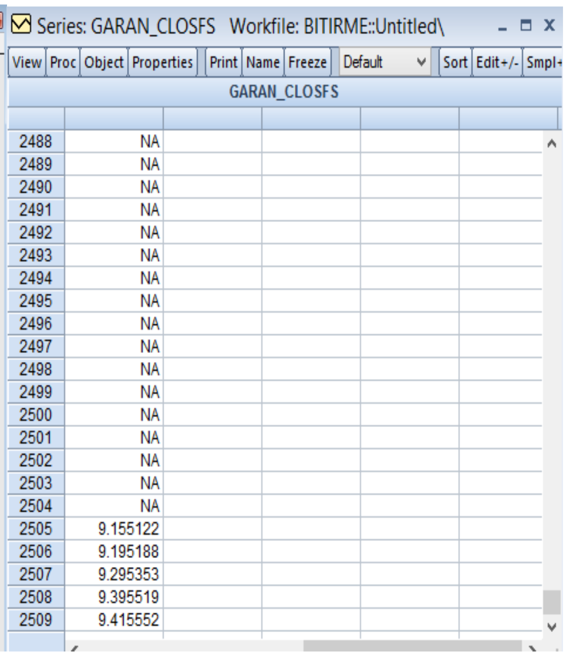
4.4.3.1 First Step



At the first step, we forecast last 5 terms in our data which are modelled by AR with EGARCH and our forecast method is static forecast.

Table 4.36: Forecast of GARAN at first step



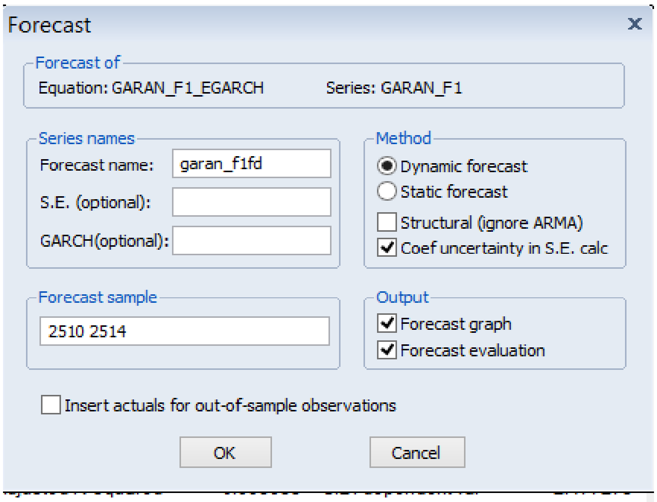


	GARAN_CLOSFS
2488	NA
2489	NA
2490	NA
2491	NA
2492	NA
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	9.155122
2506	9.195188
2507	9.295353
2508	9.395519
2509	9.415552

Table 4.37: Forecast Graph of Step 1

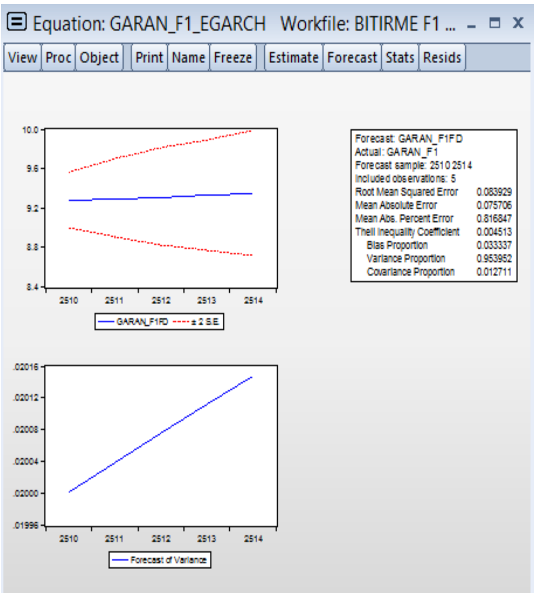
Table 4.38: Forecast Values of Step 1

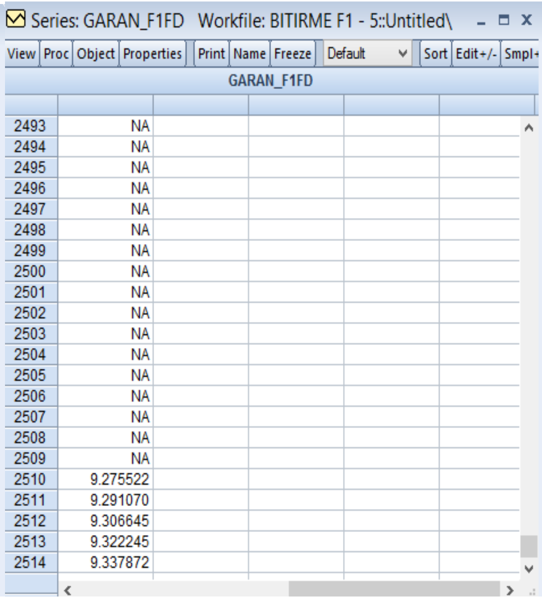
4.4.3.2 Second Step



At the second step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.39: Forecast of GARAN at second step



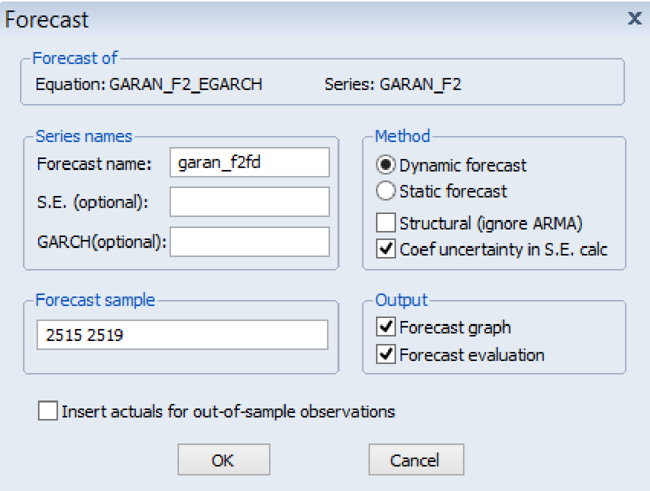

Series: GARAN_F1FD Workfile: BITIRME F1 - 5::Untitled\

	GARAN_F1FD
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	9.275522
2511	9.291070
2512	9.306645
2513	9.322245
2514	9.337872

Table 4.40: Forecast Graph of Step 2

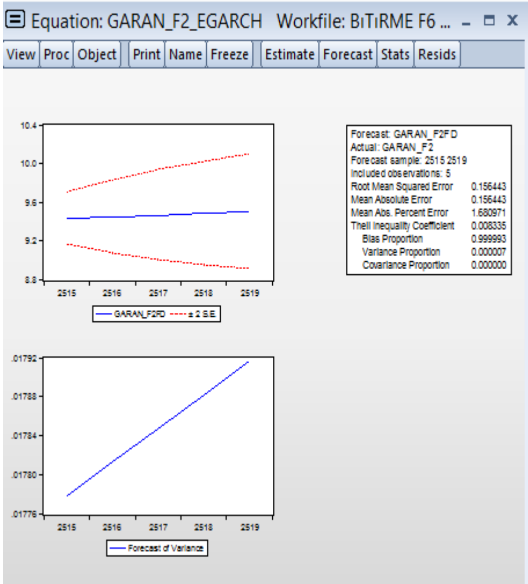
Table 4.41: Forecast Values of Step 2

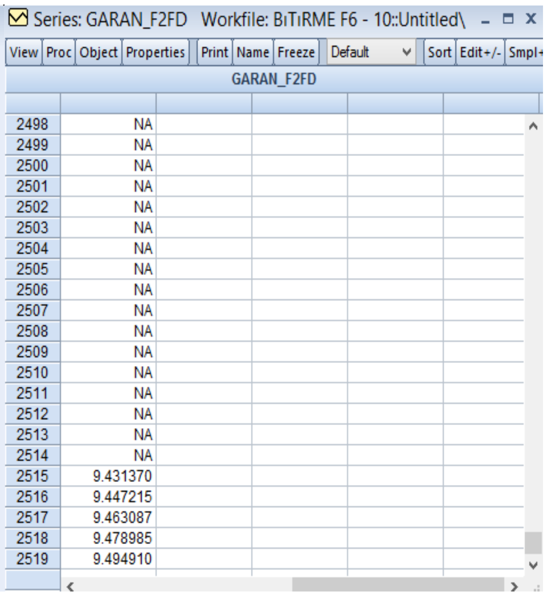
4.4.3.3 Third Step



At the Third step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.42: Forecast of GARAN at third step



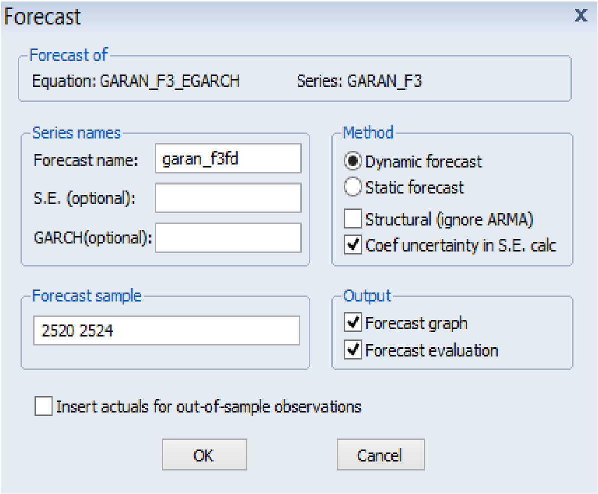


	GARAN_F2FD
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	9.431370
2516	9.447215
2517	9.463087
2518	9.478985
2519	9.494910

Table 4.43: Forecast Graph of Step 3

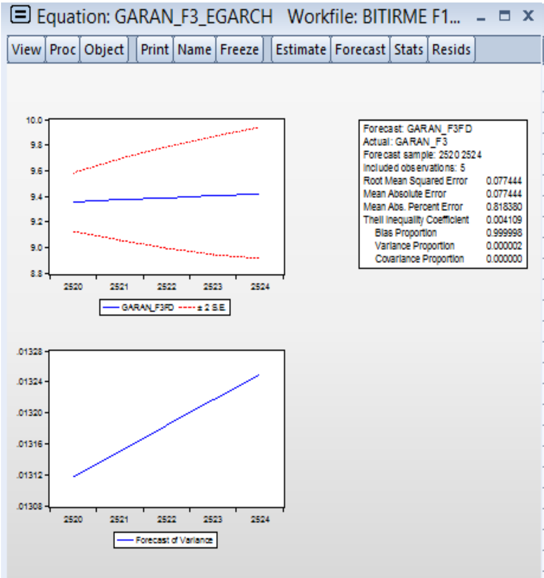
Table 4.44: Forecast Values of Step 3

4.4.3.4 Fourth Step



At the Fourth step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.45: Forecast of GARAN at fourth step



Series: GARAN_F3FD Workfile: BITIRME F11 - 15::Untitle...

	GARAN_F3FD
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	NA
2516	NA
2517	NA
2518	NA
2519	NA
2520	9.353768
2521	9.369692
2522	9.385643
2523	9.401621
2524	9.417626

Table 4.46: Forecast Graph of Step 4

Table 4.47: Forecast Values of Step 4

Date	Real Values	Forecasted Values	|RV-FV|	difference %
02/01/2013	8,98	9,155	0,175	1,911523758
03/01/2013	9,06	9,195	0,135	1,468189233
04/01/2013	9,1	9,295	0,195	2,097902098
07/01/2013	9,04	9,395	0,355	3,778605641
08/01/2013	9,12	9,415	0,295	3,133297929
09/01/2013	9,06	9,275	0,215	2,318059299
10/01/2013	9,1	9,291	0,191	2,055752879
11/01/2013	9,1	9,306	0,206	2,213625618
14/01/2013	9,2	9,322	0,122	1,308732032
15/01/2013	9,22	9,337	0,117	1,253079147
16/01/2013	9,48	9,431	0,049	0,519563143
17/01/2013	9,82	9,447	0,373	3,948343389
18/01/2013	9,92	9,463	0,457	4,829335306
21/01/2013	9,96	9,478	0,482	5,085461068
22/01/2013	10,16	9,494	0,666	7,014956815
23/01/2013	10,1	9,353	0,747	7,986742222
24/01/2013	10,25	9,369	0,881	9,403351478
25/01/2013	10,3	9,385	0,915	9,749600426
28/01/2013	9,86	9,401	0,459	4,882459313
29/01/2013	9,46	9,417	0,043	0,456621005
		3,77076009	Average Difference	

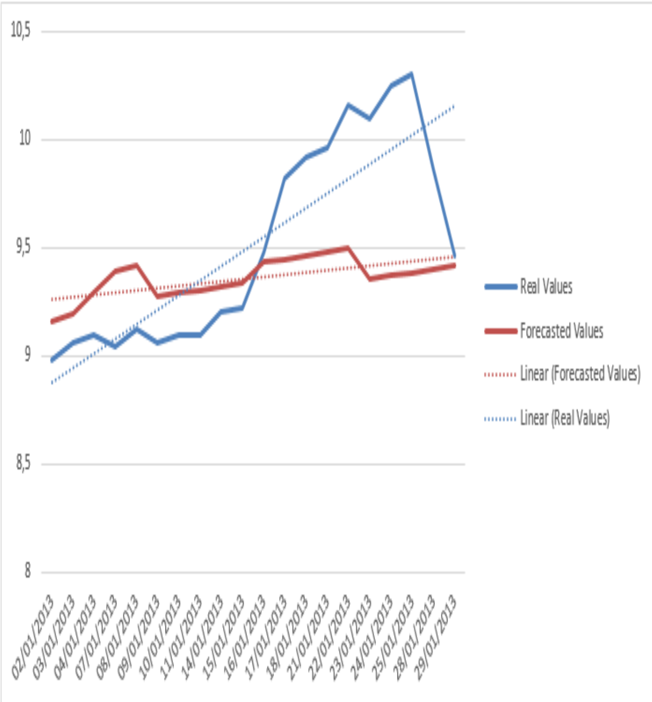


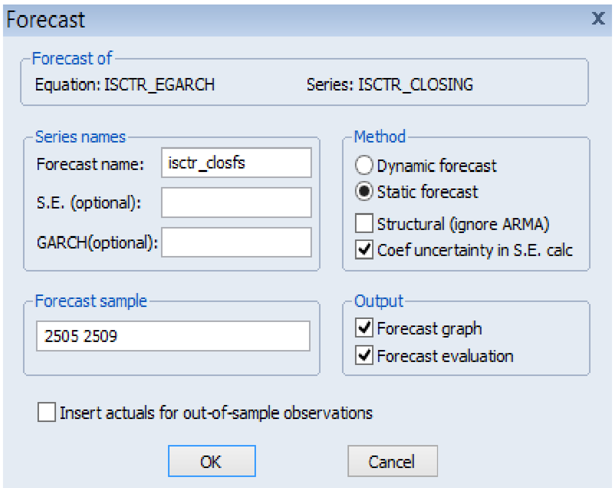
Figure 4.2: Comparison of Real Values and Forecasted Values of GARAN

Forecast result of GARAN is successful, because last data of real values and last data of forecasted values are very close. This means that when we make a long term investment we can benefit from this study.

4.4.4. Forecast of ISCTR

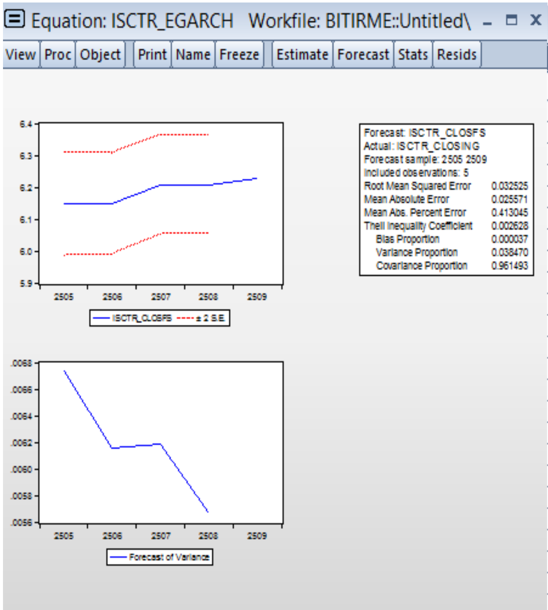
Our data will be forecasted step by step in 4 degree. We mentioned that there are two types of forecast. Static forecast and Dynamic Forecast. We use static forecast at the first step. Dynamic forecast is used for the other steps.

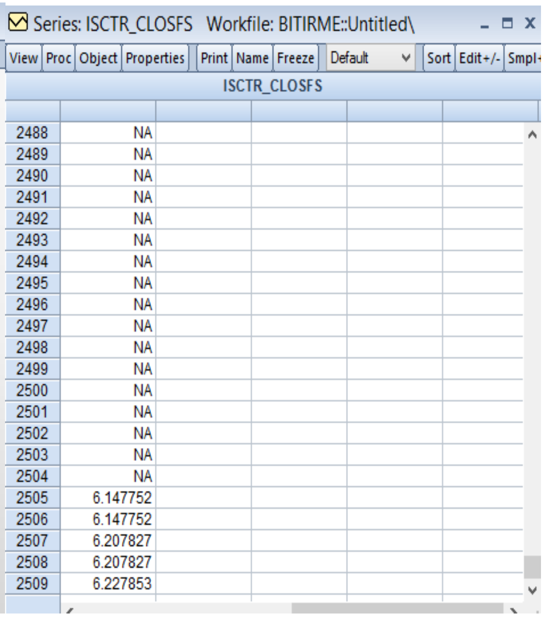
4.4.4.1 First Step



At the first step, we forecast last 5 terms in our data which are modelled by AR with EGARCH and our forecast method is static forecast.

Table 4.48: Forecast of ISCTR at first step



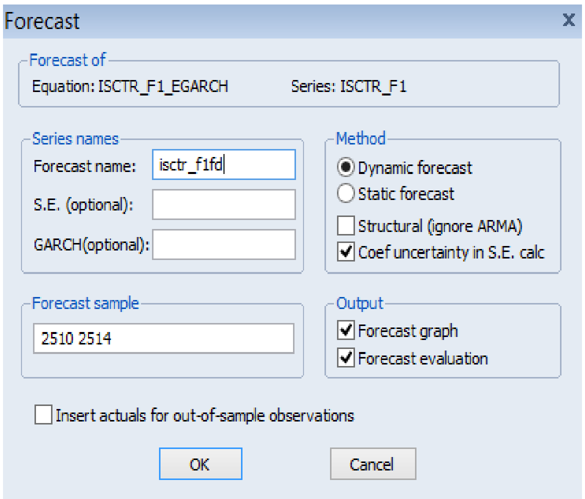


	ISCTR_CLOSFS
2488	NA
2489	NA
2490	NA
2491	NA
2492	NA
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	6.147752
2506	6.147752
2507	6.207827
2508	6.207827
2509	6.227853

Table 4.49: Forecast Graph of Step 1

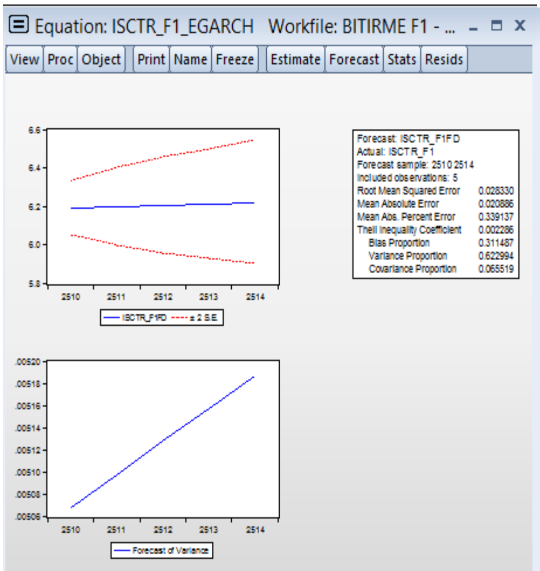
Table 4.50: Forecast Values of Step 1

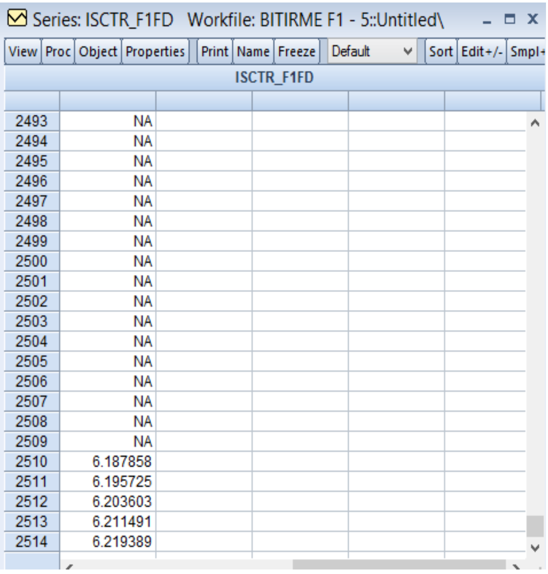
4.4.4.2 Second Step



At the second step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.72: Forecast of ISCTR at second step



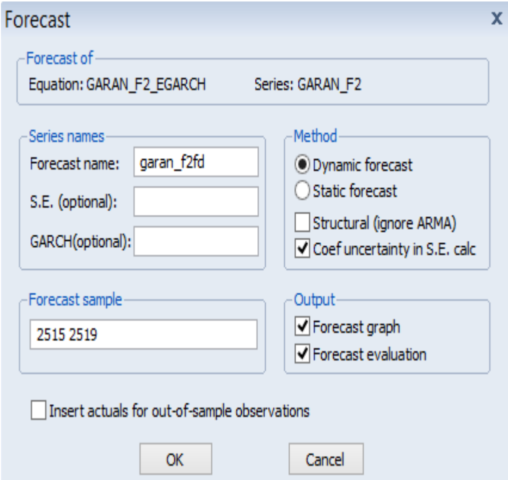


	ISCTR_F1FD
2493	NA
2494	NA
2495	NA
2496	NA
2497	NA
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	6.187858
2511	6.195725
2512	6.203603
2513	6.211491
2514	6.219389

Table 4.51: Forecast Graph of Step 2

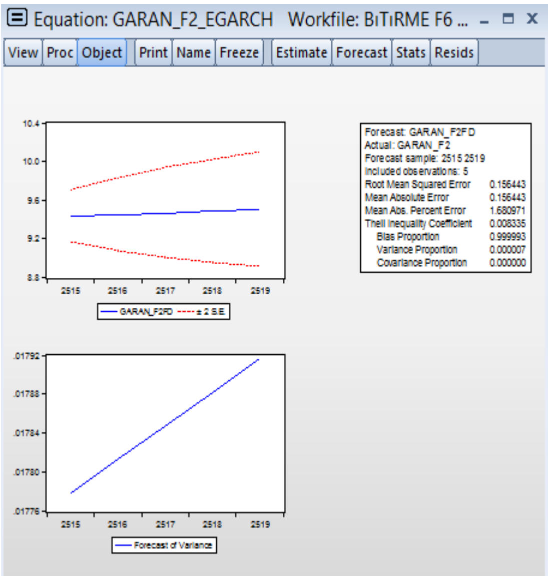
Table 4.52: Forecast Values of Step 2

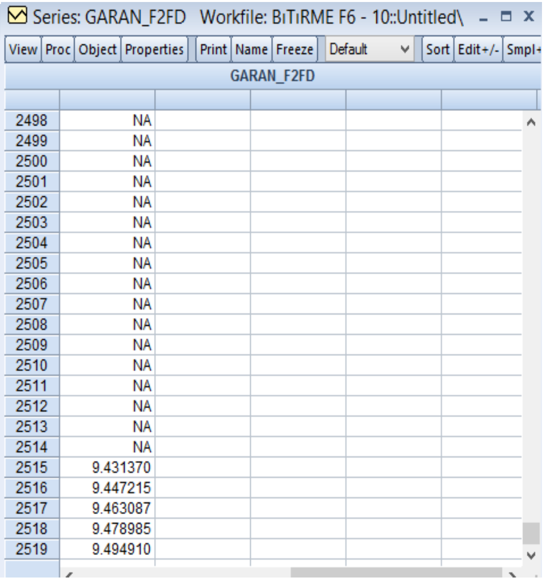
4.4.4.3 Third Step



At the Third step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.53: Forecast of ISCTR at third step



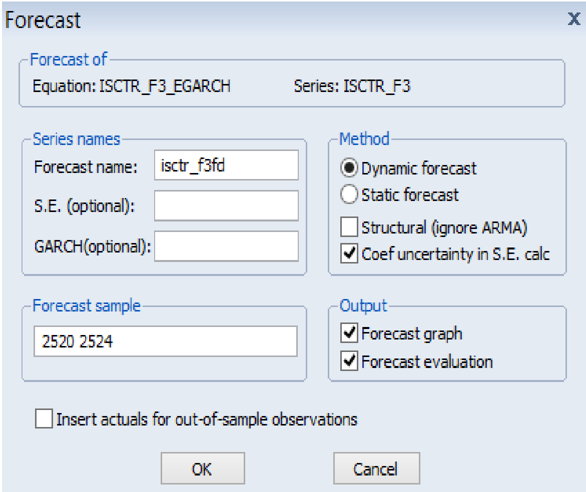


	GARAN_F2FD
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	9.431370
2516	9.447215
2517	9.463087
2518	9.478985
2519	9.494910

Table 4.54: Forecast Graph of Step 3

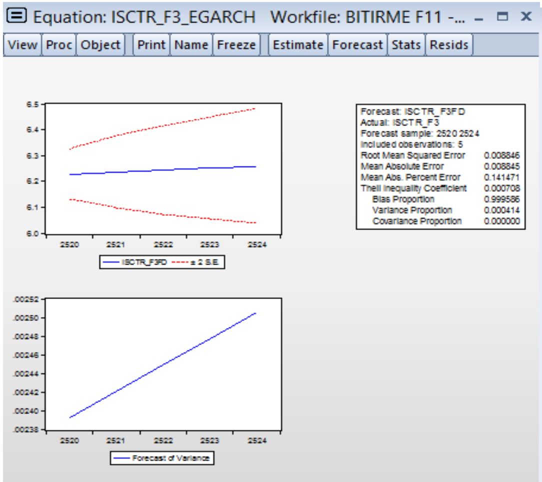
Table 4.55: Forecast Values of Step 3

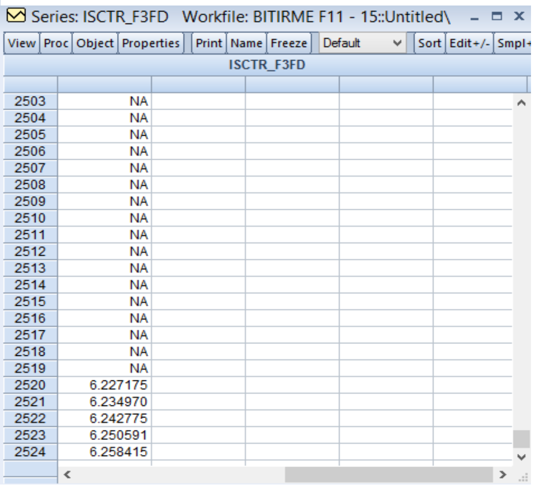
4.4.4.4 Fourth Step



At the Fourth step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.56: Forecast of ISCTR at fourth step



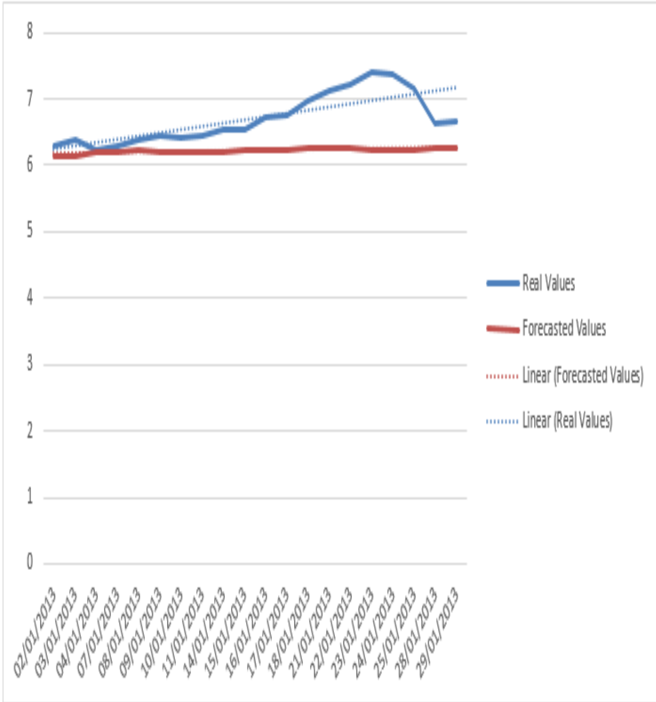


	ISCTR_F3FD
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	NA
2516	NA
2517	NA
2518	NA
2519	NA
2520	6.227175
2521	6.234970
2522	6.242775
2523	6.250591
2524	6.258415

Table 4.57: Forecast Graph of Step 4

Table 4.58: Forecast Values of Step 4

Date	Real Values	Forecasted Values	|RV-FV|	difference %
02/01/2013	6,3	6,147	0,153	2,489019034
03/01/2013	6,38	6,147	0,233	3,790466894
04/01/2013	6,24	6,207	0,033	0,531657806
07/01/2013	6,3	6,207	0,093	1,498308362
08/01/2013	6,38	6,227	0,153	2,457041914
09/01/2013	6,46	6,187	0,273	4,412477776
10/01/2013	6,42	6,195	0,225	3,631961259
11/01/2013	6,44	6,203	0,237	3,820731904
14/01/2013	6,54	6,211	0,329	5,297053615
15/01/2013	6,54	6,219	0,321	5,161601544
16/01/2013	6,72	6,235	0,485	7,778668805
17/01/2013	6,76	6,243	0,517	8,281275028
18/01/2013	6,96	6,251	0,709	11,34218525
21/01/2013	7,14	6,259	0,881	14,07573095
22/01/2013	7,22	6,267	0,953	15,20663794
23/01/2013	7,4	6,227	1,173	18,83732134
24/01/2013	7,38	6,234	1,146	18,38306064
25/01/2013	7,16	6,242	0,918	14,70682474
28/01/2013	6,64	6,25	0,39	6,24
29/01/2013	6,66	6,258	0,402	6,423777565



average

7,718290118 Average Difference

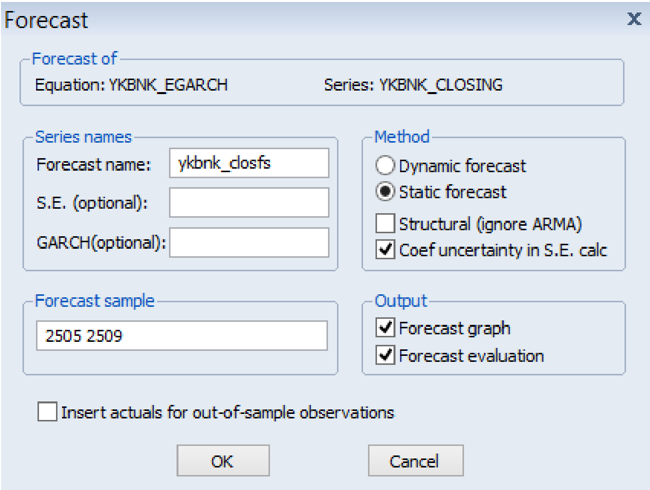
Figure 4.3: Comparison of Real Values and Forecasted Values of ISCTR

Forecast result of ISCTR is very close to real values. The biggest difference is graph of real values is starting upward trend when political choices are changed.

4.4.5. Forecast of YKBNK

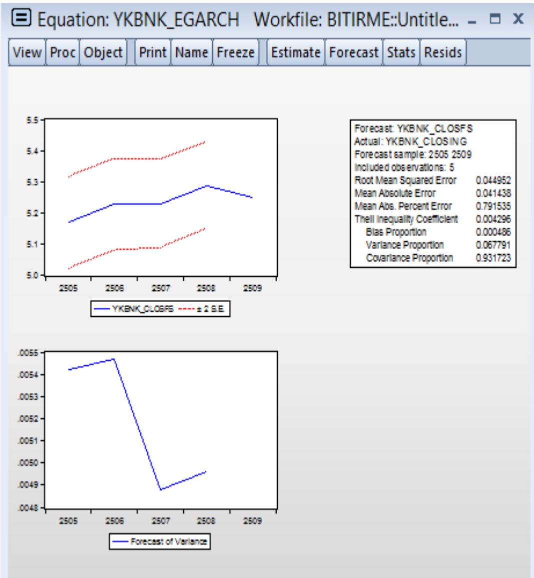
Our data will be forecasted step by step in 4 degree. We mentioned that there are two types of forecast. Static forecast and Dynamic Forecast. We use static forecast at the first step. Dynamic forecast is used for the other steps.

4.4.5.1 First Step



At the first step, we forecast last 5 terms in our data which are modelled by AR with EGARCH and our forecast method is static forecast.

Table 4.59: Forecast of YKBNK at first step



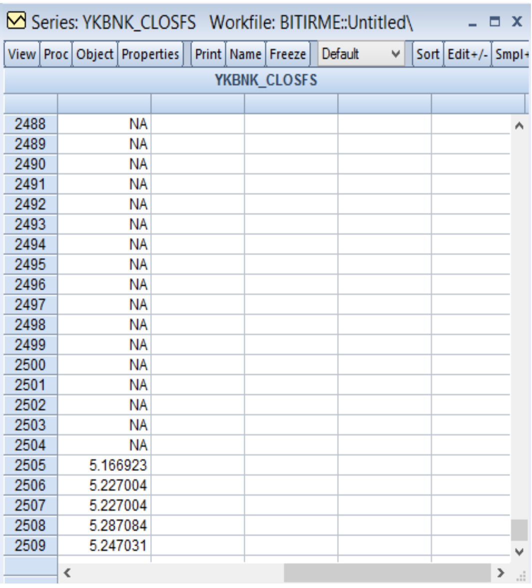
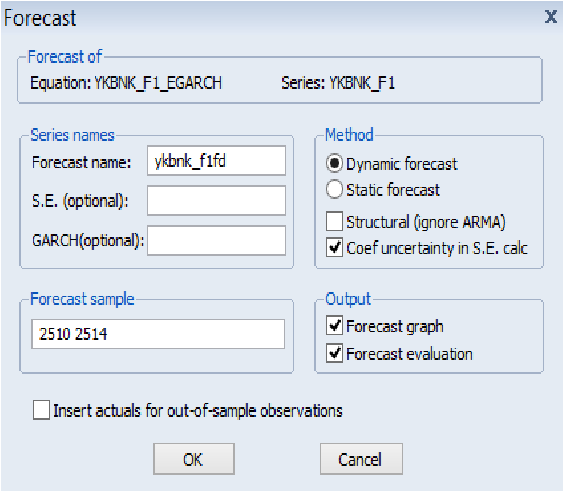


Table 4.60: Forecast Graph of Step 1

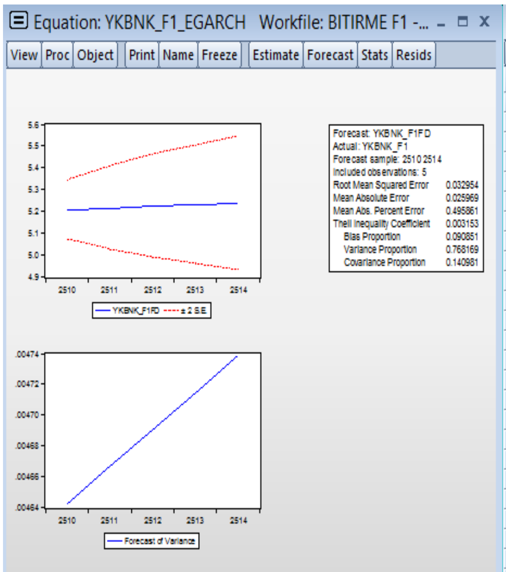
Table 4.61: Forecast Values of Step 1

4.4.5.2 Second Step



At the second step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.62: Forecast of YKBNK at second step



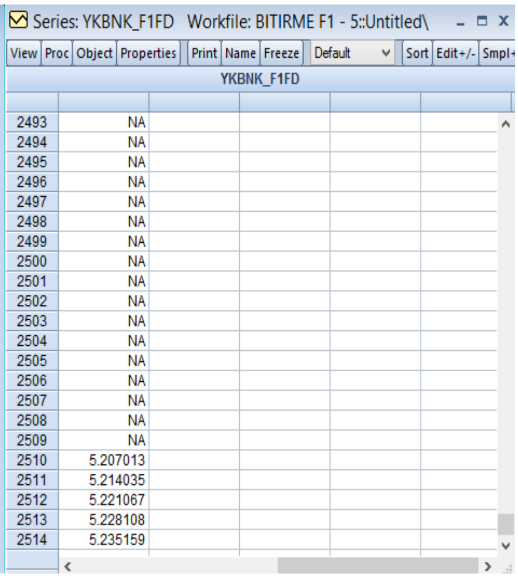
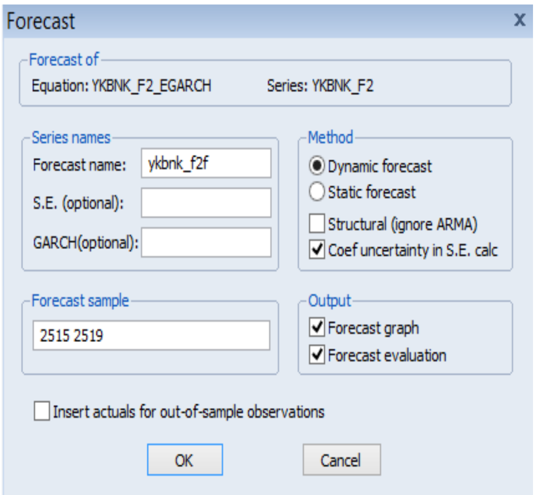


Table 4.63: Forecast Graph of Step 2

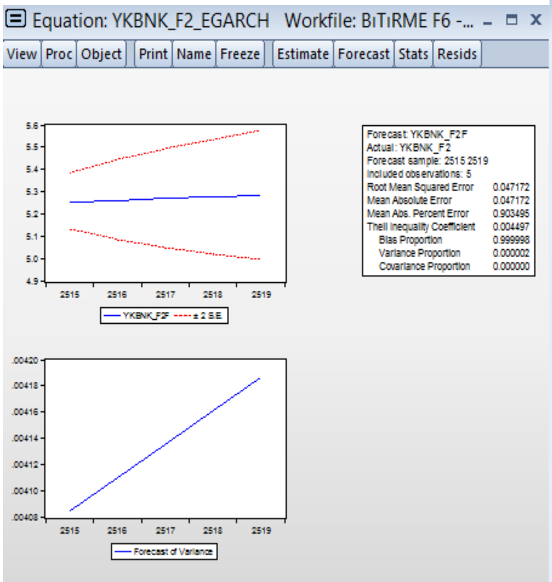
Table 4.64: Forecast Values of Step 2

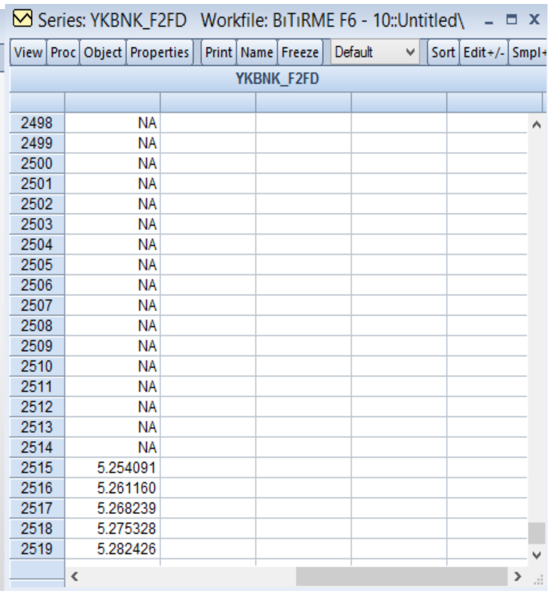
4.4.5.3 Third Step



At the Third step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.65: Forecast of YKBNK at third step



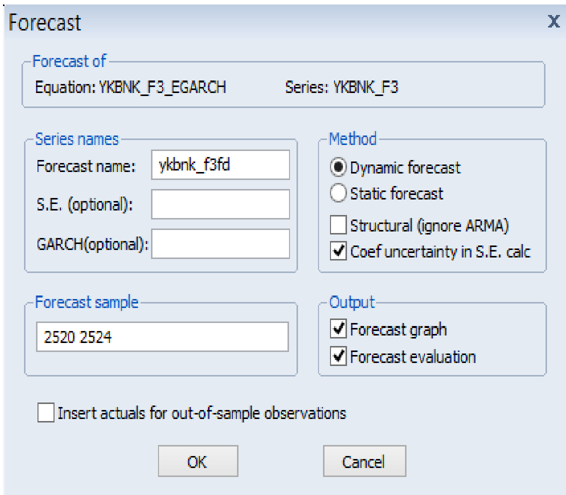


	YKBNK_F2FD
2498	NA
2499	NA
2500	NA
2501	NA
2502	NA
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	5.254091
2516	5.261160
2517	5.268239
2518	5.275328
2519	5.282426

Table 4.66: Forecast Graph of Step 3

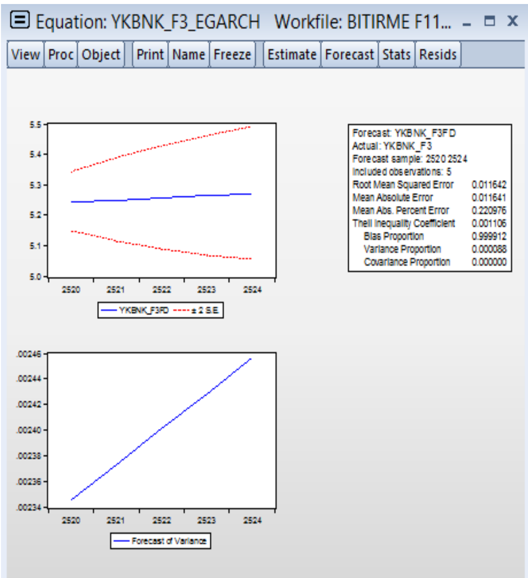
Table 4.67: Forecast Graph of Step 3

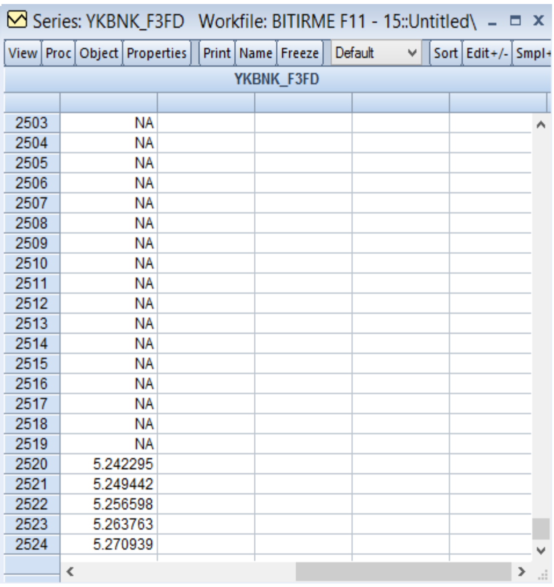
4.4.5.4 Fourth Step



At the Fourth step, we forecast last 5 terms again after first 5 forecasted terms added end of the first model and modelled again by AR with EGARCH. Our forecast method is dynamic forecast.

Table 4.68: Forecast of YKBNK at fourth step





	YKBNK_F3FD
2503	NA
2504	NA
2505	NA
2506	NA
2507	NA
2508	NA
2509	NA
2510	NA
2511	NA
2512	NA
2513	NA
2514	NA
2515	NA
2516	NA
2517	NA
2518	NA
2519	NA
2520	5.242295
2521	5.249442
2522	5.256598
2523	5.263763
2524	5.270939

Table 4.69: Forecast Graph of Step 4

Table 4.70: Forecast Values of Step 4

Date	Real Values	Forecasted Values	|RV-FV|	difference %
02/01/2013	5,32	5,166	0,154	2,98102981
03/01/2013	5,46	5,227	0,233	4,457623876
04/01/2013	5,36	5,227	0,133	2,544480582
07/01/2013	5,44	5,287	0,153	2,893890675
08/01/2013	5,44	5,247	0,193	3,678292358
09/01/2013	5,6	5,207	0,393	7,547532168
10/01/2013	5,46	5,214	0,246	4,718066743
11/01/2013	5,5	5,221	0,279	5,343803869
14/01/2013	5,58	5,228	0,352	6,732976282
15/01/2013	5,62	5,235	0,385	7,35434575
16/01/2013	5,76	5,254	0,506	9,630757518
17/01/2013	5,8	5,261	0,539	10,24520053
18/01/2013	5,84	5,268	0,572	10,85801063
21/01/2013	5,76	5,275	0,485	9,194312796
22/01/2013	5,66	5,282	0,378	7,156380159
23/01/2013	5,78	5,242	0,538	10,2632583
24/01/2013	5,72	5,249	0,471	8,973137741
25/01/2013	5,62	5,256	0,364	6,925418569
28/01/2013	5,24	5,263	0,023	0,43701311
29/01/2013	5,38	5,27	0,11	2,087286528
		6,2011409	Average Difference	

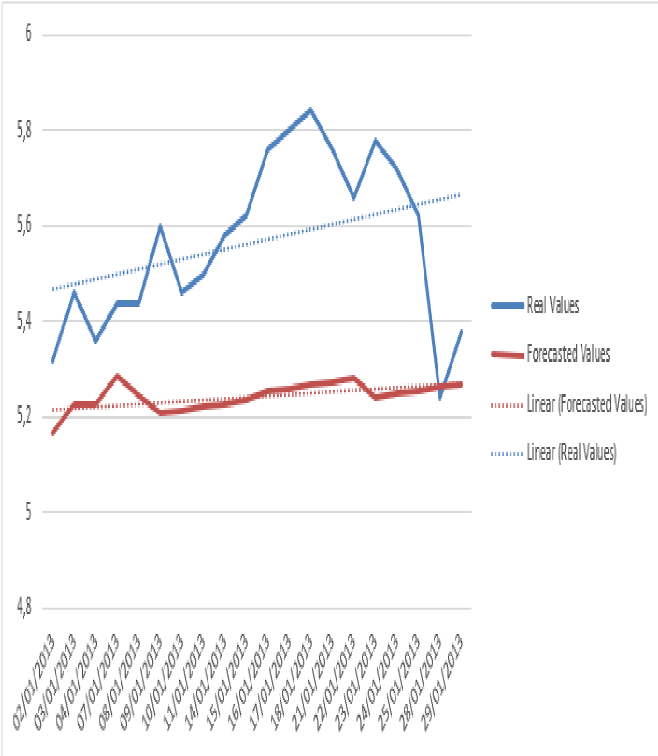


Figure 4.4: Comparison of Real Values and Forecasted Values of YKBNK

Forecast result of YKBNK’s trend line and trend line of real values like each other. Cause of the biggest difference between trend lines is political choices were changed at this time interval.

5. CONCLUCION

Forecast applications are one of the most important parts of the decision stages of investment strategies. To estimate future stock prices, proper models and methods must be used in forecast application. In our study, we forecasted 20 days stock prices of four banks in BIST. Then we compared real values and forecasted values of stock prices and calculated error.

In our study, we made tests on our data which are ADF Unit Root Test and comparative GARCH-EGARCH test. Then we used AR Model and EGARCH method according to our test results. We divided our application into 4 steps and used same method and model in every step. In addition to this method we used static forecast in first step and used dynamic forecast in other steps.

Firstly we analyzed the correlogram of the data and consider the lags which are out of the confidence interval. Then we used AR Model to clear lags from autocorrelation and partialcorrelation. In our first data (stock price of AKBANK), we applied GARCH and EGARCH methods separately. EGARCH method gives better results then GARCH method, so we used EGARCH method for all of our data. According to our Forecast results, real data and forecasted data acted like each other by a particular error interval.

In conclusion, if we make mathematical approach to forecast results, EGARCH Method is the best method for Forecasting stock price values which contain volatility and they are also financial time series data.

REFERENCES

[1] Kale, İsmet. *Volatilite Değerleme ve Tahmini İçin Garch Modellerinin Kullanılması.* Retrieved March 12,2013 from http://www.belgeler.com/blg/11yp/volatilite-deerleme-ve-tahmini-iin-garch-modellerinin-kullanimi-use-of-garch-models-for-estimating-and-forecasting-volatility

[2] Akar, Cüneyt (2007). *Volatilite Modellerinin Öngörü Performansları:ARCH, GARCH VE SWARCH Karşılaştırması.* İşletme Fakültesi Dergisi, Volume 8,Number 2,Pages 201-217.

[3] Songül, Hüseyin (2010). *Otoregresif Koşullu Değişen Varyans Modelleri:Döviz Kurları Üzerine Modelleme.* Türkiye Cumhuriyet Merkez Bankası Araştırma ve Para Politikası Genel Müdürlüğü,Ankara.

[4] Ser-Huang Poon (2005). *A Practical Guide to Forecasting Financial Market Volatility*. John Wiley & Sons Ltd,England.

[5] Kotze, A. A. (2005). *Stock Price Volatility:a primer*.Financial Chaos Theory, South Africa.

[6] *Augmented Dickey-Fuller Unit Root Test.* Retrieved March 24,2013 from http://faculty.smu.edu/tfomby/eco6375/BJ%20Notes/ADF%20Notes.pdf

[7] Klose, Christoph, Pircher, Marion, Sharma, Stephen (2004).*Univariate Time Series Forecasting.* Retrieved April 9,2013 from http://homepage.univie.ac.at/robert.kunst/proguni.pdf

[8] Sorensen, Bent E.(2005). *ARCH and Generalization.*Retrieved April 9,2013 from http://www.uh.edu/~bsorense/arch.pdf

[9] *Chapter 3:Forecasting From Time Series Models, Part 1:White Noise and Moving Average Models.* Retrieved April 16,2013 from http://people.stern.nyu.edu/churvich/Forecasting/Handouts/Chapt3.1.pdf

[10] Acquah, Henry de-Graft (2010).*Comparison of Akaike information criterion (AIC) and Bayesian information criterion (BIC)in selection of an asymmetric price relationship.* Retrieved April 16,2013 from http://www.academicjournals.org/jdae/PDF/Pdf2010/Jan/Acquah.pdf

[11] Zheng, Songfeng (n.d.). *Methods of Evaluating Estimators.* Retrieved April 16,2013 from http://people.missouristate.edu/songfengzheng/Teaching/MTH541/Lecture%20notes/evaluation.pdf

[12] *Forecasting Using Eviews 2.0:An Overview.*Retrieved April 17,2013 from http://faculty.washington.edu/ezivot/introforecast.PDF

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