USING EVMA AND GARCH METHODS IN VAR CALCULATIONS: APPLICATION ON ISE-30 INDEX

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ABSTRACT

Volatility tends to happen in clusters. The assumption is that volatility remains constant at all times can be fatal. In order to forecast volatility in stock market, there must be methodology to measure and monitor volatility modeling. Recently, EWMA and GARCH models have become critical tools for time series analysis in financial applications.

In this study, after providing brief descriptions, ISE-30 Index return volatility and individual stocks return volatility have been tested by using EWMA and GARCH methods.

JP Morgan Riskmetrics method has been used for EWMA method. Various data ranges (number of days) have been selected to use in calculations. It is determined that the most recent data have asserted more influence on future volatility than past data.

RATS program has been used for GARCH methodology. Time series has been used to estimate volatility and give more weights to recent events as opposed to older events. The outcome is GARCH provides more accurate analysis than EWMA.

Daily VaR numbers have been calculated by using EWMA and GARCH models for stocks inside the ISE-30 Index. The results are satisfactory for forecasting volatility at 95% and 99% confidence level. These two methods enhance the quality of the VaR models.

These findings suggest that traders and risk managers are able to generate portfolio profit and minimize risks if they obtain a better understanding of how volatility is being forecasted.

Keywords: Volatility, EWMA, GARCH, VaR, and ISE-30
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1. Introduction

Recently, the barriers on capital flows have eased gradually while the financial activity has increased tremendously. Although competition has increased among companies in the finance sector, the risks that financial institutions bear have been escalating. Besides domestic risks, financial institutions have to face new risks that are associated with international financial activities.

One key factor that caused recent financial crisis in many regions is the lack of efficient risk management in the industry. After these crisis, local and international authorities have tried to establish and force companies to apply effective risk mesurement systems for risks related to balance sheet or outside balance sheet operations.

As it is well known that, the price volatility in equity and derivative markets leave individual and institutional investors face with financial risks. Volatility in returns increases the demand of accurate portfolio risk measurements. Investors are more perceptive about their return and loss on their investments. A trend that is so crucial to many investing parties ever since the financial markets have downside risk measurment.

The need of downside risk measurement force scholars and institutions to work on the measurement technique. Finally, in 1994 the new concept was initiated by JP Morgan they named Value at Risk (VaR). Basically, VaR initiated by JP Morgan is to measure market risks and record in a standard way of results. Although VaR itself cannot be perfect solution for measuring the market risks, it plays an important role to convey the other risk studies and enhance investors' risk understanding.

There are two important studies that have put incentives to stimulate the exploration of financial risk management. The first academic study is to estimate and forecast volatility in a dynamic way. Volatility estimation models have been initially studied by Engle (1982) in the academic world. Hundreds of new studies follow Engle`s original volatility estimation work. The second study is from Wall Street developed by JP Morgan named RiskMetrics method in 1994. It basically measures the portfolio's market risks using mathematical and statistical methodology.

When measuring VaR numbers, it attempts to model the financial assets behavior. Those behaviors include the changes in price, the increase in assets prices, the effects on assets, and the correlations between two assets are to be determined.

VaR methods are widely used by financial institutions and other firms to evaluate their risks, forecast their cash flows risk that help to derive at the hedging decisions.

2. VaR and JP Morgan`s RiskMetrics

According to Verity and Carmody (1999), JP Morgan has achieved one of the best milestone in financial risk management area for their introduction of riskmetrics method in October 1994. The VaR method is easy to calculate and interpret that makes it capable of providing standardization in international aspects which are acceptable for many institutions. Similar comments made by Colombia Business School about the advantage of RiskMetrics is users can download the riskmetrics program through internet beginning May of 1995. RiskMetrics allow users to download assets historical data from internet site. 280 pages of technical documents about riskmetrics manual can be also downloaded which can be applied in any currency portfolio position that has proven to be attractive to financial users.

Despite of the fact that VaR is widely accepted by the practioners in the financial market industry, Beder (1995) has stated the handicap of VaR method. VaR could come out with different risk numbers for the same portfolio based on the method users choose. Just to name a few methods, they are historical simulation, Monte Carlo simulation methods, riskmetrics, and BIS/Basle. These methods assume different correlations between financial assets that may derive at different VaR numbers.

The VaR result could vary on the method chosen and the assumption of the correlation. Although VaR and other methods are accepted as effective risk management tools, they are not sufficient enough to monitor and control risk at all. The hope is to have only one powerful risk mesurment program that can solve the problems of investors and institutions, and able to measure risk effectively and systematically.

Barone-Adesi and Giannopoulos (2000) have mentioned in their work that the VaR number can be reached by either variane-covarience or simulation techniques. The using of statistics and the characteristics of financial assets would affect the reliability of VaR methods. In order to measure the VaR numbers and compare the results, they test the simulation method from January 1997 to November 1999 for S&P100 portfolio including options. In order to remove the gaps for their findings, they suggest to use filtered historical simulation techniques.

Hendricks (1996) randomly selects 1,000 currency options portfolio to test the effectiveness of VaR models. The objective of his study is to demonstrate and compare the similarity of the risk number measured by VaR method and real risk. The one factor he considers is market risk along with utilizing three fundamental methods:

(i) Equally weighted moving average
(ii) Exponentially weighted moving average
(iii) Historical simulation method

Based on the methods above, he has concluded with different VaR numbers. Yet, he cannot conclude that one method is superior to others. In his test, he also shows that 95% and 99% of confidence level produce different VaR numbers.

Vlaar (1998) has chosen 12-year maturity and 8 different years to maturity Netherlands government bonds with 25 hypothetical portfolios applied in three different VaR models (historical, Monte Carlo, and variance-Covariance) that are based on 99% confidence level for a 10-day time horizon for comparison. His findings are, (i) historical simulation can be successful if and only if there is ample of historical data, (ii) Monte Carlo methods requires load of data in order to derive at accurate VaR number, finally (iii) Based on normal distribution and changing variance through time models when applying Monte-Carlo and variance-covariance together generates better VaR results than others.

Simons (1996) defines the risks associated with financial assets and states two restictions related to VaR: (i) VaR concentrates on only one point in distribution of profit and loss; however a representation of all distributions can be more favorable, (ii) VaR can be weak to measure the accurate risk number in extreme market conditions.

Although VaR is accepted as an useful tool to measure the market risk for portfolios by individual, institutional investors, bankers, and academicians, the limitations of the model is openly discussed in the industry.

Dowd (1998) has listed three Var restrictions:

- Using historical data to forecast the future behavior.
- Model was built under assumptions that not valid for all conditions. Users should be aware of the model restrictions and formulate their calculations.
- Forecasting VaR numbers could be good for those who possess solid understanding and knowledge of vaR concepts.

Jorion (2000) has mentioned the intricate parts of VaR calculations in his work. During the time when portfolio position is assumed to be constant that in reality does not apply to practical life. The disadvantage of VaR is it cannot determine where to invest. Jorion (1997) has similar critics about VaR that it is not a perfect measurement tool. VaR simply illustrates the various speed of risk that are embbeded from the derivative instruments.

It seems that VaR's use is multi purpose; reporting risk, limiting risk, regulatory capital, internal capital allocation and performance measurement. Yet, VaR is not the answer for all risk management challenges. No theory exists to demonstrate that VaR is the appropriate measure upon which to build optimal decision rules. VaR does not measure "event" (e.g., market crash) risk, so the portfolio stress tests are recommended to supplement VaR. While VaR does not readily capture liquidity differences among instruments, the limits on both tenors and option greeks are still useful. Since VaR doesn't readily capture model risks, the model reserves are also necessary. Because VaR does not capture all relevant information about market risk, its best use as a tool in the hands of a good risk manager. Nevertheless, VaR is a very promising tool; one that will continue to evolve rapidly due to the intense interest by practitioners, regulators, investors, and academics (Schachter: 2002).

3. The Concept of VaR

In 1994, Procter and Gamble lost 100 million USD and Orange County lost 1.64 billion USD in United States financial derivative markets. After similiar losses happened Barings Bank branch in Far East Asia lost billions of dollars and the bank almost went bankrupt amid wrong and uncontrolled derivative instruments speculations. These three huge loses in financial markets force the institutions to protect and hedge themselves from unexpected huge loses. Therefore, they want to measure the risk that they bear from their risky investments. (Korkmaz, 1999:109). VaR is much on the minds of risk managers and regulators these days, because of the promise it holds for improving risk management. It is common to hear the question asked, “could VaR have prevented Barings, or Orange County, or Sumitomo”. Further analysis need to perform to search for conclusion (Schachter: 2002).

Especially the public companies have to force to publish their portfolio positions and risk number associated with their financial decisions under their financial tables. In addition, they have to mention the methods on how they calculate the risk numbers, standard deviation of the calculations, the amount of collateral reserved for their risky investments. These numbers are also being audited by the independent auditors. Both the inside and outside investors have high interests in VaR numbers that public companies disclose. The reason is VaR serves as one important criteria is rating the companies. All these developments have stirred up the companies to set up VaR as part of the risk management system.

VaR is a statistical definition that states one number of maximum loss per day, per week or per month. In other words, VaR is a statistical summary of financial assets or portfolio in terms of market risk (Culp, Mensink, Neves, 1999:3).

A VaR calculation is aimed at making a statement that the investors are x percent certain that they will not lose more than V a month of money in the next N days.

VaR is a good tool that risk mangers should be aware of in order to act on hedging their risky positions. VaR is also being accepted as a standard measurement to specify banks regulatory capital by BIS (Karelse, 2001). Therefore, many parties in the financial markets such as institutions, wealthy investors, authorities, auditors, and rating agencies are able to monitor market risk regularly and accept different confidence level for their VaR calculations (Culp, Mensink, Neves, 1999).

When comparing two different portfolios’ VaR number, the time horizon must be the same. To compare one day and ten days, VaR numbers are not meaningful (Penza, Bansal, 2001:63).

In financial market, the typical time horizon is 1 day to 1 month. Time horizon is chosen based on the liquidity capabilitity of financial assets or expectations of the investments. Confidence level is also crucial to measure the VaR number. Typically in the financial markets, VaR number calculates between 95% to 99% of confidence level. Confidence level is choosen based on the objective such as Basel Committee requests 99% confidence level for banks regulatory capital. For insiders, confidence level could be lower.

For instance, JP Morgan use 95%, Citibank 95.4% and Bankers Trust 99% use confidence level for their VaR calculations (Nylund, 2001:2).

4. Volatility

Volatility is a statistical measurement of assets prices movement. The higher the volatility means the possibility of higher return or loss. VaR measures the risk therefore estimate the accurate loss number volatility is used.

In real life applications, some financial models assume the volatility is constant through time. This may be a mistake or can be misleading the results. Any financial assets that could currently have a lower volatility may have a much higher volatility in the future (Butler, 1999:190).

The methods that measure volatility demonstrate different characteristics that have direct effect on VaR numbers. The followings are the general volatility methods:

- Standard deviation
- Simple moving average
- Historical simulation
- Exponential weighted moving average
- GARCH (Generalized Autoregressive Conditional Heteroscedastic)

Volatility models accept volatility is constant in some period of time and return in any day is equal to other days. However in real life, volatility and correlations change through time. For instance, low volatilty term can be followed by high volatility term. High return can be followed by another higher return term. This means that serial correlations between financial assets returns.

Economic news also explains the financial assets returns. Economic news have effects on that day`s assets return while the following day the news effect will be gradually decline.

In order to forecast volatility, having serial correlations between assets returns are considered crucial inputs. In other words, the latest return give more insights about forecasting volatility than the old return data.

For VaR calculations, EWMA (Exponentially Weighted Moving Average) and GARCH models assume returns on financial assets have serial correlations. Both models give more weight to the latest returns than the old ones. Therefore, volatility is estimated on latest return numbers by EWMA and GARCH models (Best, 1999:69).

Mandelbort (1963) and Fama (1965) observe on their work is, the big price changes in financial assets prices tend to follow another big price changes; while small price changes in financial assets tend to follow small price changes. Similar findings are also reported on Baillie (1996), Chou (1988) and Schwert (1989)'s works on financial assets behavior. The existence of today`s volatility cluster the effect on future forecasted volatility. (Engle, Paton, 2000:6).

Although most of the researchers accept the fact that volatility can be forecasted, how this volatility can be modelled are still ongoing disputes. Lately, there are many work on volatility modelling in academic and practical life. One interesting model is assymetric models that forecaste volatility of good and bad news that have different effect on market. Pagan and Schwert (1990) comapare different volatility models with different criterias. Balaban also mentions that many reserach works on ISE shows volatility exists in ISE. Even the volatility in ISE has been tested by macroeconomic factors but cannot substantiate any meaningful relationships (Güneş, 1998).

5. EWMA Model

RiskMetrics measure the volatilty by using EWMA model that gives the heaviest weight on the last data. Exponentially weighted model give immediate reaction to the market crashes or huge changes. Therefore, with the market movement, it has already taken these changes rapidly into effect by this model. If give the same weight to every data, it is hard to capture extraordinary events and effects. Therefore, EWMA is considered to be a good model to solve the problem.

If the exponential coefficient choose as a big number, current variance effects will be small over total variance.

EWMA model assumes that the weight of the last days is more than old days. EWMA is a model that assumes assets price changes through time.

JP Morgan uses EWMA model for VaR calculation. EWMA responds the volatility changes and EWMA does assume that volatility is not constant through time.

Using EWMA to modelling volatility, the equation will be:

$$\sigma = \sqrt{(1-\lambda)\sum_{t=n}^{t=1} \lambda^t (X_t - \mu)^2}$$

Where λ is an exponential factor and n is a number of days. In equation μ is the mean value of the distribution, which is normally assumed to be zero for daily VaR.

The equation can be stated for exponential weighted volatility:

$$\sigma = \sqrt{\lambda \sigma_{t-1}^2 + (1-\lambda) X_t^2}$$

This form of the equation directly compares with GARCH model. The crucial part of the performance of the model is the chosen value factor.

JP Morgan`s RiskMetrics model uses factor value as of 0,94 for daily and 0,97 for monthly volatility estimations.

For EWMA calculation, the necessary number of days can be calculated by the following formula (Best, 1999:70).

Necessary data number = log (required accuracy)/log(factor value)

For asset *i* at time *t*, exponential weighted volatility can be written as follows:

$$\sigma_{i,t} = \sqrt{(1-\lambda)\sum_{j=0}^{\infty} \lambda^j r_{t-j}^2}$$

In equation λ is an exponential factor, $r_{i,t}$ represent logarithmic return of asset *i* at time *t*. Thus, $r_{i,t}$ is calculated by $\ln(P_{i,t} / P_{i,t-1})$ formula.

If there are loads of data for past years, the data chosen for the model should be selective. The criteria given by RiskMetrics is 99% of the all available data. This can be formulated as stated $1/(1-\lambda)$. Here n number of return data`s serial weight is equal to $(1-\lambda^n)/(1-\lambda)$. Thus if 99% of the weight wants to be included, the number of data should be calculated as $n = \ln(0.01)/\ln(\lambda)$ formula. Effective data number for forecasting volatility is based on exponential factor numbers. As seen on the formula, high exponential factor number means more data requirements.

In this case' RiskMetrics volatility can be formulate as follows:

$$\sigma_{i,t} = \sqrt{\frac{1-\lambda}{1-\lambda^n} \sum_{j=0}^{n} \lambda^j r_{i,t-j}^2}$$

5.1. Choosing the Exponential Factor Number in EWMA Model

Assuming the daily average return is zero, it can be written as $E[r_{i,t+1}^2] = \sigma_{i,t}^2$.

To minimize the average of error squares, it needs to identify the number of exponential factor with variance is the function of exponential factor. By using this methodology, it is determined that daily volatility forecasting for 0.94 and for monthly volatility forecasting is 0.97.

The factor to choose the number of exponential factor is based on investors` time horizon. For individual investors, the time horizon is generally more than one day. As a result, the volatility forecasting is correct at some point of time. Using exponential factor 0.97 is much more stable than 0.94 (RiskGrades Technical Document, 2001:8).

5.2. Shadow Effect

Shadow effect is an interesting phenomena when constructing volatility modelling. Risk managers use 100 days of data to eliminate sampling errors. But, for example unexpected event happened in stock markets, its effects will continue during these 100 days. Only one day that peak happened in the market will affect the future volatility estimation and increase the volatility level which is deviate from the market reality. In order to solve this problem, risk mangers use EWMA model' to give more weight on the latest data and less on the previous data (Butler, 1999:200). In EWMA model, JP Morgan use λ as an exponential factor and the vaule could change between 0 and 1. Previous data denotes by *n* number of days multiple by λ^n. As *n* getting higher, λ^n will be smaller. This kind of extraordinary events effect will be less on variance and covariance. Extraordinary events that are carried on past and shadow effects will not be valid for a long time (Alexander, 1996:4).

6. ARCH Model

ARCH (Auto Regressive Conditional Heteroscadisticity) model is commonly used in volatilty forecasting that was initially introduced by Engle in 1982.

In ARCH(1) model, at time t conditional volatility depends on previous time $t-1$ volatility. If volatility in period $t-1$ is large, also at time t huge volatility is expected.

In ARCH model, it is possible to explain clustering volatility and that vary from high volatility to low volatility.

ARCH(p) process can be explain as follows;

$$R_t = \beta X_t + e_t$$

$$e_t \text{I} I_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-1}^2$$

Where

$R_t =$ Explainotary variable (independent), linear functions of X_t.

$\beta =$ Vector of dependent parameters

$e_t =$ Error term, assuming of mean is zero, variance h_t which is normally distributed, in time $t-1$ based on conditional information I_{t-1}.

$h_t =$ Conditional variance

$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-1}^2$ is the general ARCH model that is the weighted average of error squares that shows current volatility is strongly affected from the past volatility. In ARCH model, all paraemters are calculated from the old data and use for future volatility forcasting. Furthermore, if $\alpha_1 \rangle \alpha_2$, old data is proven to have less effect on the current volatility.

7. GARCH Model

GARCH (Generalized Auto Regressive Conditional Heteroscadisitcity) is widely used in financial markets researches but have many versions. GARCH metod is initially developed by Bollerslev in 1986. Bollerslev developed the ARCH model after Engle to come up with GARCH model. Some other researchers have added different improvements through time. The equation for basic GARCH(1,1) model;

$$\sigma = \sqrt{\omega + \beta\sigma_{t-1}^2 + \alpha X_{t-1}^2}$$

where σ_{t-1} = volatility of previous day

α, β and ω are the predicted parameters. $\alpha + \beta$ values are called "persistence" and must be greater than 1. GARCH parameters is difficult to calculate for this estimation requires maximum likelihood functions.

If GARCH parameters $\alpha + \beta$ are high means high average volatility.

Comparing EWMA and GARCH equations,

$$\sigma = \sqrt{\lambda\sigma_{t-1}^2 + (1-\lambda)X_t^2}$$
$$\sigma = \sqrt{\omega + \beta\sigma_{t-1}^2 + \alpha X_{t-1}^2}$$

As seen on the equations above, β parameter is the same as λ (exponential factor) in EWMA equation. Similarly, α parameter is the same as (1- λ) in EWMA equation. In GARCH equation, the acceptance of ω=0 makes EWMA equation a special version of GARH equation.

Accumulating the accurate results in regression variance of error terms use h_t notation.

$$r_t = m_t + \sqrt{h_t}\varepsilon_t$$

In this equation, variance of error term is 1. GARCH model for variance:

$$h_{t+1} = \omega + \alpha(r_t - m_t)^2 + \beta h_t = \omega + \alpha h_t \varepsilon_t^2 + \beta h_t$$

In equation ω, α, β parameters should be calculated. Weights are $(1-\alpha-\beta, \beta, \alpha)$ and long term average variance is $\sqrt{\omega/(1-\alpha-\beta)}$. If $\alpha + \beta \langle 1$, the formula will be valid. Moreover, having acceptable results, coefficients must be positive.

Typical GARCH model is GARCH (1,1). The first notation of (1,1) shows ARCH effect and second one is moving average. In order to get GARCH parameters, it needs maximum likelihood estimation method. There are many softwares available to perform this task.

Basically, GARCH (p,q) model is given as follows.

$$R_t = \beta X_t + e_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{p}\alpha_i e_{t-i}^2 + \sum_{j=p+1}^{q}\alpha_j h_{t-j}$$

In truly determined process, parameters must be $\alpha_0, \alpha_i, \alpha_j \geq 0$. Moreover, Bollerslev (1986) mentions that for volatility process, it must satisfy $\alpha_i + \alpha_j$<1 condition.

8. Optimum Lag Lenght

In order to build a correct model, the first thing must be determined is the optimal lag length. For this Akaike-AIC (1973) and Schwarz-SIC (1978) models can be used.

AIC ve SIC work with maximum likelihood method so these two models have wide range of applications.

The criteria for these two methods are given below:

AIC : T ln (sum of squares errors) + 2n

SIC : T ln (sum of squares errors) + n ln(T)

Where, T is usable observations, n is the number of independent variables.

$\ln(T)$ will be greater than 2 so SIC will be a greater number than AIC. When working on lag lengths, it is observed that some data will be missing. Therefore, in order to have a better model, the small AIC or SIC will be selected.

9. Objective of the Study

The publicly traded companies inside ISE-30 Index have their VaR numbers individually determined. EWMA and GARCH models are used to calculate VaR. In order to compare these two methods, it needs to capture better volatility forcasting. Lastly, a report of the failures of the models upon extraordinary events that impact ISE.

10. Data

The daily data is collected from the ISE Statistical Department. The data is from January 5, 1998 to January 31, 2002. The stocks in ISE-30 Index is selected due to their highest daily trade volume. In addition, they are the blue chips of Turkish market. The company names and the codes are given below:

Ak Enerji (Akenr), Akbank (Akbnk), Aksa (Aksa), Aksigorta (Akgrt), Alarko Holding (Alark), Anadolu Efes (Aefes) Arcelik (Arclk) Doğan Holding (Dohol), Dogan Yayın Hol. (Dyhol), Enka Holding (Enka) Eregli Demir Celik (Eregl), Ford Otosan (Froto), Garanti Bankasi (Garan), Hurriyet Gzt. (Hurgz), Is Bankasi C (Isctr), Is Gmyo (Isgyo), Koc Holding (Kchol), Migros (Migrs), Netas Telekom. (Netas), Petkim (Petkm), Petrol Ofisi (Ptofs), Sabanci Holding (Sahol), Sise Cam (Sise), Tansas (Tnsas), Tofas Oto. Fab. (Toaso), Trakya Cam (Trkcm), Turkcell (Tcell), Tupras (Tuprs), Vestel (Vestl), Yapi ve Kredi Bank. (Ykbnk).

The reason the data begins on January 5, 1998 is to have at least 1,000 trade days to obtain a more accurate calculation and result. Furthermore, the full data is just available for 25 companies. There are 5 companies (Ak Enerji, Dogan Yayin Holding, Is Gmyo, Turkcell, and Anadolu Efes) do not have all the data due to various reasons.

11. Testing ISE-30 Index Return Volatility and Individual Stocks Return Volatility by Using EWMA and GARCH Methods.

Before testing the return volatilities by EWMA and GARCH methods, Table 1 will show a descriptive statistics about ISE-30 Index and the inside stocks. The stocks return are calculated as follows (Benninga, 1997:68):

$$A_t = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right)$$

Where;

A_t = return on stock A at time t,

ln = natural logarithm,

P_t = Stock A price at time t,

D_t = For stock A at time t dividend payment.

P_{t-1} = Stock A price at t-1.

Sharpe ratio (William Sharpe) is also used for comparing historical stock performance. Sharpe ratio formula is as follows: (Ceylan ve Korkmaz, 2000:263):

$$SR = \frac{\overline{A} - r_f}{\sigma} \qquad \text{(VI-9)}$$

SR = Sharpe ratio,

$\overline{A}$ = Average return for stock A,

σ = Standard deviation of stock A return,

r_f = Risk free rate.

In this study, Sharpe ratio is calculated as follows and risk free rate is ignored amid lack of data.

$$SR = \frac{\overline{A}}{\sigma}$$

To find results for all the calculations, WINRATS 4.0 Times Series program is used and the tables are given at the end of this research paper.

11.1. EWMA Results

EWMA model in RiskMetrics uses the following formula $\sigma_{i,t} = \sqrt{\frac{1-\lambda}{1-\lambda^n}\sum_{j=0}^{n}\lambda^j r_{i,t-j}^2}$ to calculate the volatility standard deviation. The same formula is used to identify and determine the volatility in this research. 0.94 (for daily standard deviation) is accepted for exponential factor. 99% confidence level requires data number n and 74 days are found. For 95% confidence level required days are taken is 50 days. The findings of the standard deviation is to multiply for 99% confidence level 2.326 and for 95% confidence level, 1.645 to reach the daily stocks VaR numbers.

The required number of days have changed such as 5, 8, 11, 15, 20, and 26 means when the days number getting smaller, the standard deviation getting higher (See Figure 1a, 1b, 1c, 1d). These results verify that the last day data has more effect than old day data. However, this does not warrant to obtain better VaR number when considering small number of days. In this case, previous events cannot be impacted on standard deviation.

11.2. Optimal Lag Lengths

In order to calculate EWMA and GARCH numbers, two steps should be taken. First step is to determine the optimal lag length. As mentioned before, AIC and SIC methods apply for 25 stocks inside the ISE 30 Index. These results are given as Table 2. For all the stocks' returns, the optimal lag length found 1. Low lag length makes the useable data more useful to forecast the return and volatility.

11.3. ARCH Effects

In order to test ARCH effects, the following equations are applied for 25 stocks in ISE 30 Index.

$$R_{i,t} = \beta_i I_{t-1} + e_{i,t}$$

$$h_{i,t} = Var(e_{i,t}) = \alpha_0 + \alpha_1 e_{i,t-1}^2$$

Chi-Square in the study 5% significance level and 1 degree of freedom creates a reference in order to accept or reject X^2 distribution is zero. If TR^2 is large enough, ARCH effect hypothesis will be accepted.

Table 3 gives the result of ARCH (1) which is calculated by $h_{i,t} = Var(e_{i,t}) = \alpha_0 + \alpha_1 e_{i,t-1}^2$. ISE 30 Index and 25 stocks TR^2 values are well above the 5% significance level and 1 degree of freedom X^2 critical value 3.842. Therefore, the result verifies that there is an ARCH effect.

ENKA, TRKCM, and PTOFS stocks have relatively higher TR^2 value them EREGL, HURG means that they have higher changing variance.

If there is an ARCH effect, one forward step can be taken to test the GARCH model.

11.4. GARCH Results

Table 4 gives the GARCH parameters coefficients. The parameters numbers are similar for most of the stocks. For old stocks, $\alpha_0, \alpha_i, \alpha_j \geq 0$ and $\alpha_i + \alpha_j$<1 constraints are successfully satisfied. The calculated standard deviation multiplied by 99% confidence level 2.326 and for 95% confidence level 1.645 to derive at the stocks daily VaR number.

11.5. Comparison of the EWMA and GARCH Methods

Analyzing VaR numbers calculated from EWMA and GARCH methods, the results seem relatively close. Yet, using GARCH number to calculate VaR provides better result than EWMA.(See Figure 2) In addition, both methods' deviations can be at acceptable levels.

The VAR is calculated for each day it can then be compared to the following day's price change. If the following day's price change is greater, then that day is an exception. The total number of exceptions is totalled.The results (%number of exceptions) from each stocks collected in Table 5 and 6.

The economic crisis that occurred in November 2000 and February 2001 of Turkey signifies the fact that VaR number cannot capture the extraordinary events or crisis as VaR's role is to measure the bearing of portfolio risks.

12. Conclusion

Volatility forecasting is an important task for most of the investing parties in the financial markets. Calculating volatility number is not sufficient for stock portfolios to control risk but needs to be used in VaR calculations. VaR brings standardization when comparing risky portfolios. In recent years, the advantages of VaR make it a contemporary risk management tool.

Volatility tends to happen in clusters. The assumption is that volatility remains constant at all times can be fatal. In order to forecast volatility in stock market, there must be methodology to measure and monitor volatility modeling. Recently, EWMA and GARCH models have become critical tools for time series analysis in financial applications.

In this study, ISE-30 Index return volatility and individual stocks return volatility have been tested by using EWMA and GARCH methods to compare results.

JP Morgan RiskMetrics method has been used for EWMA method. Various data ranges (number of days) have been selected to use in calculations. It is determined that the most recent data have asserted more influence on future volatility than past data.

ARCH effects have been recorded for all the stocks in ISE 30 Index in this study, then GARCH model is tested.

Time series has been used to estimate volatility and give more weights to recent events as opposed to older events. The constraints of all GARCH parameters are satisfied. The outcome is GARCH provides more accurate analysis than EWMA.

Daily VaR numbers have been calculated by using EWMA and GARCH models for stocks inside the ISE-30 Index. The results are satisfactory for forecasting volatility at 95% and 99% confidence level. These two methods enhance the quality of the VaR models.

The findings in this research support the idea of VaR does not measure "event" (e.g., market crash) risk, so the portfolio stress tests are recommended to supplement VaR. The economic crisis that occurred in November 2000 and February 2001 of Turkey signifies the fact that VaR number cannot capture the extraordinary events or crisis as VaR’s role is to measure the bearing of portfolio risks.

These findings suggest that traders and risk managers are able to generate portfolio profit and minimize risks if they obtain a better understanding of how volatility is being forecasted.

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Tables and Figures

Table 1. A Descriptive Statistics About ISE-30 Index and The Inside Stocks

Series	Obs	Mean	Std Error	Minimum	Maximum	Sharpe Ratio
AKBNK	999	0.0013841812	0.0444806750	-0.2263149549	0.1923695668	3.1119%
AKGRT	999	0.0016807879	0.0471266210	-0.2186871780	0.1814705189	3.5665%
AKSA	999	0.0017223457	0.0444272300	-0.1923715480	0.2076387167	3.7790%
ALARKO	999	0.0023179919	0.0442802073	-0.1949026668	0.1732719129	5.2348%
ARCLK	999	0.0016171660	0.0491748628	-0.1967103415	0.2182534788	3.2886%
DOHOL	999	0.0015485292	0.0539469832	-0.2135784078	0.1844272633	2.8705%
ENKA	999	0.0022746563	0.0484571690	-0.2102960826	0.1929034730	4.6942%
EREGL	999	0.0012569927	0.0470729220	-0.2231435513	0.2025242641	2.5876%
FROTO	999	0.0015613669	0.0481132140	-0.1690763300	0.1854084584	3.2452%
GARAN	999	0.0016872560	0.0509609434	-0.2444566525	0.1854181784	3.3109%
HURGZ	999	0.0019732155	0.0547547543	-0.2336153424	0.2029420097	3.6037%
ISCTR	993	0.0013128027	0.0462925996	-0.2076390854	0.2076387354	2.6798%
KCHOL	999	0.0013661615	0.0465575852	-0.1929037658	0.1823216616	2.9343%
MIGRS	999	0.0016865634	0.0408889074	-0.2006706955	0.1950605688	4.1247%
NETAS	999	0.0011790240	0.0487466759	-0.2135740541	0.1892421374	2.4187%
PETKM	999	0.0016452530	0.0510135373	-0.1823210787	0.2102958357	3.2251%
PTOFS	997	0.0023226426	0.0521029144	-0.2267734641	0.1857169874	4.1842%
SAHOL	999	0.0017808477	0.0450690726	-0.1941562736	0.1823203518	3.9514%
SISE	999	0.0009749040	0.0482495821	-0.2379586371	0.1941560144	2.0205%
TNSAS	999	0.0019107178	0.0504074927	-0.2318016141	0.2063331578	3.7905%
TOASO	999	0.0014328430	0.0512587024	-0.2261256044	0.2273886673	2.7953%
TRKCM	999	0.0013153123	0.0466100985	-0.2113065204	0.1929031747	2.8219%
TUPRS	999	0.0018850742	0.0465236421	-0.1863289843	0.1962792865	3.3208%
VESTL	999	0.0020852053	0.0503193070	-0.2200652751	0.2231430129	4.1439%
YKBNK	999	0.0018858716	0.0538801229	-0.2076390763	0.1823219748	3.5001%
ISE 30	999	0.0014202408	0.0393867302	-0.2006760153	0.1764651977	3.6059%

Tablo 2. Akaike and Schwarz Criterion for ISE-30 Index and The Inside Stocks

Lags	Akaike	Schwarz	Lags	Akaike	Schwarz	Lags	Akaike	Schwarz
Akbnk			Akgrt			Aksa		
1	-144.9587	-138.0825	1	-110.6482	-103.7721	1	-217.5664	-210.6902
2	184.0868	194.4011	2	169.9704	180.2847	2	233.5425	243.8567
3	330.3398	344.0921	3	306.6239	320.3762	3	395.9745	409.7268
4	406.9349	424.1253	4	365.6586	382.849	4	467.8641	485.0545
5	472.8939	493.5224	5	437.3837	458.0122	5	538.8794	559.5079
6	511.7939	535.8604	6	471.7442	495.8107	6	576.9969	601.0635
7	552.4103	579.9149	7	518.544	546.0487	7	615.2989	642.8035
8	582.8478	613.7905	8	548.8364	579.7791	8	648.4091	679.3518
9	615.3967	649.7775	9	579.0872	613.468	9	677.05	711.4307
10	634.7527	672.5716	10	600.1305	637.9494	10	692.8929	730.7118
11	667.7227	708.9796	11	623.6135	664.8705	11	717.7251	758.9821
12	680.8971	725.5922	12	638.142	682.8371	12	731.6648	776.3599
13	692.9859	741.1190	13	652.729	700.8621	13	751.8507	799.9838
14	713.7581	765.3293	14	666.268	717.8392	14	770.4726	822.0438
15	735.2727	790.2820	15	676.2402	731.2494	15	792.6935	847.7027
16	754.7401	813.1875	16	687.2685	745.7159	16	808.477	866.9243
17	773.1296	835.0151	17	692.4124	754.2978	17	823.5272	885.4127
18	790.2222	855.5457	18	702.2308	767.5544	18	837.0744	902.3979
19	803.2145	871.9761	19	710.1205	778.882	19	843.0664	911.8279
20	817.3582	889.5579	20	718.8195	791.0191	20	854.0017	926.2013
21	829.1390	904.7767	21	725.4075	801.0453	21	861.0076	936.6454
22	841.0424	920.1182	22	733.2994	812.3752	22	867.3221	946.3979
23	853.8503	936.3642	23	738.9977	821.5116	23	870.6266	953.1405
24	861.8305	947.7825	24	744.6188	830.5708	24	874.4761	960.4281
Alarko			Arclk			Dohol		
1	-159.7561	-152.8799	1	-118.9492	-112.073	1	-142.6945	-135.8184
2	199.5721	209.8863	2	176.552	186.8662	2	181.4329	191.7472
3	349.2865	363.0388	3	320.352	334.1043	3	317.1194	330.8717
4	406.9894	424.1798	4	386.8508	404.0412	4	391.5047	408.6951
5	484.4297	505.0581	5	453.1197	473.7482	5	454.9042	475.5327
6	508.5557	532.6222	6	487.0257	511.0923	6	498.792	522.8586
7	538.5687	566.0733	7	537.3895	564.8942	7	543.9735	571.4781
8	567.3716	598.3143	8	567.4701	598.4128	8	572.6592	603.6019
9	584.0056	618.3864	9	602.9523	637.3331	9	602.6652	637.046
10	604.3154	642.1343	10	628.7436	666.5624	10	619.4659	657.2848
11	626.5536	667.8105	11	665.3231	706.58	11	646.9979	688.2549
12	636.5801	681.2752	12	692.135	736.83	12	662.5137	707.2088
13	652.5677	700.7008	13	717.2445	765.3777	13	684.6528	732.7859
14	663.8276	715.3988	14	732.2358	783.8069	14	699.5674	751.1386
15	673.5504	728.5596	15	751.6336	806.6429	15	715.8808	770.8901
16	688.2203	746.6676	16	773.1012	831.5485	16	728.7853	787.2326
17	694.4629	756.3483	17	785.3084	847.1938	17	736.4769	798.3623
18	703.1594	768.4829	18	801.0924	866.4159	18	745.5758	810.8993
19	712.5967	781.3583	19	811.3291	880.0907	19	753.829	822.5906
20	721.6546	793.8542	20	825.0097	897.2094	20	762.9137	835.1134
21	732.6053	808.2431	21	832.3192	907.957	21	774.5389	850.1766
22	744.8509	823.9268	22	842.8671	921.9429	22	788.8267	867.9025
23	756.6399	839.1538	23	854.5709	937.0848	23	803.8789	886.3928
24	765.1677	851.1197	24	863.0379	948.9899	24	814.3221	900.2741

Tablo 2. continued

Lags	Akaike	Schwarz	Lags	Akaike	Schwarz	Lags	Akaike	Schwarz
Enka			Eregl			Froto		
1	-111.5802	-104.7041	1	-129.8498	-122.9736	1	-156.1327	-149.2566
2	194.8344	205.1486	2	180.4529	190.7672	2	191.3283	201.6426
3	296.1478	309.9002	3	336.2348	349.9871	3	319.8164	333.5688
4	372.7265	389.9168	4	410.2385	427.4289	4	403.8333	421.0237
5	438.8073	459.4358	5	471.8415	492.4699	5	469.0968	489.7252
6	470.8981	494.9646	6	508.0653	532.1318	6	502.3405	526.4071
7	513.9432	541.4478	7	551.6827	579.1873	7	536.5900	564.0947
8	550.2049	581.1476	8	583.5731	614.5158	8	560.8162	591.7589
9	571.4876	605.8684	9	608.2485	642.6293	9	580.7582	615.1390
10	594.5877	632.4066	10	629.6281	667.4469	10	590.5403	628.3591
11	614.8472	656.1042	11	654.6584	695.9153	11	605.1035	646.3604
12	626.8058	671.5009	12	671.8019	716.4969	12	619.4089	664.1039
13	649.2540	697.3871	13	695.6003	743.7334	13	633.6427	681.7758
14	659.5218	711.0930	14	716.0839	767.6551	14	649.0190	700.5901
15	669.3601	724.3694	15	736.3039	791.3132	15	659.6864	714.6957
16	681.5568	740.0042	16	751.6268	810.0741	16	670.4898	728.9372
17	688.8255	750.7109	17	762.2191	824.1046	17	681.5380	743.4235
18	696.2997	761.6232	18	771.8756	837.1991	18	686.9678	752.2913
19	705.6431	774.4047	19	781.7963	850.5579	19	694.3924	763.1540
20	711.8214	784.0211	20	792.8530	865.0526	20	701.4028	773.6025
21	720.9930	796.6307	21	800.8619	876.4997	21	706.7440	782.3817
22	727.3579	806.4337	22	812.6166	891.6925	22	716.6207	795.6965
23	736.6388	819.1527	23	824.2959	906.8098	23	727.7014	810.2153
24	741.6712	827.6232	24	834.6470	920.5990	24	734.2166	820.1686
Garan			Hurgz			İsctr		
1	-115.7329	-108.8567	1	-104.7845	-97.9083	1	-171.0330	-164.1568
2	172.4645	182.7787	2	170.4141	180.7283	2	202.7523	213.0666
3	311.8630	325.6153	3	299.5781	313.3304	3	331.3773	345.1297
4	380.8691	398.0595	4	361.9313	379.1217	4	431.0076	448.1980
5	460.2297	480.8582	5	425.8628	446.4912	5	496.4899	517.1184
6	501.4657	525.5323	6	461.3977	485.4643	6	562.0117	586.0783
7	548.2532	575.7579	7	493.9137	521.4183	7	616.6448	644.1495
8	585.9390	616.8817	8	530.0215	560.9642	8	657.8064	688.7491
9	621.6594	656.0401	9	561.6462	596.0270	9	695.0709	729.4517
10	644.5225	682.3413	10	584.7017	622.5206	10	723.3932	761.2121
11	674.3664	715.6234	11	618.0095	659.2665	11	760.2389	801.4958
12	693.9225	738.6176	12	634.4208	679.1158	12	770.5792	815.2743
13	707.2877	755.4208	13	652.6962	700.8293	13	787.2295	835.3626
14	720.9567	772.5279	14	668.3426	719.9138	14	805.3471	856.9183
15	731.3604	786.3697	15	678.6390	733.6483	15	825.2736	880.2829
16	744.4330	802.8803	16	693.9546	752.4019	16	837.4432	895.8906
17	755.0386	816.9240	17	705.0574	766.9429	17	853.8656	915.7511
18	762.1996	827.5231	18	717.3621	782.6857	18	871.8050	937.1286
19	769.9039	838.6655	19	729.4981	798.2596	19	881.8001	950.5617
20	780.0624	852.2621	20	737.7971	809.9968	20	896.8545	969.0542
21	786.2567	861.8945	21	744.7610	820.3987	21	909.3460	984.9837
22	793.9040	872.9798	22	751.9770	831.0528	22	926.5357	1005.6115
23	801.6875	884.2014	23	763.8295	846.3434	23	941.8798	1024.3937
24	807.9075	893.8595	24	771.2380	857.1900	24	953.5154	1039.4673

Tablo 2. continued

Lags	Akaike	Schwarz	Lags	Akaike	Schwarz	Lags	Akaike	Schwarz
Kchol			Migrs			Netas		
1	-161.8855	-155.0094	1	-182.4474	-175.5712	1	-131.3436	-124.4675
2	189.6598	199.9740	2	228.5107	238.8249	2	180.3770	190.6913
3	354.8996	368.6519	3	384.4348	398.1871	3	303.4118	317.1642
4	426.0508	443.2412	4	464.5736	481.7640	4	370.4732	387.6636
5	496.8397	517.4682	5	541.8826	562.5110	5	422.6323	443.2608
6	529.4817	553.5482	6	595.0348	619.1014	6	454.1098	478.1763
7	572.5450	600.0496	7	634.9535	662.4581	7	479.8525	507.3571
8	600.6305	631.5732	8	671.3521	702.2948	8	498.7660	529.7087
9	628.1144	662.4952	9	710.7400	745.1208	9	521.2016	555.5824
10	647.7236	685.5425	10	739.8853	777.7042	10	534.2091	572.0280
11	670.3522	711.6091	11	773.7042	814.9611	11	553.2555	594.5125
12	685.1464	729.8414	12	795.3352	840.0302	12	563.6443	608.3394
13	704.6615	752.7946	13	819.3182	867.4513	13	579.4023	627.5354
14	722.0741	773.6453	14	844.6273	896.1985	14	594.9855	646.5567
15	734.8275	789.8367	15	871.6437	926.6530	15	611.7959	666.8052
16	750.7036	809.1510	16	891.3976	949.8450	16	625.7527	684.2000
17	760.3343	822.2197	17	907.4505	969.3360	17	645.1333	707.0188
18	771.7223	837.0458	18	921.9622	987.2857	18	663.9258	729.2493
19	780.2668	849.0284	19	935.5879	1004.3494	19	676.2702	745.0318
20	793.3695	865.5692	20	948.4600	1020.6597	20	689.1704	761.3700
21	801.0822	876.7199	21	962.4728	1038.1106	21	699.3291	774.9669
22	812.5270	891.6028	22	976.4410	1055.5168	22	707.2410	786.3169
23	823.5956	906.1095	23	992.3853	1074.8992	23	720.9333	803.4472
24	831.2417	917.1937	24	1003.6304	1089.5823	24	730.4034	816.3554
Petkm			Ptofs			Sahol		
1	-140.7775	-133.9013	1	-64.7921	-57.9160	1	-131.8723	-124.9962
2	165.0123	175.3265	2	176.1363	186.4506	2	161.7438	172.0581
3	305.3802	319.1325	3	289.9100	303.6623	3	316.5840	330.3363
4	377.2779	394.4683	4	358.9950	376.1854	4	375.0331	392.2235
5	439.3101	459.9385	5	440.9687	461.5971	5	446.6665	467.2950
6	465.5059	489.5724	6	479.1902	503.2568	6	481.5007	505.5673
7	499.9852	527.4898	7	522.9558	550.4604	7	519.3317	546.8363
8	524.3431	555.2858	8	549.3474	580.2901	8	549.3543	580.2970
9	540.2615	574.6423	9	571.6070	605.9878	9	578.0892	612.4700
10	557.6116	595.4305	10	587.2279	625.0468	10	601.0643	638.8832
11	572.5917	613.8487	11	610.9176	652.1745	11	628.1805	669.4375
12	581.4322	626.1272	12	628.0566	672.7516	12	643.3693	688.0643
13	598.0410	646.1741	13	657.5902	705.7234	13	661.8337	709.9668
14	615.8456	667.4168	14	679.8942	731.4654	14	681.4686	733.0398
15	634.5904	689.5997	15	695.3082	750.3174	15	702.2136	757.2228
16	649.7589	708.2062	16	712.4782	770.9255	16	720.6612	779.1085
17	662.1515	724.0369	17	730.7242	792.6096	17	729.4106	791.2960
18	680.6635	745.9870	18	744.6929	810.0164	18	744.1441	809.4676
19	692.2836	761.0451	19	753.3823	822.1439	19	755.3945	824.1561
20	706.9787	779.1783	20	765.0191	837.2187	20	768.0473	840.2469
21	718.2140	793.8517	21	779.5250	855.1628	21	779.5771	855.2148
22	729.7092	808.7850	22	793.0245	872.1003	22	793.1926	872.2684
23	738.2480	820.7619	23	807.2406	889.7545	23	806.7703	889.2842
24	747.1225	833.0745	24	814.5732	900.5252	24	816.3547	902.3067

Tablo 2. continued

Lags	Akaike	Schwarz	Lags	Akaike	Schwarz	Lags	Akaike	Schwarz
Sise			Tnsas			Toaso		
1	-172.6549	-165.7788	1	-184.3514	-177.4752	1	-162.1402	-155.2640
2	198.2776	208.5919	2	212.2360	222.5503	2	200.0295	210.3437
3	312.1199	325.8723	3	328.5902	342.3425	3	325.8367	339.5891
4	383.0196	400.2100	4	405.8035	422.9939	4	395.5012	412.6916
5	438.1460	458.7744	5	471.0677	491.6962	5	469.9734	490.6019
6	472.7246	496.7912	6	501.0245	525.0910	6	503.9018	527.9683
7	503.5289	531.0335	7	538.4676	565.9722	7	534.3692	561.8738
8	533.4560	564.3987	8	579.5229	610.4656	8	556.7974	587.7401
9	560.0777	594.4585	9	620.9180	655.2988	9	573.2853	607.6661
10	579.6079	617.4268	10	652.1436	689.9625	10	587.7865	625.6053
11	599.7579	641.0148	11	686.8020	728.0590	11	608.2228	649.4798
12	615.0349	659.7299	12	703.9451	748.6401	12	617.8801	662.5752
13	633.6925	681.8256	13	715.4398	763.5729	13	635.1935	683.3266
14	650.8078	702.3790	14	728.5702	780.1414	14	649.2402	700.8113
15	671.3138	726.3230	15	739.5303	794.5396	15	664.0318	719.0411
16	684.7464	743.1938	16	749.0825	807.5299	16	675.0598	733.5072
17	693.9553	755.8407	17	757.6923	819.5778	17	682.4528	744.3382
18	703.2174	768.5410	18	764.1247	829.4482	18	686.9746	752.2981
19	716.4807	785.2422	19	770.6006	839.3621	19	693.4099	762.1715
20	725.0531	797.2528	20	775.5052	847.7049	20	700.0509	772.2505
21	738.3318	813.9696	21	781.7028	857.3405	21	707.4449	783.0826
22	756.0589	835.1347	22	787.9271	867.0029	22	715.8633	794.9392
23	775.5182	858.0321	23	795.1064	877.6203	23	725.1705	807.6844
24	787.3108	873.2628	24	801.8372	887.7892	24	730.5395	816.4914
Trkcm			Vestl			Ykbnk		
1	-145.9431	-139.0670	1	-99.5659	-92.6898	1	-52.5993	-45.7231
2	164.1665	174.4807	2	160.3832	170.6975	2	149.1276	159.4419
3	311.9238	325.6761	3	300.2760	314.0283	3	269.3922	283.1445
4	371.1172	388.3076	4	368.2281	385.4185	4	317.6052	334.7956
5	429.7968	450.4253	5	432.8790	453.5075	5	389.3544	409.9829
6	455.5158	479.5824	6	471.4844	495.5509	6	429.9862	454.0527
7	486.3313	513.8359	7	514.2574	541.7620	7	468.1038	495.6084
8	517.1537	548.0964	8	551.4625	582.4053	8	507.5372	538.4799
9	549.1194	583.5002	9	586.6486	621.0294	9	538.7865	573.1673
10	564.8678	602.6867	10	615.3648	653.1837	10	560.2069	598.0257
11	585.4916	626.7486	11	644.6274	685.8843	11	586.3833	627.6403
12	604.1554	648.8505	12	672.6939	717.3889	12	604.1685	648.8635
13	623.5524	671.6855	13	687.5712	735.7043	13	621.3267	669.4598
14	638.8777	690.4489	14	704.4060	755.9772	14	638.4628	690.0340
15	655.3739	710.3831	15	718.5247	773.5340	15	652.0876	707.0968
16	666.5910	725.0384	16	734.4958	792.9431	16	676.0110	734.4583
17	676.9415	738.8269	17	748.7445	810.6299	17	689.0566	750.9420
18	688.2274	753.5509	18	761.3893	826.7128	18	704.6757	769.9992
19	700.9933	769.7549	19	778.1968	846.9584	19	716.6232	785.3848
20	714.9994	787.1990	20	793.8080	866.0077	20	731.5250	803.7246
21	728.7754	804.4131	21	805.4987	881.1364	21	743.7932	819.4309
22	742.9841	822.0600	22	823.8284	902.9043	22	752.7493	831.8251
23	751.9734	834.4873	23	841.7211	924.2350	23	764.0584	846.5723
24	764.4073	850.3592	24	853.1735	939.1255	24	771.6980	857.6499

Tablo 2. continued

Lags	Akaike	Schwarz
ISE-30		
1	-223.1602	-216.2841
2	240.0457	250.3600
3	392.8530	406.6053
4	469.8439	487.0343
5	543.5839	564.2123
6	586.1973	610.2638
7	631.0314	658.5360
8	664.8799	695.8226
9	694.4004	728.7812
10	715.0704	752.8893
11	742.5621	783.8190
12	755.5112	800.2062
13	770.9188	819.0519
14	786.2488	837.8200
15	802.6568	857.6660
16	819.0895	877.5368
17	828.6683	890.5537
18	838.9359	904.2594
19	847.2479	916.0095
20	858.6604	930.8600
21	868.4491	944.0868
22	880.0531	959.1290
23	892.4330	974.9469
24	899.2616	985.2136

Tablo 3. ARCH Test Result for ISE-30 Index and The Inside Stocks

STOCKS	Constant	ε_{t-1}^2	$T \times R^2$
AKBNK	0,0016475768	0.1670809068	27,792994
AKGRT	0,0018361201	0.1669464443	27,837616
AKSA	0,0013750047	0.3033175352	91.727.365
ALARKO	0.0014931523	0.2398309067	57.313.275
ARCLK	0.0019043639	0.2109887994	44.391.721
DOHOL	0.0023261133	0.2006036944	40.132.987
ENKA	0.0014948964	0.3632790187	131.049.758
EREGL	0.0018467865	0.1611874985	25.901.922
FROTO	0.0018520080	0.2001352092	39.875.890
GARAN	0.0019099919	0.2587427251	66.750.546
HURGZ	0.0024944880	0.1668124564	27.688.820
İSCTR	0.0017785394	0.1712544698	29.001.622
KCHOL	0.0017204561	0.2034522895	41.277.029
MİGRS	0.0011627092	0.3068867341	93.553.997
NETAS	0.0018236739	0.2314589201	53.424.060
PETKM	0.0020005112	0.2291076225	52.329.640
PTOFS	0.0016155002	0.3994689081	158.775.554
SAHOL	0.0015876450	0.2160937843	46.558.474
SİSE	0.0019016291	0.1825201336	33.210.014
TNSAS	0.0020049148	0.2031528435	41.155.579
TOASO	0.0019422651	0.2578134072	66.270.124
TRKCM	0.0014148491	0.3491898010	121.544.881
TUPRS	0.0015675720	0.2758270154	75.868.032
VESTL	0.0018091732	0.2863981108	81.784.853
YKBNK	0.0021718763	0.2466025793	60.613.342
ISE-30	0.0011889869	0.2325026876	53.883.904

Tablo 4. GARCH Results for ISE-30 Index and The Inside Stocks

Variable	Coeff	Std	T-Stat	Signif
akbnk				
B0	0.001338676	0.001698829	0.78800	0.43069705
B1	-0.334797803	0.243693881	-1.37385	0.16948957
B2	0.348454030	0.241286919	1.44415	0.14869734
A0	0.000116009	0.000040037	2.89756	0.00376075
A1	0.100213013	0.022944336	4.36766	0.00001256
A2	0.843049665	0.036353866	23.19010	0.00000000
akgrt				
B0	0.000804768	0.000877154	0.91748	0.35889318
B1	0.667987688	0.293251695	2.27786	0.02273464
B2	-0.649776700	0.320942064	-2.02459	0.04290929
A0	0.000193692	0.000060414	3.20605	0.00134571
A1	0.120180436	0.026461572	4.54170	0.00000558
A2	0.793834227	0.043397948	18.29198	0.00000000
aksa				
B0	0.002552914	0.002440550	1.04604	0.29554236
B1	-0.842704988	0.103952888	-8.10660	0.00000000
B2	0.809964052	0.112884073	7.17518	0.00000000
A0	0.000209829	0.000085672	2.44921	0.01431713
A1	0.097377513	0.024969652	3.89983	0.00009626
A2	0.792699747	0.061803668	12.82610	0.00000000
alarko				
B0	0.004637732	0.002240188	2.07024	0.03842971
B1	-0.797113598	0.143659901	-5.54862	0.00000003
B2	0.774003866	0.154149606	5.02112	0.00000051
A0	0.000225313	0.000065761	3.42626	0.00061195
A1	0.150529916	0.031430638	4.78927	0.00000167
A2	0.737176437	0.049761921	14.81407	0.00000000
arclk				
B0	0.000510338	0.000735549	0.69382	0.48779590
B1	0.601727991	0.244471468	2.46134	0.01384182
B2	-0.567358878	0.249770920	-2.27152	0.02311570
A0	0.000592544	0.000185059	3.20192	0.00136515
A1	0.191837845	0.046135658	4.15813	0.00003209
A2	0.561629063	0.102057457	5.50307	0.00000004
dohol				
B0	0.000131817	0.000213212	0.61824	0.53641607
B1	0.927486494	0.085614292	10.83331	0.00000000
B2	-0.911456450	0.095785388	-9.51561	0.00000000
A0	0.000429736	0.000129948	3.30699	0.00094303
A1	0.186498151	0.038310849	4.86802	0.00000113
A2	0.669907180	0.067258802	9.96014	0.00000000

Tablo 4. continued

Variable	Coeff	Std	T-Stat	Signif
enka				
B0	0.000127096	0.000397147	0.32002	0.74895027
B1	0.951342640	0.152166294	6.25199	0.00000000
B2	-0.941525485	0.171811242	-5.48000	0.00000004
A0	0.000266942	0.000095237	2.80291	0.00506432
A1	0.165705710	0.033298065	4.97644	0.00000065
A2	0.718277854	0.065848940	10.90796	0.00000000
eregl				
B0	0.002895245	0.002461970	1.17599	0.23960007
B1	-0.800496897	0.164441336	-4.86798	0.00000113
B2	0.775255470	0.175732405	4.41157	0.00001026
A0	0.000269252	0.000090141	2.98702	0.00281714
A1	0.124820297	0.028683216	4.35168	0.00001351
A2	0.752319150	0.058171755	12.93272	0.00000000
froto				
B0	0.001471912	0.001789598	0.82248	0.41080273
B1	-0.276981462	0.584100918	-0.47420	0.63535631
B2	0.262798307	0.576124764	0.45615	0.64828337
A0	0.000272838	0.000083114	3.28269	0.00102822
A1	0.143174765	0.031838349	4.49693	0.00000689
A2	0.741146717	0.056275596	13.16995	0.00000000
garan				
B0	0.000299475	0.000463018	0.64679	0.51776809
B1	0.796679095	0.211817295	3.76116	0.00016913
B2	-0.772916296	0.220394215	-3.50697	0.00045324
A0	0.000358768	0.000095238	3.76705	0.00016519
A1	0.201420036	0.039277213	5.12817	0.00000029
A2	0.662571893	0.059313105	11.17075	0.00000000
hurgz				
B0	0.000763965	0.000828796	0.92178	0.35664466
B1	0.554200610	0.315503708	1.75656	0.07899315
B2	-0.520010427	0.314476787	-1.65357	0.09821424
A0	0.000406065	0.000127961	3.17335	0.00150692
A1	0.137781557	0.030491397	4.51870	0.00000622
A2	0.728709769	0.061136412	11.91941	0.00000000
isctr				
B0	0.001680588	0.002331712	0.72075	0.47106148
B1	-0.574896222	0.402050738	-1.42991	0.15274296
B2	0.544815106	0.393861391	1.38327	0.16658329
A0	0.000420987	0.000185355	2.27124	0.02313219
A1	0.112214499	0.033513457	3.34834	0.00081297
A2	0.686381250	0.111381805	6.16242	0.00000000

Tablo 4. continued

Variable	Coeff	Std	T-Stat	Signif
kchol				
B0	0.000044959	0.000096406	0.46635	0.64096198
B1	0.942552751	0.075903085	12.41785	0.00000000
B2	-0.936024216	0.090493131	-10.34359	0.00000000
A0	0.000319091	0.000094084	3.39155	0.00069499
A1	0.189293548	0.042133635	4.49269	0.00000703
A2	0.667103096	0.068885070	9.68429	0.00000000
Migrs				
B0	0.001321190	0.001183692	1.11616	0.26435338
B1	0.191691327	0.430852353	0.44491	0.65638344
B2	-0.159186426	0.430591676	-0.36969	0.71161177
A0	0.000175106	0.000063059	2.77687	0.00548844
A1	0.163433701	0.036881300	4.43134	0.00000936
A2	0.733542814	0.064763519	11.32648	0.00000000
Netas				
B0	0.001320978	0.001561410	0.84602	0.39754394
B1	-0.173028289	0.576661619	-0.30005	0.76413773
B2	0.210424761	0.565669850	0.37199	0.70989867
A0	0.000409840	0.000093126	4.40092	0.00001078
A1	0.211451403	0.041424120	5.10455	0.00000033
A2	0.620783806	0.059235740	10.47989	0.00000000
Petkm				
B0	0.001449087	0.002030577	0.71363	0.47545407
B1	-0.500838696	0.312120567	-1.60463	0.10857478
B2	0.454191004	0.325410844	1.39575	0.16279088
A0	0.000392877	0.000093698	4.19300	0.00002753
A1	0.200804371	0.037744860	5.32005	0.00000010
A2	0.653188852	0.056427320	11.57576	0.00000000
Ptofs				
B0	0.004041434	0.002228889	1.81321	0.06980011
B1	-0.572836080	0.286886294	-1.99674	0.04585391
B2	0.557301867	0.287595902	1.93779	0.05264825
A0	0.000300605	0.000076237	3.94305	0.00008045
A1	0.223102984	0.036293715	6.14715	0.00000000
A2	0.673659702	0.046158377	14.59453	0.00000000
Sahol				
B0	0.000450892	0.000601777	0.74927	0.45369600
B1	0.559337881	0.250378954	2.23397	0.02548536
B2	-0.563553083	0.242375281	-2.32513	0.02006522
A0	0.000239255	0.000078636	3.04256	0.00234575
A1	0.186989913	0.041922116	4.46041	0.00000818
A2	0.700756389	0.066840325	10.48404	0.00000000

Tablo 4. Continued

Variable	Coeff	Std	T-Stat	Signif
Sise				
B0	0.000689243	0.000916461	0.75207	0.45200871
B1	0.494194727	0.396633468	1.24597	0.21277418
B2	-0.482594464	0.393644327	-1.22597	0.22021156
A0	0.000220573	0.000076770	2.87317	0.00406377
A1	0.175006327	0.033648307	5.20104	0.00000020
A2	0.732801950	0.055287062	13.25449	0.00000000
Tnsas				
B0	0.000578714	0.000554873	1.04297	0.29696369
B1	0.784592146	0.139858457	5.60990	0.00000002
B2	-0.711924634	0.158757664	-4.48435	0.00000731
A0	0.000238021	0.000055224	4.31007	0.00001632
A1	0.215412895	0.037801843	5.69848	0.00000001
A2	0.701362018	0.041082903	17.07187	0.00000000
Toaso				
B0	0.000622035	0.001126354	0.55226	0.58077354
B1	0.356275081	0.413656882	0.86128	0.38908294
B2	-0.325873600	0.416808177	-0.78183	0.43431384
A0	0.000476095	0.000165937	2.86913	0.00411603
A1	0.133068759	0.035221716	3.77803	0.00015807
A2	0.679456332	0.088977273	7.63629	0.00000000
Trkcm				
B0	0.000479497	0.000000000	0.00000	0.00000000
B1	0.626728028	0.000000000	0.00000	0.00000000
B2	-0.598281572	0.000000000	0.00000	0.00000000
A0	0.000401218	0.000105089	3.81791	0.00013459
A1	0.203937243	0.032696941	6.23720	0.00000000
A2	0.608475316	0.068913830	8.82951	0.00000000
Tuprs				
B0	0.004247467	0.001860286	2.28323	0.02241666
B1	-0.582681013	0.202609115	-2.87589	0.00402893
B2	0.495790580	0.221943561	2.23386	0.02549236
A0	0.000235157	0.000067814	3.46765	0.00052503
A1	0.201974291	0.034814547	5.80143	0.00000001
A2	0.694392924	0.051767120	13.41378	0.00000000
Vestl				
B0	0.003225904	0.002180250	1.47960	0.13897927
B1	-0.710574282	0.249308463	-2.85018	0.00436943
B2	0.679770683	0.248618501	2.73419	0.00625336
A0	0.000314582	0.000077810	4.04298	0.00005278
A1	0.249155539	0.040038764	6.22286	0.00000000
A2	0.639127477	0.051798656	12.33869	0.00000000

Tablo 4. Continued

Variable	Coeff	Std	T-Stat	Signif
Ykbnk				
B0	0.001393937	0.001391763	1.00156	0.31655525
B1	0.310904104	0.366643452	0.84797	0.39645247
B2	-0.268224705	0.374724157	-0.71579	0.47411954
A0	0.000210912	0.000132504	1.59174	0.11144254
A1	0.119568723	0.048088668	2.48642	0.01290348
A2	0.807196464	0.089562695	9.01264	0.00000000
ISE-30				
B0	0.002602761	0.002140282	1.21608	0.22395329
B1	-0.838181172	0.180058490	-4.65505	0.00000324
B2	0.834492877	0.187222366	4.45723	0.00000830
A0	0.000206181	0.000063969	3.22314	0.00126792
A1	0.178151543	0.037029973	4.81101	0.00000150
A2	0.690841372	0.064908266	10.64335	0.00000000

Table 5. Exception Results (%95 confidence level)

Stocks Type	VAR Coverage
AKBNK EWMA	4.3%
AKBNK GARCH	3.9%
AKGRT EWMA	3.9%
AKGRT GARCH	3.7%
AKSA EWMA	4.4%
AKSA GARCH	3.9%
ALARKO EWMA	4.2%
ALARKO GARCH	4.0%
ARCLK EWMA	4.8%
ARCLK GARCH	3.7%
DOHOL EWMA	5.0%
DOHOL GARCH	4.5%
ENKA EWMA	4.3%
ENKA GARCH	4.5%
EREGL EWMA	4.1%
EREGL GARCH	3.7%
FROTO EWMA	3.2%
FROTO GARCH	3.4%
GARAN EWMA	4.7%
GARAN GARCH	3.6%
HURGZ EWMA	5.1%
HURGZ GARCH	5.0%
ISCTR EWMA	4.1%
ISCTR GARCH	3.7%
KCHOL EWMA	4.5%
KCHOL GARCH	4.1%
MIGRS EWMA	3.8%
MIGRS GARCH	3.2%
NETAS EWMA	3.8%
NETAS GARCH	4.3%
PETKM EWMA	3.4%
PETKM GARCH	3.5%
PTOFS EWMA	3.6%
PTOFS GARCH	3.7%
SAHOL EWMA	4.6%
SAHOL GARCH	3.8%
SISE EWMA	4.4%
SISE GARCH	3.9%
TNSAS EWMA	4.4%
TNSAS GARCH	3.9%
TOASO EWMA	4.8%
TOASO GARCH	4.0%
TRKCM EWMA	4.7%
TRKCM GARCH	4.1%
TUPRS EWMA	4.2%
TUPRS GARCH	4.0%
VESTL EWMA	4.1%
VESTL GARCH	4.1%
YKBNK EWMA	5.1%
YKBNK GARCH	4.6%
ISE 30 EWMA	4.7%
ISE 30 GARCH	4.5%

Table 6. Exception Results (%99 confidence level)

Stocks Type	VAR Coverage
AKBNK EWMA	1.0%
AKBNK GARCH	1.3%
AKGRT EWMA	1.2%
AKGRT GARCH	1.3%
AKSA EWMA	1.2%
AKSA GARCH	1.8%
ALARKO EWMA	1.6%
ALARKO GARCH	1.2%
ARCLK EWMA	0.9%
ARCLK GARCH	1.4%
DOHOL EWMA	1.1%
DOHOL GARCH	1.4%
ENKA EWMA	1.4%
ENKA GARCH	1.6%
EREGL EWMA	1.0%
EREGL GARCH	1.4%
FROTO EWMA	1.5%
FROTO GARCH	1.4%
GARAN EWMA	1.2%
GARAN GARCH	1.4%
HURGZ EWMA	1.2%
HURGZ GARCH	1.4%
ISCTR EWMA	1.5%
ISCTR GARCH	1.5%
KCHOL EWMA	1.2%
KCHOL GARCH	1.3%
MIGRS EWMA	0.6%
MIGRS GARCH	1.6%
NETAS EWMA	1.3%
NETAS GARCH	1.4%
PETKM EWMA	0.6%
PETKM GARCH	1.0%
PTOFS EWMA	1.3%
PTOFS GARCH	1.5%
SAHOL EWMA	0.8%
SAHOL GARCH	1.0%
SISE EWMA	1.2%
SISE GARCH	1.5%
TNSAS EWMA	1.3%
TNSAS GARCH	1.9%
TOASO EWMA	1.5%
TOASO GARCH	1.6%
TRKCM EWMA	1.6%
TRKCM GARCH	1.6%
TUPRS EWMA	1.1%
TUPRS GARCH	1.7%
VESTL EWMA	1.5%
VESTL GARCH	1.4%
YKBNK EWMA	0.9%
YKBNK GARCH	1.3%
ISE 30 EWMA	1.3%
ISE 30 GARCH	1.5%

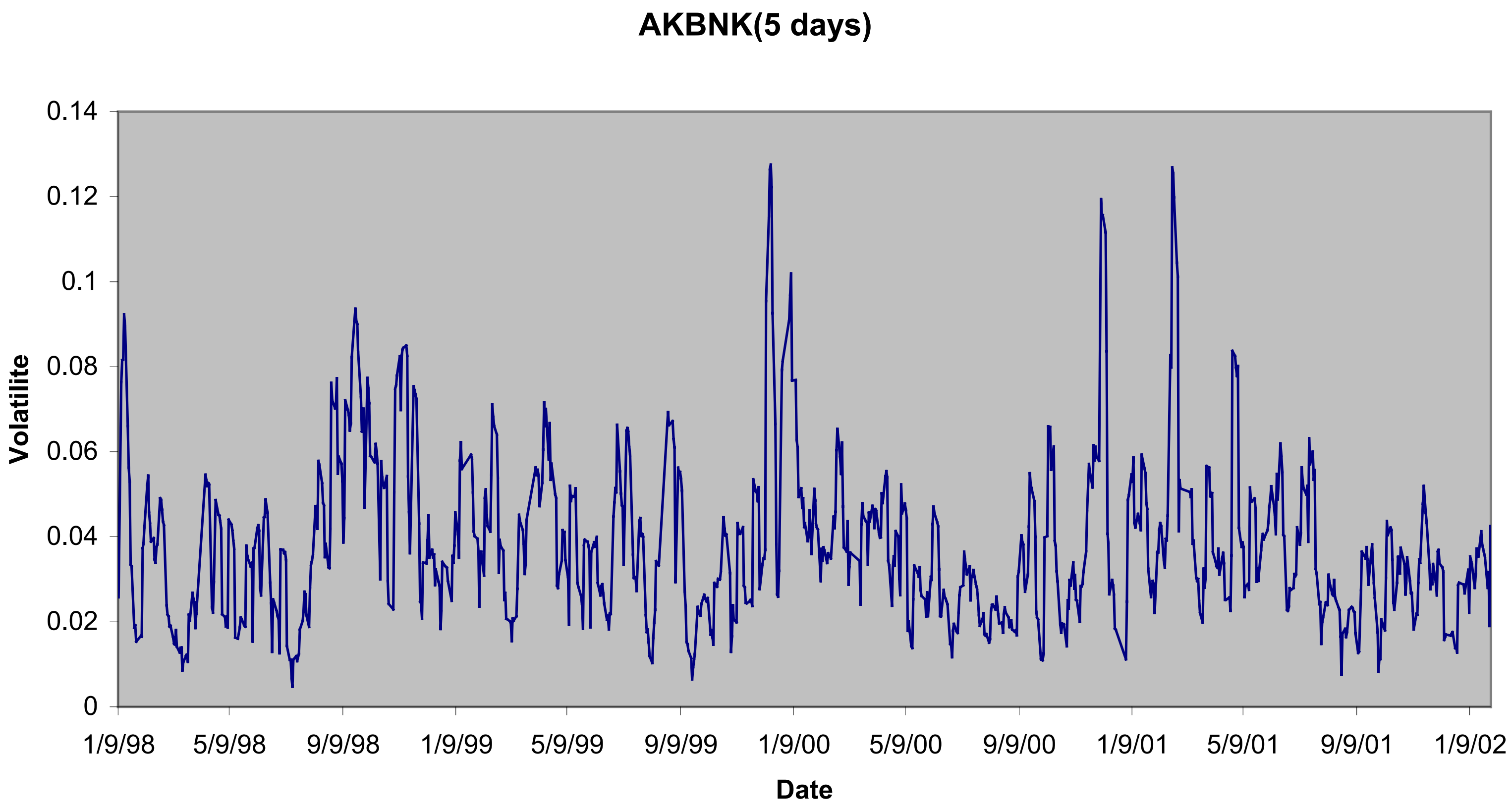


Figure 1a. AKBNK (5 days) EWMA results

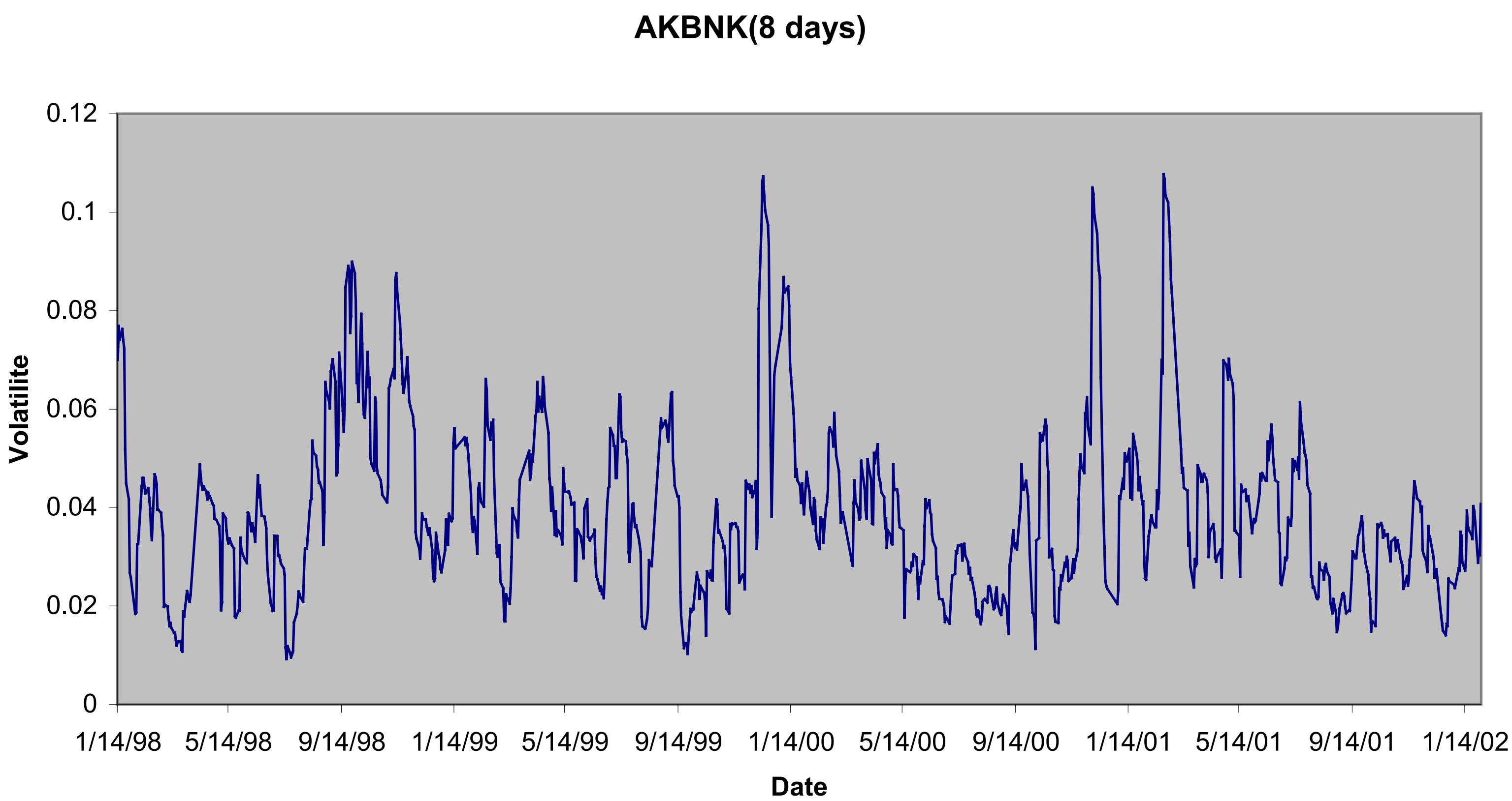


Figure 1b. AKBNK (8 days) EWMA results

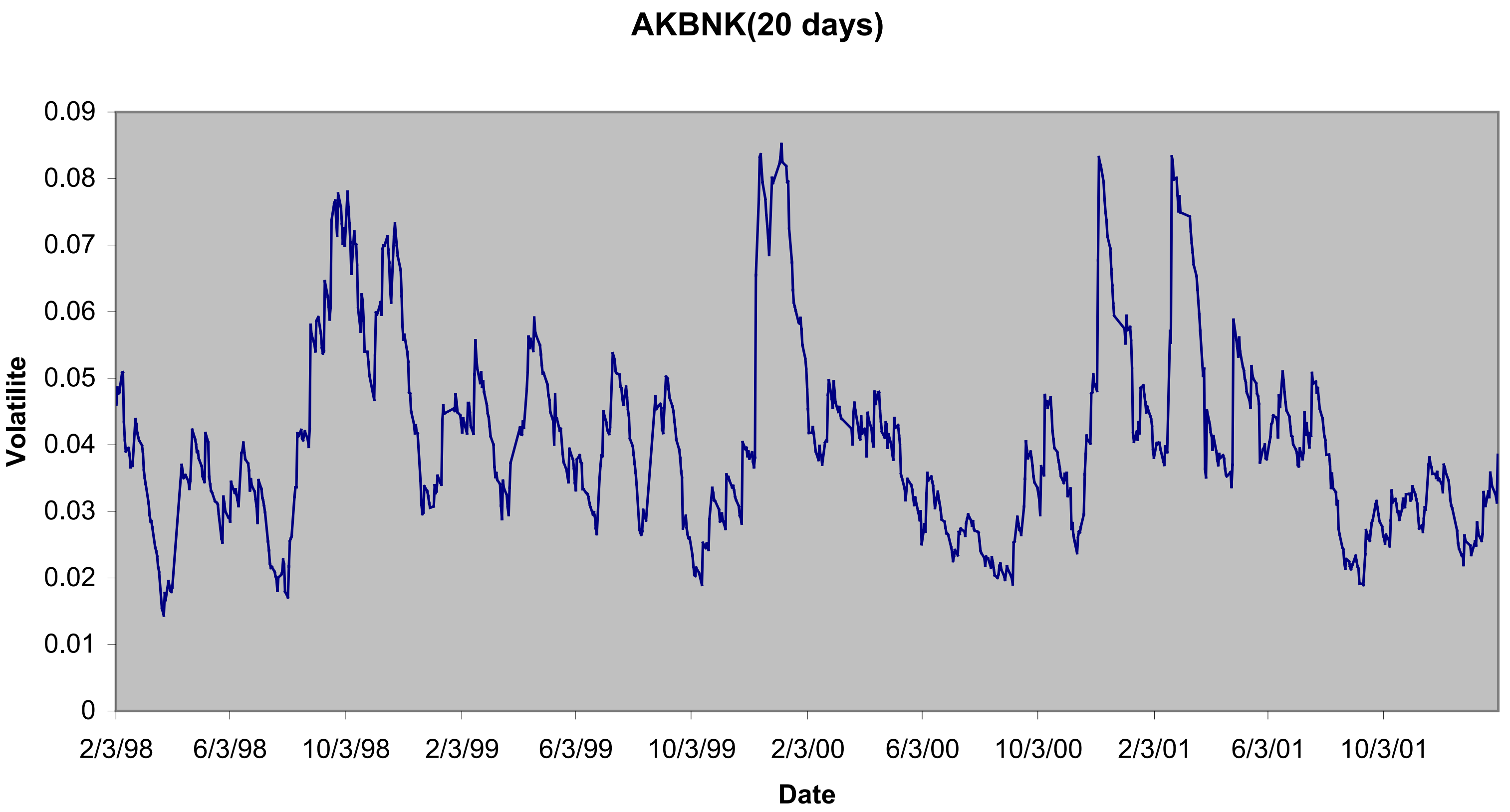


Figure 1c. AKBNK (20 days) EWMA results

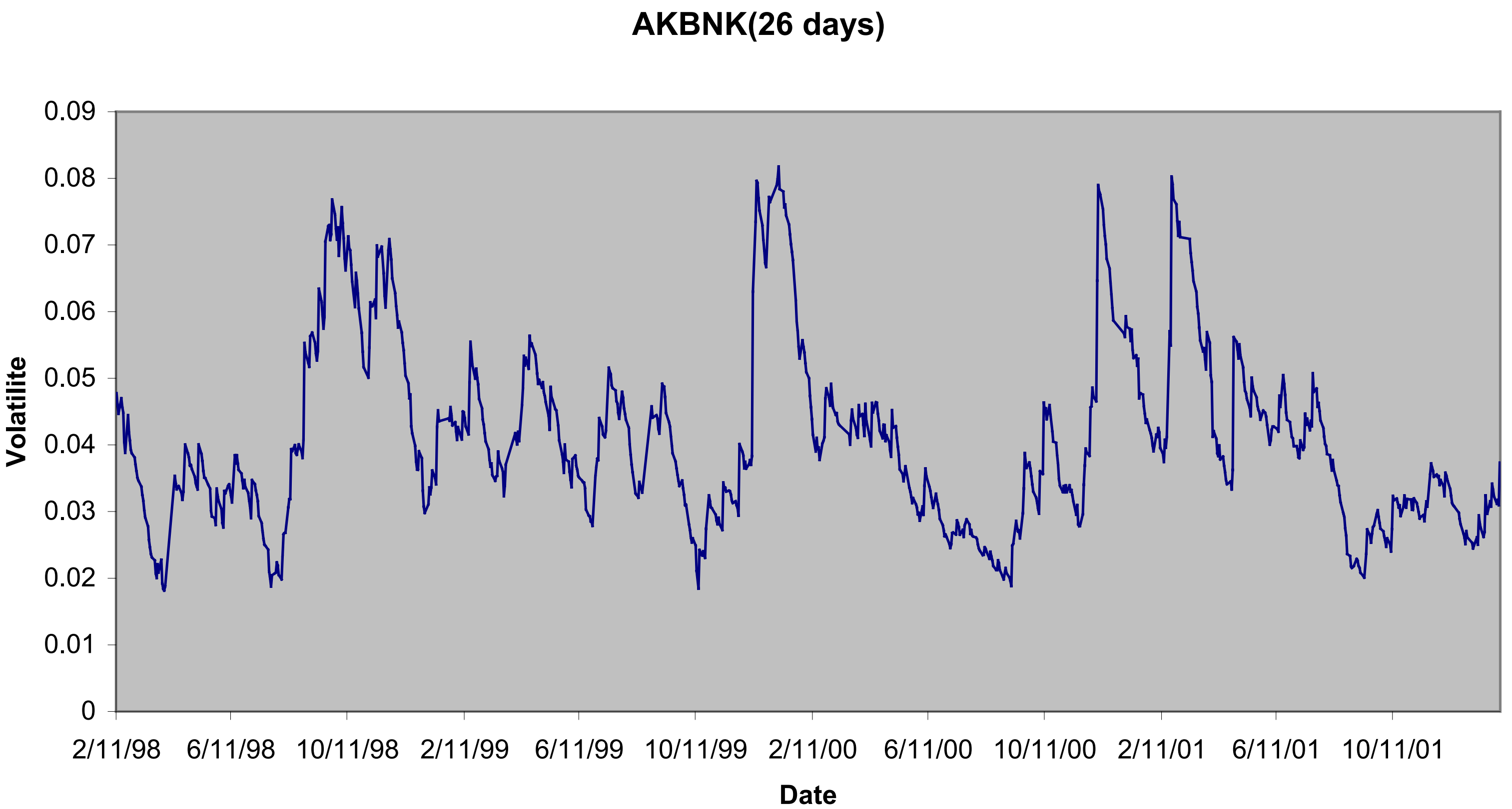
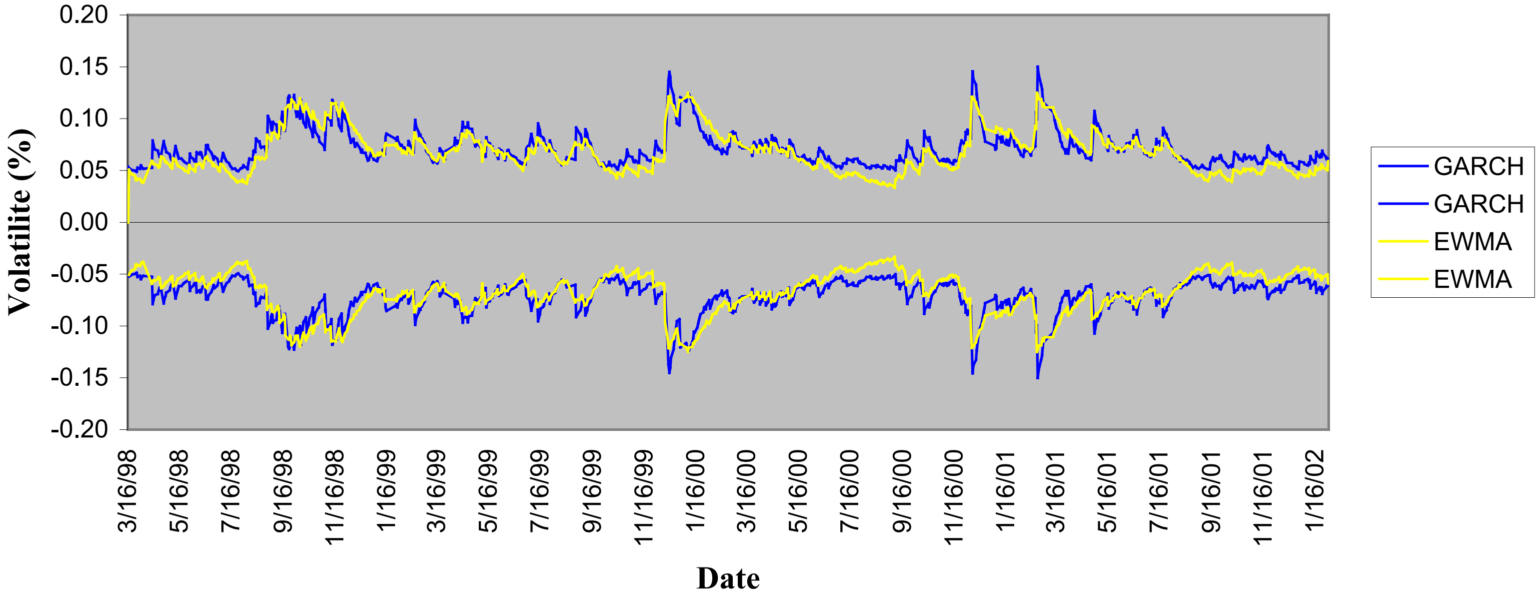


Figure 1d. AKBNK (26 days) EWMA results

AKBNK
GARCH (1,1) and EWMA (0,94)
%95 Confidence Level



AKBNK
GARCH (1,1) and EWMA (0,94)
%99 Confidence Level

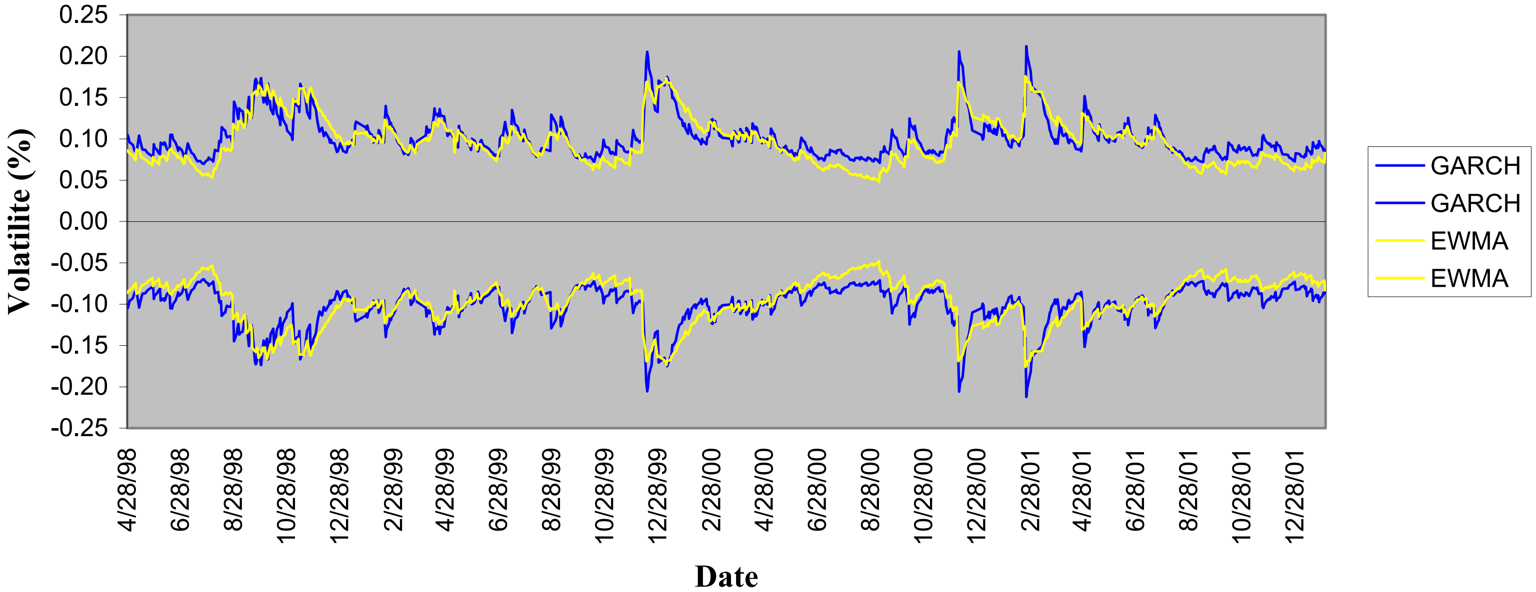


Figure 2. AKBNK Results