ESTIMATING VALUE AT RISK USING GARCH MODELS: EVIDENCE FROM THE TURKISH BANKS

BY

ÇİÇEK YILMAZ

JANUARY 2008

ESTIMATING VALUE AT RISK USING GARCH MODELS: EVIDENCE FROM THE TURKISH BANKS

A THESIS SUBMITTED TO

THE GRADUATE SCHOOL OF SOCIAL SCIENCES

OF

IZMIR UNIVERSITY OF ECONOMICS

BY

ÇİÇEK YILMAZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF MASTER OF ART

IN

THE GRADUATE SCHOOL OF SOCIAL SCIENCES

JANUARY 2008

Approval of the Graduate School of Social Sciences

____

(Title and Name)
Director

I certify that this thesis satisfies all the requirements as a thesis

for the degree of Master of Science/Doctor of Philosophy.

____
(Title and Name)
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science/Doctor of Philosophy.

	_________________
(Title and Name)	(Title and Name)
Co-Supervisor	Supervisor

Examining Committee Members

(Title and Name in alphabetical order of last name)

....	_____________________
....	_____________________
....	_____________________
....	_____________________
....	_____________________

ABSTRACT

ESTIMATING VALUE AT RISK USING GARCH MODELS:
EVIDENCE FROM THE TURKISH BANKS

Yılmaz, Çiçek

MA in Financial Economics, Graduate School of Social Sciences

Supervisor: Assoc. Prof. Dr. Adnan Kasman

January 2008, 122 pages

This thesis investigates the behaviour and characteristics of Turkish stock markets with a special focus on listed bank equities. The analysis is based on the fitting of GARCH model to financial return series for four different time period. The estimation of the parameters in the model is examined with two distributional assumptions for the innovations; Gaussian distribution and Student-t distribution. Furthermore, today's Value at Risk figures are obtained via GARCH specifications, and also one-step ahead VaR figures are forecasted. The results indicate that GARCH (1, 1) model is suitable for modelling bank and index return series, hence, the VaR captures well stocks' price movements.

Keywords: *volatility, garch, value at risk*

ÖZET

RİSKE MARUZ DEĞERİN GARCH MODELLERİ İLE HESAPLANMASI: TÜRK BANKALARI ÜZERİNE BİR ÖRNEK ÇALIŞMA

Yılmaz, Çiçek

Finans Ekonomisi Yüksek Lisans Programı, Sosyal Bilimler Enstitüsü

Tez Yoneticisi: Doç. Dr. Adnan Kasman

Ocak 2008, 122 sayfa

Bu çalışma, Türkiye'deki menkul kıymet borsasının davranışını ve karakteristiğini banka hisselerini odak noktası alarak incelemektedir. Yapılan analizler GARCH modelini, dört farklı periyod için, finansal zaman serilerine uygulayabilmek üzerine kurulmuştur. Model parametreleri Normal dağılım ve Student-t dağılımı olmak üzere iki farklı dağılım varsayımı altında tespit edilmiştir. Temin edilen parametreler vasıtasıyla bugünün ve bir adım sonrasının Riske Maruz Değer rakamları tahmin edilmiştir. Elde edilen sonuçlar GARCH (1, 1) modelinin banka ve endeks getiri serilerini modellemede uygun olduğunu göstermektedir. Dolayısıyla, buradan hareketle hesaplanan RMD değerlerinin fiyat hareketlerini yakalamada son derece başarılı olduğu izlenmiştir.

Anahtar Kelimeler: *volatilite, garch, riske maruz değer*

To My Parents

ACKNOWLEDGMENTS

I express sincere appreciation to Assoc. Prof. Dr. Adnan Kasman for his guidance and insight throughout the research. To my family, I offer sincere thanks for their unshakable faith in me and their willingness to endure with me the vicissitudes of my endeavors.

TABLE OF CONTENTS

LIST OF TABLES

TABLE

LIST OF FIGURES

FIGURE

CHAPTER 1

INTRODUCTION

Security prices are assumed to reflect the value of a firm. Major economic events, such as changes in interest rates, earnings announcements, announcements of mergers and acquisitions, announcements of increases or decreases in dividends, financing decisions as the issuance of new shares or plans to repurchase old ones and actions of government regulators, can affect this value. These events may affect only a firm, group of firms or even the entire market. It is important to study how such events that cause the volatility in financial markets to increase affect stock prices since huge trading volume of these stocks has made the measurement of market risk to a primary concern in the financial world.

Many previous studies used the conventional methods (unconditional variance) for measuring risk of assets. This measure of the unconditional volatility does not take into account that there might be a predictable pattern in the stock market volatility. However, practices show that for the high frequency data, variance is not constant over time. Also, many financial time series have a number of common characteristics. These are:

a. Asset prices are generally nonstationary. Asset returns are usually stationary and some financial time series are fractionally integrated.

b. Return series usually show no or little autocorrelation.

c. Serial independence between the squared values of the series is often rejected pointing towards the existence of non-linear relationships between subsequent observations.

d. Volatility of the return series appears to be clustered.

e. Normality is usually rejected in favour of some thick-tailed distribution.

f. Some series exhibit so-called leverage effect that is changes in stock prices tend to be negatively correlated with changes in volatility. A firm with debt and equity outstanding typically becomes more highly leveraged when the value of the firm falls. This raises equity returns volatility if returns are constant.

g. Volatility of different securities very often moves together.

Engel (1982) provides ARCH (autoregressive conditional heteroscedasticity) model which takes into account excess kurtosis (i.e. fat tail behaviour) and volatility clustering, two important characteristics of financial time series. He modelled conditional variance as squared of regression model's error terms. Bollerslev (1986), treated time-varying conditional variance as function of moving averages of past squared residuals, and added this model the lagged values of the variance, consequently he suggested GARCH model.

Many extensions of the simple GARCH model have been developed in the literature such as the EGARCH of Nelson (1991), asymmetric models of Glosten, Jaganathan Runkle (1993), Zakoian (1994), Engle and Ng (1993) and power models such as Higgins and Bera (1992), Engle and Bollerslev (1986), and Ding, Granger and Engle (1993) joined models such as SWARCH, STARCH, and QARCH and many more. Hence, volatility, which is explained by conditional variance, is accepted as a measure of risk in the literature.

Providing accurate forecasts of variances and covariances of asset returns through its ability to be modelled as time-varying conditional variances, one can apply GARCH models to such diverse fields as risk management, portfolio management and asset allocation, option pricing, foreign exchange, and the term structure of interest rates.

One can find highly significant GARCH effects in equity markets, not only for individual stocks, but for stock portfolios and indices, and equity futures markets as well. These effects are important in such areas as value-at-risk (VaR) and other risk management applications that concern the efficient allocation of capital. Also, GARCH models can be used to examine the relationship between long- and short-term interest rates. As the uncertainty for rates over various horizons changes through time, one can also apply GARCH models in the analysis of time-varying risk premiums. Foreign exchange markets, which have highly persistent periods of volatility with significant fat tail behaviour, are particularly well suited for GARCH modelling.

In the context of risk, forecasting volatility also received great concern from the policy makers. Particularly in emerging markets, the financial liberalization process is not a smooth path. During last two decades, emerging markets experienced many financial crises caused or were leaded by huge capital inflows or outflows. While this is the situation, volatility is a good indicator for monitoring financial stability and understanding the mechanisms and exact relations behind those crises; because stability of economy is much related with the stability of its financial market. With this impetus, Bank for International Settlements (BIS) has recognized internal models to determine the capital charges of banks, so that market participants began to deal with efficient computation of Value-at-Risk (VaR). Requiring estimation of the variables, VaR began to benefit from GARCH models. Calculating VaR needs a probability distribution of changes in portfolio value. This distribution is derived from by placing assumptions on 1) how the portfolio function is approximated, and 2) how the state variables are modelled. The GARCH models are exerted for calculating the 2^{nd} point of the process. The variance acquired from GARCH processes can be used as an input to the VaR formulation.

Several researchers have used GARCH models to investigate volatility in Turkey. Some of them are Okay (1998), Lee, Saltoğlu (2002), Kutan and Aksoy (2004), Mazıbaş (2004), Çinko (2004), Artan (2006), Duran and Şahin (2006), Telatar,Binay (2002), Bildirici et al. (2007), Berument et al. (2003), Turanlı et al. (2007), Gökçe (2001), Akgül and Sayyan (2007).

Despite the mentioned literature on volatility forecasting, the paper makes contributions to the related literature in several respects: First, this study pays particular attention to the listed banking firms in Turkey as well as ISE-30, ISE-100 and banking index. This allows us to perceive whether banks evolve with the indexes or not. Second, we also study four different time horizons. By dividing sample data into some sub periods, we are able to compare the results of GARCH models among the sub periods. Moreover, two different error distribution assumptions are exerted, namely normal distribution and student's t distribution. Lastly, the one-step ahead VaR is forecasted by benefiting estimated GARCH models specifying two different confidence intervals.

The rest of this thesis is organized as follows. The Part 2 presents literature review for the GARCH models. The Part 3 discusses the volatility models. The Value at Risk models are discussed in Part 4. The Part 5 discusses the data and reports the empirical results. Finally, the Part 6 contains some concluding remarks.

CHAPTER 2

LITERATURE REVIEW

Bollerslev (1986) introduced the generalized ARCH (GARCH) model. After the introduction of the model, the family of GARCH has grown at a tremendous rate. A bunch of models have been built up, and also used in the VaR calculations. Nelson (1991) (EGARCH); Glosten, Jagannathan and Runkle (1993) (GJR); Ding, Granger and Engle (1993) (APARCH); Tse (1998) (FIAPARCH); Alexander and Lazar (2006) (NMGARCH) tested various GARCH models for the different financial market data, and claimed that these models have ability to capture instantaneous volatility changes.

The GARCH models are also constructed with different assumptions on normality distribution. Palm (1996), Pagan (1996), and Bollerslev, Chou and Kroner (1992) used fat-tailed distributions in the literature. Bollerslev (1987), Hsieh (1989), Baillie and Bollerslev (1989), and Palm and Vlaar (1997) show that these distributions perform better in capturing the higher observed kurtosis.

Skewness, one of the characteristics of the high frequency financial time series, is explored in many researches. Christoffersen and Jacobs (2004) show that a simple asymmetric GARCH captures the leverage effect, and performs best of all GARCH models considered. Wu (2001) display the fact that the 'leverage effect' in stocks determines a strong negative correlation between returns and volatility, which is the most important reason for skewness in stock returns.

So and Yu (2006), studies seven GARCH models, including RiskMetrics and two long memory GARCH models, in Value at Risk (VaR) estimation. Both long and short positions of investment are considered. They apply seven models to 12 market indices and four foreign exchange rates to assess each model in estimating VaR at various confidence levels. The results indicate that both stationary and fractionally integrated GARCH models outperform RiskMetrics. Although, most return series show fat-tailed distribution and satisfy the long memory property, it is more important to consider a model with fat-tailed error in estimating VaR. Asymmetric behaviour is also discovered in the stock market data that t-error models give better VaR estimates than normal-error models in long position.

Burns (2002) estimates VaR using univariate GARCH models. Long history of the S&P 500 is used to compare the estimators with several other common approaches to Value at Risk estimation. The test results indicate that GARCH estimates are superior to the other methods in terms of the accuracy and consistency of the probability level.

Varma (1999) provides empirical tests of different risk management models in the VaR framework in the Indian stock market. It is found that the GARCH-GED (Generalised Auto-Regressive Conditional Heteroscedasticity with Generalised Error

Distribution residuals) performs exceedingly well at all common risk levels (ranging from 0.25% to 10%).

Andersen et al. (2005) examine computation of portfolio VaR via historical simulation, exponential smoothing, and GARCH models including univariate and multivariate models on S&P 500 index. They claim that Multivariate GARCH models are outperformed the others.

However, there are some contradictory empirical results obtained from GARCH-in-mean-type models. French, et al. (1987) find evidence that conditional variance is statistically significant and positively related to conditional mean for the US equity index, as expected. However, Baillie and DeGennaro (1990), using the same data, claim that the coefficient on conditional variance is insignificant when the conditional distribution was a t- distribution rather than a normal distribution.

Chou (1988) provides evidence in support of a GARCH-in-mean model for a U.S. equity index. Also, Bali and Peng (2006) find a positive and statistically significant relation between the conditional mean and conditional volatility of market returns at the daily level. Choudhry (1996), however, does not find statistically significant evidence of a risk premium for six emerging market indices.

Goyal (2000) focuses on GARCH models ability to deliver one period ahead forecasts of volatility by using daily and monthly series of the CRSP value weighted returns. He claims that simpler ARIMA specifications give better forecasts than the GARCH models.

In addition above contradictory results, there are some questions concerning these models' forecasting ability. The most pronounced criticism is about the models' inability to capture structural breaks and regime changes. Aiolfi and Timmermann (2004) criticises these models being insufficient on catching volatility clustering and structural breaks. According to Hendry and Clements (2002), GARCH is temporarily affected from today's rising volatility. When volatility starts to fall, VaR moves backward to its old degree. As a result, GARCH performs well in the short term, however, not in the long term.

Despite their drawbacks, GARCH models predominantly are used in the stock markets, both in the emerged and emerging. After the financial crisis, especially experienced in emerging markets, studies on these models have been emphasized and accumulated.

Fabozzi, et al.(2004) reveal that there is significant evidence of volatility clustering and a strong presence of serial correlation in the Chinese stock markets; Shenzen and Shangai. They investigate a series of GARCH models in estimating the volatility parameters and found that the daily data on the Shenzhen is fitted well by a GARCH(1,1) model while the data on the Shanghai exchange by a TAGARCH (1,1) model. These two models are suggested that capture well the dynamics of the volatility.

Jayasuriya, et al. (2005) estimate the magnitude of assymmetric volatility for seven mature markets and fourteen emerging markets. They find that both mature and emerging markets exibit large magnitude of assymetric volatility, and claim the reasons as transaction costs such as capital gains taxes, and certain trading strategies, e.g. short-selling.

Pan and Zhiang (2006) explore a number of linear and GARCH type models for predicting the daily volatility of two equity indices in the Chinese stock market. Under the framework of three distributional assumptions, the forecasts are evaluated for setting Value at Risk framework. They test seven models, namely; moving average model, historic mean model, random walk model, GARCH model, GJR model, EGARCH model and APARCH model. The best models are different for Shenzen and Shangai stock markets. They conclude a number of results. First, for the Shenzhen stock market, the traditional method seems superior, and the moving average model is favoured for the forecasting of daily volatility. For the Shanghai index the GARCH-t model, APARCH-N model and moving average models are favoured. Second, in the Shenzhen stock market, the asymmetry model, i.e. the GJR and EGARCH model perform better than other GARCH-type models, but with little gain. The models with skewed student t distribution rank better than models with other distributions, but again the difference is small. For the Shanghai stock market, there is no evidence that the asymmetric model or skewed student t distribution is superior. Third, although they cannot find one model that performs best under all the criteria, it does appear that the random walk model is a poor performer, irrespective of both the series on which it is estimated and the loss function used to evaluate the forecast.

Shin (2005) examines the relationship between expected stock returns and conditional volatility in fourteen emerging international stock markets. Using both a parametric and a flexible semiparametric GARCH in mean model, he suggests that a positive relationship prevails for the majority of the emerging markets, while such a relationship is insignificant in most cases.

Yu (2002) evaluates the performance of nine alternative models for predicting stock price volatility using daily New Zealand NZSE40 data. The models contain both simple models such as the random walk and smoothing models and complex models such as ARCH-type models and a stochastic volatility model. The main results are found as the following: (1) The stochastic volatility model provides the best performance among all the candidates; (2) ARCH-type models can perform well or badly depending on the form chosen: the performance of the GARCH(3,2) model, the best model within the ARCH family, is sensitive to the choice of assessment measures; and (3) the regression and exponentially weighted moving average models do not perform well according to any assessment measure.

Balaban, et al. (2004) evaluate the out-of-sample forecasting accuracy of eleven models for weekly and monthly volatility in fourteen stock markets namely Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Netherlands, Philippines, Singapore, Thailand, the UK and the US. Volatility is defined as within-week (within-month) standard deviation of continuously compounded daily returns on the stock market index of each country for the ten-year period 1988 to 1997. The following models are employed; a random walk model, a historical mean model, moving average models, weighted moving average models, exponentially weighted moving average models, an exponential smoothing model, a regression model, an ARCH model, a GARCH model, a GJR-GARCH model, and an EGARCH model. Two set of conclusions are obtained. (1) When employing the standard symmetric error metrics to assess volatility forecasting performance, it is found that the Exponential Smoothing approach dominates in providing superior forecasts of weekly volatility. (2) Employing the non-standard asymmetric error metrics to assess volatility forecasting performance, interestingly, the results are changed. The asymmetric loss functions, that penalize under/over-prediction, are employed. Specifically, when under-predictions are penalized, more heavily ARCH-type models provide the best forecasts while the random walk is worst.

Angelidis and Degiannakis (2004) examine the performance of various volatility models in forecasting the realized volatility based on intra day data and in calculating the VaR numbers based on the returns of Athens Stock Exchange. They make the evaluation of the risk management techniques on two grounds. First, the volatility forecasts are compared with the intra-day realized variance based on the 5-minute intra day returns. Second, under the VaR framework, they simultaneously examine whether the exception rate is statistically equal to the expected one and the independence of failures hypothesis is valid. For both equity indices, no model can forecast both the VaR number and the realized volatility, since it does not generate the most accurate VaR values and volatility predictions. For the ASE General index the exception rate of the GARCH–normal model is statistically equal to the expected one, while for the Bank index this is not the case, since the APARCH-skewed Student t model estimates the VaR number more accurately. On the other hand, the APARCH models estimate the realized intra-day volatility better than the GARCH framework. However, as in the case of the VaR predictions, there is not a particular model that can be applied for both indices. Thus, as concerns the volatility of the Greek stock market, although it is predictable, there is not an explicit model, which is the most accurate for all the forecasting tasks.

GARCH models also have found a wide field of application in Turkey, which is one of the emerging markets. Models are used in the fields extending from stock market volatility to inflation uncertainty.

Okay (1998) examines the Istanbul Stock Exchange from 1989 to end-1996. GARCH and alternatively EGARCH models are studied in the analysis. It is asserted that both models performed well to explain the dynamic volatility of the ISE, however, EGARCH is better by taking into account of the asymmetric behaviour of the stocks.

Mazıbaş (2004) evaluates the out-of-sample forecasting accuracy of fifteen symmetrical and asymmetrical GARCH models for daily, weekly and monthly volatility in composite, financial, services and industry indices of Istanbul Stock Exchange (ISE). In modelling and forecasting stock market volatility GARCH, EGARCH, GJR-GARCH, Asymmetrical PARCH and Asymmetrical CGARCH models are employed. It is found that there are asymmetry and leverage effects in daily, weekly and monthly market data, also in model forecasts, weekly and monthly forecasts are more precise than daily forecasts. The reason for the leveraged effect is claimed as investor's negative attitude towards bad news gained from severe financial crisis. Moreover, it is also found that due to high volatility in daily returns, ARCH-type models are incompetent in modelling daily volatility.

Duran and Şahin (2006) study the existence of volatility spillover and its direction between IMKB services, financial, industrial and technology indexes based on daily data from July 2000 to April 2004 by benefited from indexes volatility obtained from EGARCH model. Vector Autoregressive (VAR) model is used to test volatility spillover among the indexes. According to results obtained from the VAR model, it is found that there exists volatility spillover between IMKB indexes.

Kutan and Aksoy (2004) examine the role of public information arrival using daily composite and sector index returns in Turkey. GARCH and EGARCH frameworks are employed to capture the time-varying nature of asset returns in the market. Specifically, the paper focuses on news regarding the balance of trade (BOT), real GNP, industrial production, tourism, the construction sector, and the CPI. The findings reveal that real GDP and industrial production announcements have the most important impact on stock returns. Regarding inflation, nominal stock returns increase in response to unfavourable inflation announcements, but only for the financials sector and partially. Market volatility is more sensitive to news about real

GNP, balance of trade, tourism and construction. Overall, public information appears to play a large role in the emerging stock market of Turkey, affecting both returns and volatility. This reflects a combination of three significant changes taking place in the stock market since the late 1980s: greater participation of domestic and foreign investors, increase in the volume of transactions, and the improved transparency of the system.

Artan (2006) investigates Turkish high and persistent inflation experience and its impact on inflation uncertainty and growth. GARCH models are used to generate a measure of inflation uncertainty and quarterly data covers the period of 1987/1-2003/3. GARCH (1,1) effect is observed in the series by volatility persistence.(sum of the parameters is close to one 0.98)

Telstra and Binay (2002) investigate the applicability of PARCH modelling strategy to the İMKB index and compares the findings with the results obtained for other countries. The findings indicate that the volatility of the IMKB index is higher than that of the other countries' exchanges.

Bildirici, et al. (2007) aim to make a detailed calculation of the volatility of daily return by using a different calculation method, rather than using the method $\ln(t - t_{-1})$, a widely used method for calculating the volatility of daily return in the literature by making use of the daily closing values of Istanbul Stock Exchange(ISE) between years 1988-2006. Also, in this study, the volatility of daily return is calculated and modelled by using of the ARCH/GARCH family models (EGARCH,

TARCH, GJR-TARCH, SAARCH, PGARCH, NARCH/NGARCH, APGARCH, NPGARCH). The results obtained suggest that it is appropriate to model the volatility of daily returns in ISE by ARCH/GARCH family models.

Berument, et al. (2004) investigate the day of the week effect for return and volatility through a GARCH model for Istanbul Stock Exchange through the period 1986 and 2003. Using GARCH model, they find statistically significant evidence to report that there is the day of the week effect showing that highest volatility is observed for Mondays and lowest for Fridays. Moreover, Friday has the highest return and Monday has the lowest return.

Turanlı, et al. (2007) predict Istanbul Stock Market volatility in 2002–2006 period and make comparison between models under the light of predictions. In the study, the Istanbul Stock Exchange (ISE) 100 Index's daily closing values between the dates of 2002 and 2006 are used. The models ARCH and GARCH which are examining the characteristic of "heteroscedasticity" are used. GARCH (1,1) outperform ARCH (1) as expected by the reason of concerning both standardized residuals and its effect to the autocorrelation.

Gökçe (2001) estimates ARCH, ARCH-M, GARCH, GARCH-M, EGARCH and EGARCH-M models by using daily data on Istanbul Stock Exchange. The relationship between market returns and changes in volatility is analyzed, and positive relationship is found. Having assessed model parameters, GARCH (1,1) model have been indicated as the best fitted one.

Akgül and Sayyan (2005) investigate existence of the asymmetry effect and the long memory characteristic in the ISE30, with the help of Asymmetric Autoregressive Conditional Heteroscedasticity models. The study concludes that 13 of the stocks taking place within the IMKB-30 present asymmetry effect, and 4 of these have long memory characteristic. The findings show that APARCH and FIAPARCH models provide the most accurate volatility forecasts.

CHAPTER 3

THE VOLATILITY MODELS FAMILY

3.1. Uncertainty, Risk & Volatility

The future is, by definition, uncertain. But the developed world has many tools to quantify uncertainty and turn it into measured risk: that is, to calculate the probability of events with some certainty. However, one needs to make distinction among uncertainty, risk and volatility, and also to define the boundaries of these three phenomenons. Hence, we try to define them below.

The risk and uncertainty are related to the analysis by Frank H. Knight (1921), in his treatise "Risk, Uncertainty and Profit". Knight makes distinction between profit and rent. He characterizes the role of profit as the reward to the entrepreneur for bearing inevitable uncertainty. According to Knight, rent is a consequence of unequal income distribution, however, profit is a consequence of uncertainty which is caused by lack of information. Risk can be covered, but uncertainty cannot be calculated and forecasted. So, profit appears as uncertainty's payoff.

Knight, provides his uncertainty and risk definition. He attaches the label "probabilities" to opinions formed in the absence of symmetry or homogenous data.

He suggested that a priori and statistical probabilities reflect “measurable uncertainty” and opinions represent “unmeasurable uncertainty”. And he states, “to preserve the distinction… between the measurable uncertainty and an unmeasurable one we may use the term “risk” to designate the former and the term “uncertainty” for the latter.”

Knight explored the uncertainty and risk concepts as an economist ascertaining the world of business and the nature of profit in that world. However, in 1950s finance has emerged as a subject independent of economics. The event that marks the emergence of finance as an independent subject is the doctoral dissertation defence of Harry Markowitz. His dissertation was on the portfolio selection. He tried to describe how investors balance risk and reward in constructing investment portfolios.

Although not making a clear definition of risk, Markowitz (1952) considers variance as an “undesirable thing” and states, “… if the term “yield” were replaced by “expected yield” or “expected return”, and “risk” by “variance of return”, little change of apparent meaning would result.”

Today, the definitions of uncertainty, risk and volatility are based on the suggestions of Markowitz (1952). Say, et al. (1999) provide the following perspective of risk: “A dictionary definition of risk is that of a state in which the number of possible future events exceeds the number of actually occurring events, and some measure of probability can be attached to them.” And they state, “Risk is thus seen to differ from uncertainty where the probabilities are unknown.”

To apply the above theoretical background and illustrate the differences between risk and uncertainty for this thesis's purposes, suppose one is attempting to forecast the stock price of X Bank. S/he supposes that X is currently priced at $15 per share, and historical prices place the stock at 21.89% volatility. Now supposing that for the next 3 years, X does not engage in any risky ventures and stays the same, and also supposing the entire economic and financial world remains constant, this means that risk is fixed and unchanging; that is, volatility is unchanging for the next 3 years. However, the price uncertainty still increases over time; that is, the width of the forecast intervals will still increase over time. For instance, year 0's forecast is known and is $15. However, as one progresses one day, X will most probably vary between $14 and $16. One year later, the uncertainty bounds may be between $10 and $20. Three years into the future, the boundaries might be between $5 and $25. As in this example, uncertainties increase while risks remain the same. Therefore, risk is not equal to uncertainty.

Consequently we are able to say that making distinction among, uncertainty, risk and volatility is important. *Uncertainty* describes a situation where various possible outcomes are connected to an event, however, the assignment of probabilities to these outcomes is not possible. On the contrary, *risk* permits the assignment of probabilities to the different outcomes. *Volatility* is dedicated to risk in that it provides a measure of the possible variation or movement in a particular economic variable. However, volatility is not observable in the marketplace. So, it needs to be estimated. It is usually measured based on observed realizations of a random variable over some historical period. This is referred to as historical volatility which is different from the implied volatility calculated, for example, from the Black-Scholes formula.

Each method has its own characteristics. Implied volatilities are often referred to as a "market consensus" of volatility—an indication of risk that combines the insights of many market participants. For the most part, this is a reasonable interpretation. However, implied volatilities are essentially prices. They can be biased by such things as bid-ask spreads as well as supply and demand for options. For example, in 1995, Nick Leeson was selling so many Nikkei options that he drove that implied volatility far below its historical levels. Historical volatility, on the other hand, reflects actual market fluctuations. However, the data upon which historical volatility is based may be obsolete—perhaps encompassing a period not reflective of current market conditions.

Historical volatility measures are “backward-looking” in the sense that they rely on the history of prices that have already been observed in a time series rather than on expected future prices. Unlike these historical measures, “forward-looking” measures of volatility rely on current prices which incorporate all available information about future prices. Alternatively stated, since these current prices are determined by the best and most up-to-date information, they reflect participant’s expectations about future market conditions.

Implied volatility can be used to price options on an underlier. It is the result obtained from a theoretical option pricing model given the market price of the option. When one solve for the implied volatility of an option s/he is assuming that the theoretical value is known and that the volatility is unknown. Implied volatility can be thought of as the current market consensus of volatility for the underlying instrument assuming that everyone is using the same theoretical option pricing model. Unlike time series measures of volatility that are entirely backward-looking, option implied volatility is "backed-out" of actual option price which, in turn, are based on actual transactions and expectations of market participant and thus is inherently forward-looking.

The implied volatility of an option provides information about what market participants expect to happen with future asset returns. Implied volatility is the volatility implied by two things: the current market price of the option, and some model for calculating the theoretical price of the option such as Black-Scholes. An option pricing model is an attempt to express or calculate the fair market value of an option (net of trading costs and liquidity) as a function of observable parameters, such as maturity. The theoretical price of an option is then the fair market price of an option under the assumptions made by the corresponding valuation model. This is the well known option pricing the Black-Scholes model. However, historical volatility is an approach to estimate volatility applying techniques of time series analysis to historical data for the variable. It can be used for VaR, portfolio studies as well as underliers which implied volatilities are unavailable. Historical volatility also might be used as a reality check to supplement implied volatilities. In more basic terms, historical volatility (also called statistical volatility) gauges price movement in terms of past performance.

Historical volatility is most commonly measured by the standard deviation based on the historical data set of an economic variable. In this context, there will always be either an explicit or implicit reference to an underlying probability distribution for the variables of concern. However, if components or trends in the underlying variable are predictable, then calculating volatility might be based on the standard deviation of total variability or on the standard deviation of risk, which can be obtained as the residual from a forecasting equation for total variability.

In this process, an additional question arises: Is the volatility (variance or standard deviation) of the pure risk component constant, or does it vary over time? The idea that volatility tends to cluster, i.e. that there may be serial correlation in it, and modelling this using autoregressive conditional heteroscedasticity, was the contribution of Robert F. Engle to the literature in 1982. The research in time varying volatility modelling started with the introduction of the autoregressive conditional heteroscedasticity (ARCH) model in Engle (1982). The ARCH model relates variance of the error terms to the square of a previous period's error terms. So that, the models are able to capture much of the volatility clustering and serial correlation in financial time series.

3.2. Volatility Models

Volatility modelling techniques can be analysed in three parts. Models might be categorized as “past standard deviation based models”, “ARCH type models”, and “Stochastic Volatility models”. In this thesis, SV models are out of scope.

Accordingly, past standard deviation based models will be mentioned generally, ARCH type models will be conveyed in detail, and SV will not be covered.

3.2.1. Predictions Based on Past Standard Deviations

3.2.1.1. Random Walk Model

When faced with a time series that shows irregular growth, the best strategy is to try to predict the change that occurs from one period to the next, i.e., the quantity $Y(t)-Y(t-1)$. In other words, one need to look at the first difference of the series, to see if a predictable pattern can be discerned there. The first difference of a time series is the series of changes from one period to the next. If $Y(t)$ denotes the value of the time series Y at period t, then the first difference of Y at period t is equal to $Y(t)-Y(t-1)$. If the first difference of Y is stationary and also completely random (not autocorrelated), then Y is described by a random walk model, meaning that each value is a random step away from the previous value.

Hence, the forecasting model suggests that

$$\hat{Y}(t)-Y(t-1)=\alpha \tag{1}$$

where α is the mean of the first difference , i.e., the average change one period to the next. Rearranging this equation to put $Y(t)$ by itself on the left, one get:

$$\hat{Y}(t)=Y(t-1)+\alpha \tag{2}$$

3.2.1.2. Simple Moving Average

Extending this idea, one has the Simple Moving Average method, the Exponential Smoothing method and the Exponentially Weighted Moving Average method. The Moving Average method discards the older estimates. Similarly, the Exponential Smoothing method uses all historical estimates, and lastly the Exponentially Weighted Moving Average (EWMA) method uses only the more recent ones. But unlike the previous one, the last two exponential methods place greater weights on the more recent volatility estimates. However, the three methods reflect a tradeoff between increasing number of observations and sampling nearer to time t.

A simple moving average is the unweighted mean of the previous n data points. In this method, each data series might be converted into a new series that is a moving average over any number of periods. This moving average smoothes out irregularities and captures cyclical influences if the data is stationary and seasonally adjusted. Simple moving average models have an order as "n" and weights as "$1/n$". Any value of n may be used, but the higher the value of "n" the less the amount of variation in the forecasts. A forecast for the next period is the moving average of the current period.

For example, a 10-day simple moving average of closing price is the mean of the previous 10 days' closing prices. If the prices are P_m, P_{m-1},... P_{m-9} then the formula is:

$$SMA = \frac{P_m - P_{m-1} + P_{m-2} + \ldots + P_{m-9}}{10} \tag{3}$$

When calculating the successive values, a new value comes into the sum and an old value drops out, meaning a full summation each time is unnecessary,

$$SMA_{today} = SMA_{yesterday} - (P_{m-n+1})/n + (P_{m+1})/n \tag{4}$$

However, there are some drawbacks concerning simple average method;

a. The forecast will lag turning points if it captures them at all (oversmoothing for high values of n).

b. Forecasts will be biased when there is a strong trend in the variable.

c. Past observations are given the same weight.

3.2.1.3. Exponential Smoothing & EWMA

Exponential smoothing weights past observations with exponentially decreasing weights to forecast future values. This smoothing scheme begins by setting S_2 to y_1, where S_i stands for smoothed observation, and y stands for the original observation. Whilst the subscripts referring to the time periods, *1, 2,..., n*; for the third period, $S_3 = \alpha y_2 + (1-\alpha)S_2$; and so on. There is not a S_1; because, the smoothed series starts with the smoothed version of the second observation.

For any time period t, the smoothed value S_t is found by computing

$$S_t = \alpha y_{t-1} + (1-\alpha)S_{t-1} \qquad 0 \le \alpha \le 1, \qquad t \ge 3 \tag{5}$$

The Exponentially Weighted Moving Average ($EWMA$) is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time.

The statistic that is calculated is:

$$EWMA_t = \lambda Y_t + (1-\lambda)EWMA_{t-1} \qquad for \quad t = 1,2,\ldots,n \tag{6}$$

where

- $EWMA_t$ is the mean of historical data

- Y_t is the observation at time t

- n is the number of observations to be monitored including $EWMA_t$

- $0 < \lambda \leq 1$ is a constant that determines the depth of memory of the $EWMA$.

The parameter λ determines the rate at which 'older' data enter into the calculation of the $0 < \lambda \leq 1$ statistic. A value of $\lambda = 1$ implies that only the most recent measurement influences the $EWMA$. Thus, a large value of $\lambda = 1$ gives more weight to recent data and less weight to older data; a small value of λ gives more weight to older data.

3.2.1.4. ARMA Models

ARMA models are linear models which have two types of dynamic processes built into. Model assumes that the time series is stationary. For a time series variable y_t :

- An “autoregressive” (AR) process is one where the current value of y is influenced

by it’s own past values:

$$y_t = f(y_{t-1}, y_{t-2},...) + \varepsilon_t \tag{7}$$

• A “moving average” (MA) process is one where the contemporaneous value of y

is influenced by past as well as contemporaneous values of the innovation term, ε_t.

$$y_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, ...) + \varepsilon_t \tag{8}$$

• An MA process is one where there is a simple linear influence of past innovations

on the current value of y.

$$y_t = \alpha + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t \tag{9}$$

where $\varepsilon \approx w.n.$

3.2.1.5. ARIMA Models

ARIMA (Autoregressive Integrated Moving Average) time series analysis uses lags and shifts in the historical data to uncover patterns, e.g. moving averages, seasonality, and predict the future. ARIMA might be seen as a method for answering two questions; how much of the past should be used to predict the next observation (length of weights), and the values of the weights.

$ARIMA$ model includes three types of parameters: the autoregressive parameters (p), the number of differencing passes (d), and moving average parameters (q). In the notation, models are summarized as $ARIMA(p,d,q)$. For example, a model described as $(0,1,2)$ means that it contains 0 (zero) autoregressive (p) parameters and two moving average (q) parameters which were computed for the series after it was differenced once.

Actually, ARIMA models consist of three steps: (1) Identification, (2) Estimation, (3) Analysis of Residuals.

Identification: A general ARIMA model can be expressed as:

Zt - MA1*Zt-1 - MA2*Zt-2 -.. - MAq*Zt-q = C + at - AR1*at-1 - AR2*at-2 -.. - ARp*at-p (10)

Where Zt is obtained by differencing the original time series *d* times.

The input series for $ARIMA$ needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time. Therefore, usually the series first needs to be differenced until it is stationary, this also often requires log transforming the data to stabilize the variance. The number of times the series needs to be differenced to achieve stationarity is reflected in the d parameter.

Estimation: At the estimation stage, the parameters are estimated using function minimization procedures so that the sum of squared residuals is minimized. The estimates of the parameters are used in the forecasting stage to calculate new values of the series.

Before the estimation begins, one needs to identify the specific number and type of *ARIMA* parameters to be estimated. A majority of empirical time series patterns can be sufficiently approximated using one of the 5 basic models:

1. One autoregressive (p) parameter;

2. Two autoregressive (p) parameters;

3. One moving average (q) parameter;

4. Two moving average (q) parameters;

5. One autoregressive (p) and one moving average (q) parameter.

During the parameter estimation phase a function minimization algorithm is used to maximize the likelihood of the observed series, given the parameter values. In practice, this requires the calculation of the (conditional) sums of squares (SS) of the residuals, given the respective parameters.

Multiplicative seasonal *ARIMA* is a generalization and extension of the method introduced in the previous paragraphs to series in which a pattern repeats seasonally over time. In addition to the non-seasonal parameters, seasonal parameters for a specified lag (established in the identification phase) need to be estimated. Analogous to the simple *ARIMA* parameters, these are: seasonal autoregressive (ps), seasonal differencing (ds), and seasonal moving average parameters (qs). For example, the model $(0,1,2)$ $(0,1,1)$ describes a model that includes no autoregressive parameters, 2 regular moving average parameters and 1 seasonal moving average parameter, and these parameters were computed for the series after it was differenced once with lag 1, and once seasonally differenced.

Analysis of Residuals: The major concern is that the residuals are systematically distributed across the series (e.g., they could be negative in the first part of the series and approach zero in the second part) or that they contain some serial dependency which may suggest that the *ARIMA* model is inadequate. The analysis of *ARIMA* residuals constitutes an important test of the model. The estimation procedure assumes that the residual are not correlated and that they are normally distributed.

However, there are some limitations. The *ARIMA* method is appropriate only for a time series that is stationary (i.e., its mean, variance, and autocorrelation should be approximately constant through time) and it is recommended that there are at least 50 observations in the input data. It is also assumed that the values of the estimated parameters are constant throughout the series.

3.2.2. ARCH Class Conditional Volatility Models

3.2.2.1. ARCH Models

ARCH class models do not make use of sample standard deviations. In *ARCH* models, volatility is a linear deterministic function of historical returns. The formulation models conditional variance h_t as a linear function of the first q past squared innovations.

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 ; \tag{11}$$

The forecast errors (ε_t) are assumed to be conditionally normally distributed with a zero mean and h_t variance, based on the information set,

$$\Psi_{t-1} \infty N(0, h_t)$$

The parameter ω is equal to δV, where V is the long run volatility and δ is the weight given to V. Weights must sum to unity $\delta + \sum_{i=1}^{q} \alpha_i = 1$

For the ARCH(1) model, it can be shown that the unconditional kurtosis of ε_t is $\frac{E(\varepsilon_t^4)}{(E(\varepsilon_t^2))^2} = \frac{3(1-\alpha_1^2)}{1-3\alpha_1^2}$ if $\alpha_1^2 < 1/3$, and infinite otherwise. In general, *ARCH* models may not be finite unconditional fourth moments. In financial time series, there is a great deal of persistence, in the sense that the autocorrelations of the squared residuals and of the absolute residuals are positive at long lags. An *ARCH*(1) process can only imply substantial persistence if α_1 is close to 1, but this implies a very high level of first-order autocorrelation. Thus an *ARCH* (1) model may not possibly explain the autocorrelation in the series.

In practice, q needs to be quite large if a linear *ARCH* (q) model is to provide a reasonably good fit to most financial time series. This is undesirable for two reasons. Firstly the more parameters we have to estimate, the more costly it is to do so, and the less precise will tend to be the estimates. Secondly, when q is not small, there is a risk that some of the $\hat{\alpha}_i$ will be negative. But the α_i cannot be negative, because, if even one of them is negative, it is possible that the conditional variance will be negative for some observations.

3.2.2.2. GARCH Models

3.2.2.2.1. GARCH

A much more flexible model is *GARCH* model which generalizes the *ARCH* model by allowing the current conditional variance to depend on the first p past conditional variances as well as the q past squared innovations.

$$y_t = \sigma_t \varepsilon_t \quad \varepsilon \approx i.i.d.(0,1)$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{12}$$

By accounting for the information in the lag(s) of the conditional variance in addition to the lagged ε_{t-i}^2 terms, the *GARCH* model reduces the number of parameters required. In most cases, one lag for each variable is sufficient. The *GARCH* (1,1) model is given by

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{13}$$

This model forecasts the variance of date t return as a weighted average of a constant, yesterday's forecast, and yesterday's squared error.

The *GARCH* (1,1) model is capable of modelling financial time series reasonably well. When α_1 is small and $\alpha_1 + \beta_1$ is large, it is possible for the first-order autocorrelation coefficient to be fairly small and yet for the autocorrelations to die out quite slowly.

The *GARCH* (q, p) model includes both the information about volatility observed in the previous period, i.e. short run volatility, (*ARCH* term) and the forecasted variance from last period, i.e. long run volatility, (*GARCH* term) in order to predict the current period's variance. Thus *GARCH* models describe both the autoregressive and moving average components of time series data with the heteroscedastic variance.

3.2.2.2.2. EGARCH

Even if the GARCH models successfully capture the thick tail returns, and the volatility clustering, they are poor models if one wishes to capture the leverage effect since the conditional variance is a function only of the magnitudes of the past values and not their sign. The conditional variance σ_t^2 of X_t given information at time t, obviously must be non-negative with probability one. In GARCH models this property is assured by making σ_t^2 a linear combination (with positive weights) of positive random variables (as in the $GARCH(p,q)$ case). Another way of making σ_t^2 non-negative is by making $\ln(\sigma_t^2)$ linear in some function of time and lagged Z_t's. This formulation leads to the asymmetric GARCH model, $EcxponentialGARCH$,

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i g(Z_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2). \tag{14}$$

The value of $g(Z_t)$ depends on several elements such as the magnitude and the sign of Z_t. This leads to following;

$$g(Z_t) = \underbrace{\theta_1 Z_t}_{signaffect} + \underbrace{\theta_2 \left[|Z_t| - E[|Z_t|] \right]}_{magnitudeaffect} \tag{15}$$

With this construction, $\{g(Z_t)\}_{t=-\infty,\infty}$ is a zero-mean, *i.i.d.* random sequence. (Each component has mean zero.) Over the range $0 < Z_t < \infty$, $g(Z_t)$ is linear in Z_t with slope $\theta_1 + \theta_2$, and over the range $-\infty < Z_t \leq 0$, $g(Z_t)$ is linear with slope $\theta_1 - \theta_2$. Thus $g(Z_t)$ allows the conditional variance σ_t^2 to respond asymmetrically to rises and falls in stock price.

To perceive that the term $\theta_2\left[|Z_t| - E[|Z_t|]\right]$ represent the magnitude effect one first assumes that $\theta_1 = 0$ and $\theta_2 > 0$. This makes the innovation in $\ln(\sigma_{t+1}^2)$ positive (negative) when the magnitude of Z_t is larger (smaller) than its expected value. Assuming that $\theta_1 < 0$ and $\theta_2 = 0$. The innovation in conditional variance is now positive (negative) when returns innovations are negative (positive).

In contrast to the GARCH models, the EGARCH models do not have any restrictions on the parameters in the model. The EGARCH model always produces a positive conditional variance independently of the signs of the estimated parameters in the model and no restrictions are needed. This is preferable when the restrictions in the GARCH model sometimes create problems when estimated parameters violate the inequality constraints.

CHAPTER 4

VALUE at RISK

VaR describes the worst loss over a target horizon with a given level of confidence, and it can summarize the maximum loss in a currency value.

Daily VaR at a 99% confidence level is the smallest x for which the probability that the next day's portfolio loss exceeds x is less than 1%, or, VaR is the smallest x such that $\Pr\{Losses \geq x\} \leq .01$. For example a 10-day VaR is \$20 M at the 95% confidence level means that there is less than 5% chance that our portfolio will lose more than \$20 M in the next 10 days.

VaR measures can have many applications, and is used both for risk management and for regulatory purposes. In particular, the Basel Committee on Banking Supervision (1996) at the Bank for International Settlements (BIS) imposes to financial institutions such as banks and investment firms to meet capital requirements based on VaR estimates.

VaR models can be classified into three categories:

- Parametric (Risk Metrics and *GARCH*)
- Nonparametric (Historical Simulation)

- Semiparametric (Extreme Value Theory, CAViaR and quasi maximum likelihood *GARCH*)

In order to choose the best model, one might consider the characteristics of financial data. The empirical facts about financial markets can be summarized as follows:

1. Financial return distributions are leptokurtotic that is they have heavier tails and a higher peak than a normal distribution.

2. Equity returns are typically negatively skewed.

3. Squared returns have significant autocorrelation, i.e. volatilities of market factors tend to cluster. This is a very important characteristic of financial returns, since it allows the researcher to consider market volatilities as questionable, changing in the long run, but stable in the short period. Most of the VaR models make use of this quasi-stability to evaluate market risk.

4.1. Parametric Value at Risk

In parametric VaR approach there are two steps to follow: (1) assuming portfolio returns have a particular distribution; (2) Computing VaR by estimating parameters of that distribution.

Let R denote the rate of return and $X(t)$ the portfolio value at time t. Then,

$$R = \frac{X(1) - X(0)}{X(0)} \qquad (16)$$

The loss is $L = -[X(1) - X(0)] = -X(0)R$

Assume rates of return $\approx N(\mu, \sigma^2)$, then $Z = \frac{R-\mu}{\sigma} \approx N(0,1)$.

Then one can compute VaR from the following equation:

$$.01 = \Pr\{L \geq x =\} = \Pr\{-X(0)R \geq x\}$$

$$= \Pr\{X(0)R \leq -x\} = \Pr\left\{R \leq \frac{-x}{X(0)}\right\}$$

$$= \Pr\left\{\frac{R-\mu}{\sigma} \leq \frac{{}^{-x}\!/\!{}_{X(0)} - \mu}{\sigma}\right\} = \Pr\left\{Z \leq \frac{{}^{-x}\!/\!{}_{X(0)} - \mu}{\sigma}\right\} \tag{17}$$

Using a standard normal distribution table one can find that $\Pr\{Z \leq -2.33\} = .01$

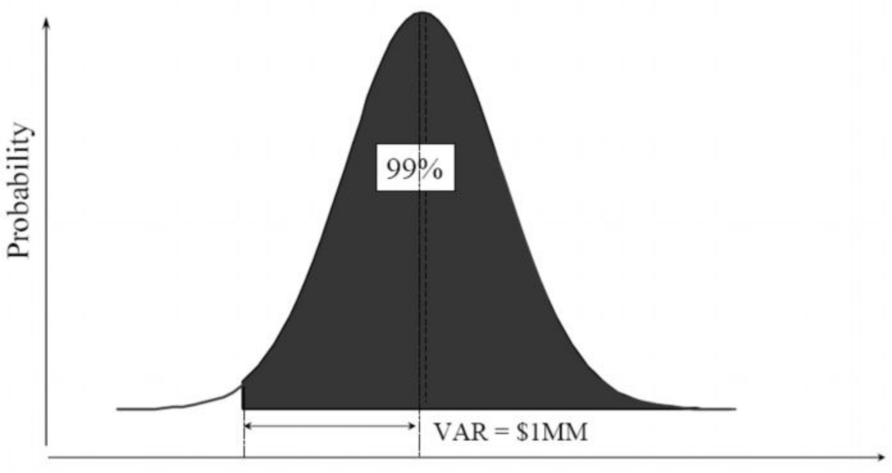
Then also can get the VaR from;

$$\frac{{}^{-x}\!/\!{}_{X(0)} - \mu}{\sigma} = -2.33 \tag{18}$$

The 99% VaR with normal distribution is:

$VaR = X(0)[2.33\sigma - \mu]$ This can be shown graphically as;

Figure 1 The 1%-value of risk of a normally distributed portfolio



The question here is how μ, σ should be estimated?

As given in equation (3), the *GARCH* model has two crucial elements: the particular specification of the variance equation and the assumption that the standardized residuals are i.i.d. The first element was inspired by the characteristics of financial data discussed above. The assumption of i.i.d. standardized residuals, instead, is just a necessary device to estimate the unknown parameters. A further necessary step to implement any *GARCH* algorithm is the specification of the distribution of the ε_t. The most generally used distribution is the standard normal. Only after this extra distributional assumption has been imposed, does it become possible to write down a likelihood function and get an estimate of the unknown parameters. Once the time series of estimated variance is computed, the 5% quartile, say, is simply computed as -1.645 (the 5% quartile of the standard normal) times the estimated standard deviation.

The general finding is that these approaches (both normal *GARCH* and RiskMetrics) tend to underestimate the Value at Risk, because the normality assumption of the standardized residuals seems not to be consistent with the behaviour of financial returns. The main advantage of these methods is that they allow a complete characterization of the distribution of returns and there may be space for improving their performance by avoiding the normality assumption.

4.2. Non-parametric Value at Risk

One of the most common methods for VaR estimation is the Historical Simulation. This approach drastically simplifies the procedure for computing the Value at Risk, since it doesn't make any distributional assumption about portfolio returns. Historical Simulation is based on the concept of rolling windows. First, one needs to choose a window of observations that generally ranges from 6 months to two years. Then, portfolio returns within this window are sorted in ascending order and the θ-quartile of interest is given by the return that leaves θ % of the observations on its left side and (1-θ)% on its right side. If such a number falls between two consecutive returns, then some interpolation rule is applied. To compute the VaR the following day, the whole window is moved forward by one observation and the entire procedure is repeated.

Even if this approach makes no explicit assumptions on the distribution of portfolio returns, an implicit assumption is hidden behind this procedure: the distribution of portfolio returns doesn't change within the window. From this implicit assumption several problems derive.

First, this method is logically inconsistent. If all the returns within the window are assumed to have the same distribution, then the logical consequence must be that all the returns of the time series must have the same distribution: if $y_{t-window},...,y_t$ and $y_{t+1-window},...,y_{t+1}$ are i.i.d., then also y_{t+1} and $y_{t-window}$ must be i.i.d., by the transitive property. Second, the empirical quartile estimator is consistent only if *k*, the window size, goes to infinity. The third problem concerns the length of the window. This is a very delicate issue, since forecasts of VaR under this approach are meaningful only if the historical data used in the calculations have (roughly) the same distribution. In practice, the volatility clustering period is not easy to identify. The length of the window must satisfy two contradictory properties: it must be large enough, in order to make statistical inference significant, and it must not be too large, to avoid the risk of taking observations outside of the current volatility cluster. Clearly, there is no easy solution to this problem.

Moreover, assume that the market is moving from a period of relatively low volatility to a period of relatively high volatility (or vice versa). In this case, VaR estimates based on the historical simulation methodology will be biased downwards (correspondingly upwards), since it will take some time before the observations from the low volatility period leave the window.

Finally, VaR estimates based on historical simulation may present predictable jumps, due to the discreteness of extreme returns. To see why, assume that we are computing the VaR of a portfolio using a rolling window of 180 days and that today's return is a large negative number. It is easy to predict that the VaR estimate will jump upward, because of today's observation. The same effect (reversed) will reappear after 180 days, when the large observation will drop out of the window. This is a very undesirable characteristic and it is probably enough to discard the historical simulation method as a reliable one.

4.3. Semiparametric Value at Risk

4.3.1. Extreme Value Theory

There are two principal distributions that are used in extreme value modelling: the generalized extreme value (GEV) distribution and the generalized Pareto distribution (GPD). An often useful method is known as the Peaks-Over-Threshold (POT) method.

Periodic (daily, monthly, yearly, etc.) maxima (or minima) follow a GEV distribution. So if one was concerned with monthly peaks in interest rates, s/he could fit a GEV distribution to the monthly maxima. Excesses over a given high threshold, however, follow a GPD. Suppose one is interested in the distribution of insurance claims over some high threshold, as s/he in catastrophe bond ratings; those excesses would be best modelled by a GPD. Alternatively, if s/he concerned about the occurrence times of the losses over some threshold and the excess distribution, s/he would fit a POT model. In a POT model, the number of events during a given time follows a Poisson process and the exceedances over a given high threshold follow a GPD. Since the number of events is Poisson, the interarrival times (time between events) are exponentially distributed. Therefore, by fitting a POT model one can estimate the average time between events of a given magnitude (threshold), and the distribution of the excess over the threshold. An underlying feature of a Poisson process is that the number of events in disjoint time intervals is independent. This is often not the case for financial data.

Financial time series data tend to be ill-behaved in that they show jumps and fluctuations that are not modelled well by standard modelling techniques. Often many assumptions must be made, such as the data come from well-defined distributions, and the data have constant variance over time. One of the biggest problems with 'typical' models is they fail to capture extreme jumps in the data and cannot describe the external behaviour. Extreme value methods outperform standard modelling techniques when the goal is to model external behaviour.

Suppose $\{X_n\}$ is a sequence of independent and identically distributed random variables and M_n is the $\max(X_t,...,X_n)$. Then if there exist constants $c_n > 0$ and $d_n \in R$ (a real number), $(M_n - d_n)/c_n$ is a cantered and normalized maximum. If $(M_n - d_n)/c_n \xrightarrow{d} H$ (that is, converges in distribution to H), for some non-degenerate distribution function H, then H belongs to one of the three families of extreme value distribution functions: Fréchet, Weibull, and Gumbel. These distributions have the following form:

Frechét:

$$\phi_{\alpha>0}(x) = \begin{cases} 0, & x \leq 0 \\ \exp\{-x^{-\alpha}\}, & x > 0 \end{cases} \tag{20}$$

Weibull:

$$\psi_{\alpha>0}(x) = \begin{cases} \exp\{-(-x)^{\alpha}\}, & x \leq 0 \\ 1, & x > 0 \end{cases} \tag{21}$$

Gumbel:

$$\Lambda(x) = \exp\{-e^{-x}\}, x \in R \tag{22}$$

The extreme value distributions represent the limit laws for the normalized maxima of i.i.d. random variables. One needs to consider the conditions on a distribution function F that imply the normalized maxima M_n converge to H. In other words the question here is how one chooses constants $c_n > 0$ and d_n such that $(M_n - d_n)/c_n \xrightarrow{d} H$? If this condition is satisfied one can say the distribution function F belongs to the maximum domain of attraction of H.

4.3.2. CAViaR

The Conditional Autoregressive Value at Risk's basic intuition is to model directly the evolution of the quartile over time, rather than the whole distribution of portfolio returns. The specification for the VaR is:

$$q_{t,\theta} = \beta_0 + \beta_{1qt-1,\theta} + \iota(\beta_2,...,\beta_p, y_{t-1}, q_{t-1}, \theta) \quad (23)$$

Different models can be estimated by choosing different specifications for the ι function such as the Symmetric Absolute Value, $\iota(.) = \beta_2|y_{t-1}|$ and the Asymmetric Slope

$$\iota(.) = \beta_2 1(y_{t-1} > 0) - \beta_3 1(y_{t-1} < 0) \quad (24)$$

4.3.3. Quasi Maximum Likelihood GARCH

In *GARCH* models, the assumption of normally distributed standardized residuals seemed to be at odds with the fact that financial data tend to be exhibit heavy tails. However, normality assumption may not be restrictive; because, Bollerslev and Woolridge (1992) show that the maximisation of the normal *GARCH* likelihood is able to deliver consistent estimates, provide that the variance equation is correctly specified, even if the standardized residuals are not normally distributed. This is referred as the quasi-maximum likelihood (*QML*) *GARCH*. The *QMLE* obtained by maximizing the Gaussian log-likelihood is known to be consistent and asymptotically normal.

If the likelihood is assumed to be Gaussian, then the QMLE is the value of $\theta \equiv T^{-1}\sum_{t=1}^{T}\iota_t(\theta)$ where the period-t conditional log-likelihood of y_t given $\Im_t, \iota_t(\theta)$,is defined as

$$\iota_t(\theta) \equiv -\ln\sigma_t - \left(\frac{y_t}{\sigma_t}\right)^2 . \qquad (25)$$

CHAPTER 5

ANALYSIS

5.1. Data

The aim of this study is to measure VaR for the listed banks in the Istanbul Stock Exchange (ISE) as well as banking index, ISE-100, and ISE-300, using GARCH model for the period July 1997-July 2007. The data consists of closing prices for the banking firms and indices and is obtained from Reuters, and expressed in local currency.

Ten commercial banks are listed in ISE 100 as of 2007. Seven of the ten banks are chosen for this study. Because, these banks' data has been observed within 10 years period, covering 1997-2007. This time period is important for our study since we like to see the impact of the some shocks over the sample period on the measures of VaR.

Seven studied banks in this paper compose of 54.02 % of total assets of the whole banking industry as of 06/2007[1]. These banks are namely, Alternatifbank, Akbank, Isbank, Finansbank, Garantibank, Sekerbank and Yapı Kredi Bank.

Detailed information on indexes and individual banks might be obtained by descriptive statistics. Descriptive statistics of ten data groups' returns are provided for the four different sample periods below[2].

Table 1 and Table 2 show that the highest standard deviations, unexceptionally, are observed in the longest term which contains the whole shock periods. However, when the time interval is set shorter, deviation is given to be lower. Variation tends to evolve around 3% and 4% which leads one to think that observed values are close to the mean value and dispersion is lower. And also, by looking at the minimum and maximum values, it may be claimed that the range between this two is not that high and consequently extreme values are not frequently observable. Among seven banks, Alternatif Bank stands out as the most volatile while ISE 100 index has the lowest standard deviation. In 1997-2007 period, Alternatif Bank experienced 4.45% standard deviation whilst ISE 100 has 2.92 %. Consequently, the other notable thing from this point is that the standard deviation tends to decrease by the diversification. For all the four time periods, drifts on the individual stocks are much higher than the indexes'.

---

[1] Source: The Turkish Banking Association

[2] Daily returns are calculated as following: $R_t = \log(P_t / P_{t-1})$,where P_t denotes the price at time t .

Table 1 Descriptive Statistics for Daily Index Returns

	Mean	Std Dev	Max	Min	Skewness	Kurtosis	JB
				IMKB 100			
07.1997 - 07. 2007	0.001	0.029	0.177	-0.199	-0.074	7.797	2.395.115 (.000)
01.2003 – 07.2007	0.001	0.019	0.109	-0.133	-0.430	8.135	1.282.386 (.000)
04.2006 - 07.2007	0.000	0.017	0.051	-0.086	-0.597	5.024	75.063 (.000)
07.2006 - 07.2007	0.001	0.015	0.051	-0.045	-0.155	3.595	4.928 (.000)
				IMKB 30			
07.1997 - 07. 2007	0.001	0.030	0.176	-0.219	-0.095	8.146	2.756.162 (.000)
01.2003 – 07.2007	0.001	0.020	0.110	-0.135	-0.299	7.480	966.325 (.000)
04.2006 - 07.2007	0.000	0.018	0.056	-0.085	-0.414	4.423	36.847 (.000)
07.2006 - 07.2007	0.001	0.016	0.056	-0.049	-0.074	3.572	3.821.553 (.147)
				BANK INDEX			
07.1997 - 07. 2007	0.001	0.033	0.172	-0.239	-0.039	7.433	2.043.127 (.000)
01.2003 – 07.2007	0.001	0.023	0.121	-0.145	-0.218	7.253	864.837 (.000)
04.2006 - 07.2007	0.000	0.019	0.056	-0.085	-0.277	3.986	17.413 (.000)
07.2006 - 07.2007	0.001	0.018	0.056	-0.050	0.017	3.383	1.619 (.444)

Note: The figures in the parentheses are p-values.

Table 1 shows that three indexes are behave similarly. The returns are skewed negatively except for the bank index's last period. The reason is thought to be recently growing interest of foreign investors to the sector and consequently realized mergers and acquisitions. Foreign investors' shares on the twenty six of the fifty Turkish banks (Sekerbank, Fortis-formerly Dışbank, Garanti Bank, Finansbank...) go beyond 50 % as of 11/2007.[3]

[3] www.bddk.org.tr

Table 2 Descriptive Statistics for Daily Stock Returns

	Mean	Std Dev	Max	Min	Skewness	Kurtosis	JB
			AKBANK				
07.1997 - 07. 2007	0.001	0.036	0.192	-0.226	0.211	6,386	1210.673
							(.000)
01.2003 – 07.2007	0.001	0.026	0.109	-0.140	-0.038	4,730	141.977
							(.000)
04.2006 - 07.2007	0.000	0.025	0.084	-0.103	-0.149	4,802	45.348
							(.000)
07.2006 - 07.2007	0.001	0.020	0.082	-0.093	0.020	4,694	31.358
							(.000)
			YAPI KREDI				
07.1997 - 07. 2007	0.001	0.044	0.182	-0.241	-0.047	6,085	987.573
							(.000)
01.2003 – 07.2007	0.001	0.029	0.169	-0.146	0.433	7,028	799.480
							(.000)
04.2006 - 07.2007	0.000	0.025	0.122	-0.088	0.393	5,268	78.305
							(.000)
07.2006 - 07.2007	0.001	0.022	0.071	-0.088	0.082	3,849	8.166
							(.016)
			SEKERBANK				
07.1997 - 07. 2007	0.001	0.043	0.535	-0.227	1,065	14,764	14819.18
							(.000)
01.2003 – 07.2007	0.002	0.035	0.179	-0.227	0.453	8,215	1322.853
							(.000)
04.2006 - 07.2007	0.001	0.036	0.179	-0.227	-0.110	11,337	939.017
							(.000)
07.2006 - 07.2007	0.003	0.031	0.168	-0.088	1,185	6,948	229.814
							(.000)
			ISC				
07.1997 - 07. 2007	0.001	0.038	0.207	-0.207	0.255	6,139	1049.866
							(.000)
01.2003 – 07.2007	0.001	0.029	0.137	-0.163	-0.116	5,872	392.894
							(.000)
04.2006 - 07.2007	-0.000	0.028	0.093	-0.109	-0.158	3,908	12.593
							(.001)
07.2006 - 07.2007	0.001	0.026	0.093	-0.088	0.021	3,675	5.005
							(.081)
			FINANS BANK				
07.1997 - 07. 2007	0.001	0.038	0.194	-0.211	0.079	6,200	1066.777
							(.000)
01.2003 – 07.2007	0.002	0.028	0.141	-0.157	0.025	6,917	725.274
							(.000)
04.2006 - 07.2007	0.000	0.017	0.141	-0.093	1,496	21,190	3710.124
							(.000)
07.2006 - 07.2007	.000	0.018	0.141	-0.139	-0.134	22,317	5054.034
							(.000)
			ALTERNATIF BANK				
07.1997 - 07. 2007	0.001	0.044	0.280	-0.223	0.386	6,564	1382.294
							(.000)
01.2003 – 07.2007	0.001	0.031	0.175	-0.147	0.465	7,133	849.178
							(.000)
04.2006 - 07.2007	-0.000	0.030	0.175	-0.140	0.441	10,910	860.499
							(.000)
07.2006 - 07.2007	0.001	0.024	0.175	-0.073	2,062	16,884	2281.491
							(.000)
			GARANTI				
07.1997 - 07. 2007	0.001	0.041	0.185	-0.244	0.012	6,037	959.328
							(.000)
01.2003 – 07.2007	0.002	0.028	0.146	-0.170	-0.209	7,150	822.879
							(.000)
04.2006 - 07.2007	0.001	0.027	0.126	-0.084	0.148	4,051	16.226
							(.000)
07.2006 - 07.2007	0.002	0.026	0.126	-0.067	0.389	4,300	25.105
							(.000)

Note: The figures in the parentheses are p-values.

Individual bank data series exhibit skewness denoting that the distributions have an asymmetric tails extending out to the right (referring to as “positively skewed” or “skewed to the right”) or extending out to the left (referring to as “negatively skewed” or “skewed to the left”). Positively skewed distributions confirm that the series have positive shocks than the negative ones, and vice versa. This also can be followed from the Figures 1, 2, 3, and 4. The rest of the figures of return distribution analysis for all the time series are given in Appendix I.

Figure 2 Distribution of Return Series for ISE 100

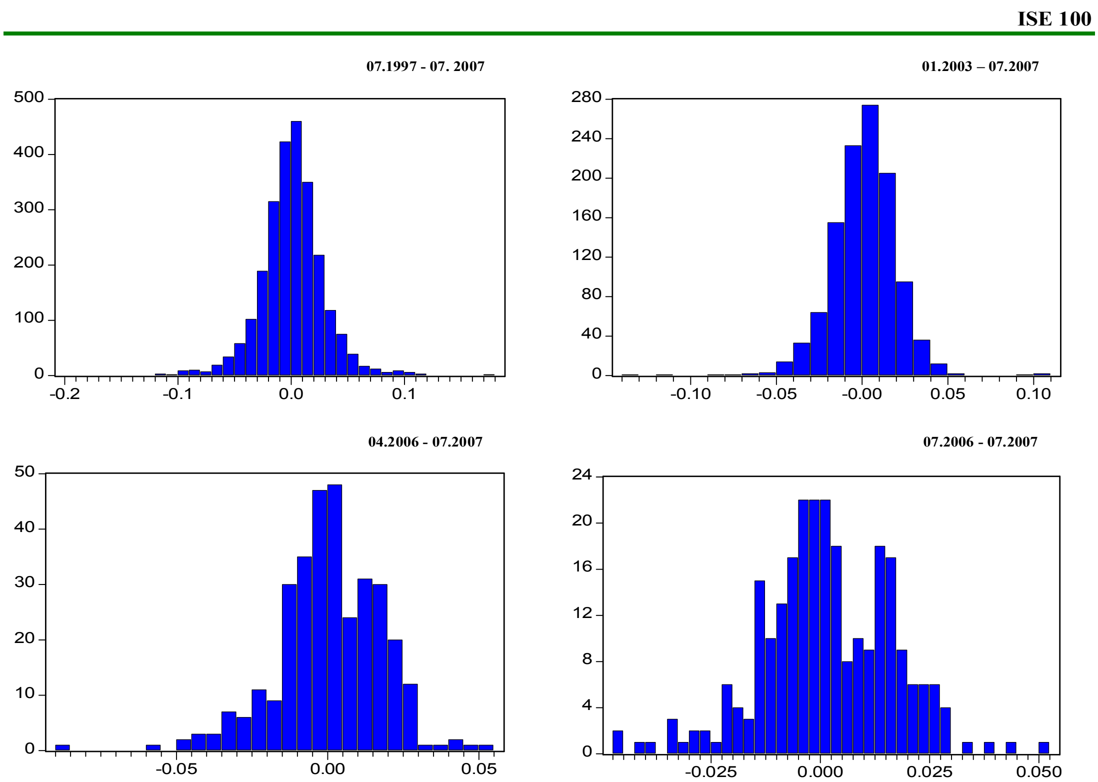


Figure 3 Distribution of Return Series for ISE 30

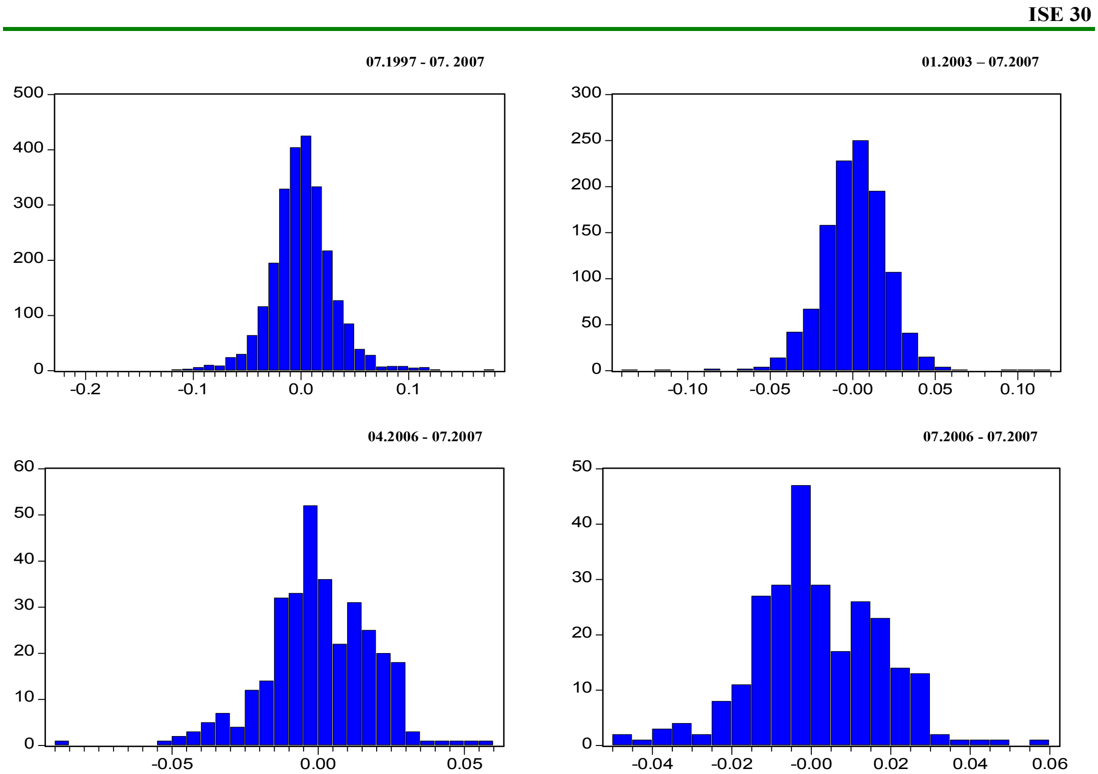


Figure 4 Distribution of Return Series for Bank Index

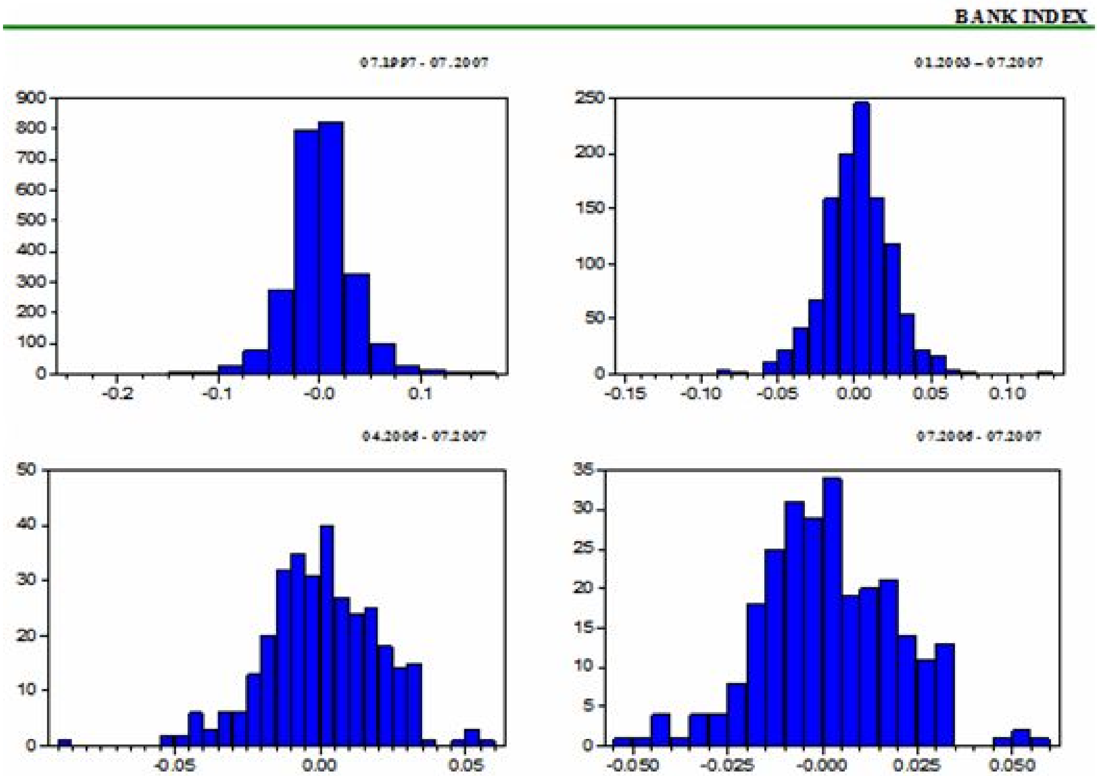
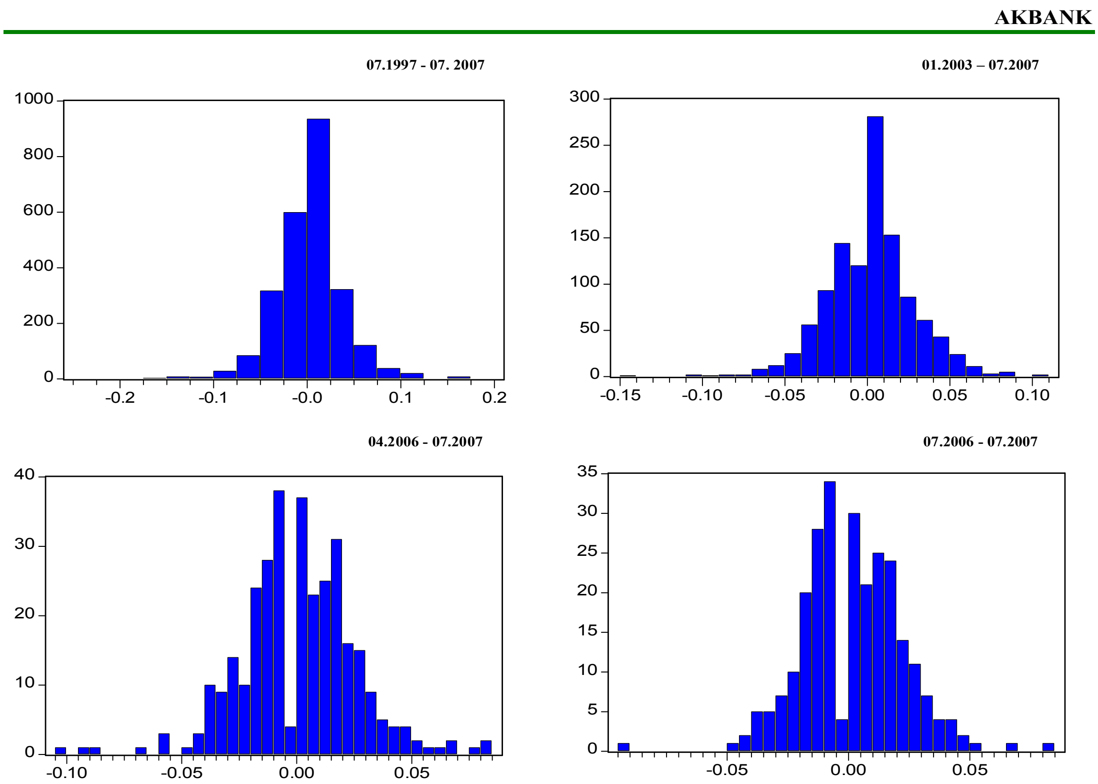


Figure 5 Distribution of Return Series for Akbank



The fourth moment, kurtosis, introduces a measure of how flat the top of a symmetric distribution is when compared to a normal distribution of the same variance. The sample series exhibit leptokurtic behaviour meaning the distribution is peaked relative to the normal distribution. Namely, fourth moment higher than 3 shows the non-normality of data series. High kurtosis also may be interpreted as the data series have large shocks than expected. Kurtosis characteristic may also be pursued from above figures.

Just as third and fourth moments of the series, Jarque-Bera statistics can be used to check normality hypothesis. JB tests the residuals for normality by testing whether the coefficient of skewness and the coefficient of excess kurtosis are jointly zero.

The high value of JB necessitates rejection of the null hypothesis which states normality. Hence, it can be affirmed that the data sets are not normally distributed.

Finally, it can be said that ten data series almost exhibit the same characteristics. They are all display skewness and excess kurtosis. Individual banks are not dispersed among themselves, any exceptional bank is encountered. Moreover, individually banks tend to evolve parallel with three indexes.

5.2. Empirical Results

In this part of the thesis, volatility of the listed banks in Turkey as well as ISE-30, ISE-100 and banking index are studied. Four different time horizons are specified to control the periods containing shocks. Two different error distribution assumptions are exerted, namely normal distribution and student's *t* distribution. Lastly, today's Value at Risk figures are found and also one-step ahead VaR is forecasted by benefiting estimated GARCH models specifying two different confidence intervals.

For the volatility analysis, GARCH model specified in equation (13) is used.[4] Subsequently, the Parametric VaR is calculated through GARCH figures. Parameter estimations and VaR results for four time periods might be followed through the Table 3 to 10.

---

[4] For the mean equation autoregressive structure is taken into consideration where significant.
$R_t = \alpha + \sum \delta_i R_{t-i} + u_t$, where δ_i is the autoregressive term.

It can be seen from the below tables that some of the VaR figures are not displayed. The reason for that is that the parameter constraints for the model are not satisfied. The GARCH (1, 1) model is capable of modelling financial time series, however, there are some restrictions for the parameter estimation. For the model, ω should be positive and α_1 and β_1 should be nonnegative.

If we define q_0 is equal to $\omega / (1-\alpha-\beta)$ the model can be rewritten as:

$$h_t = q_0 + \alpha\left(\varepsilon_{t-1}^2 - q_0\right) + \beta\left(h_{t-1} - q_0\right) \tag{26}$$

By this form of equation, the model restrictions can be understood. If last period's squared return is above unconditional variance (a positive shock to conditional variance), then the next period's conditional variance increases in a proportion to the persistence parameter β.

Following that:

- Weakly Stationary Case: When $\alpha + \beta < 1$, the process is weakly stationary with unconditional variance $h_{t-1} = \omega / (1-\alpha-\beta)$. In this case, the process is assumed to start from its unconditional mean.

- Unit Root Case: When $\alpha + \beta = 1$, the process is not weakly stationary, i.e. the unconditional variance would not exist, In this case, the process and its derivatives are assumed to start from some arbitrary value.

Evidently, if we write q_0 is equal to $\omega/(1-\alpha-\beta)$, we require that $\alpha+\beta<1$, and for it to be nonzero, $\omega>0$.

From Table 3, it can be seen that stationary does not hold for Finansbank and Alternatifbank for 1997-2007 period. According to the specified time interval, Finansbank experienced nonstationarity. However, GARCH model is not suitable for Alternative Bank independent from the period or distribution assumption. The remaining five banks and three indexes are all satisfy the model restrictions for the different periods. Hence, it can be said that these time series have GARCH effect meaning they suffer from heteroscedasticity in which the expected value of the error terms is not equal.

As we stated earlier in equation (13) h_t is the return variance and ε_{t-1} is the error term. The slope parameter, β, measures the combined marginal impacts of the lagged innovations. The slope parameter, α, on the other hand, captures the marginal impact of the most recent innovation in the conditional variance. Our study shows that β estimates are markedly higher than α estimates, i.e., variance persistence is often characterized by a low but prolonged effect of variance innovation in a given period.

The significance of parameters in the model indicates the tendency of the shock to persist. The measure of volatility persistence $\alpha+\beta$ coefficients is greater than or almost equal to unity. This indicates that the tendency for a volatility response to shocks to display a long memory. These results confirm the time varying risk in the stock returns in Turkey. Also, the conditional variance changes over time showing that periods of relatively high (or lows) volatility are found to be time-dependent.

After specifying GARCH values, we use these numbers as inputs to the parametric VaR calculation specified in equation (18) and generate one-day forecasts for both 95% and 99% confidence levels. We assume that all individual series compose separate portfolios. Tables 3 to 10 show the GARCH parameter estimations, and today's VaR and also tomorrow's VaR numbers.

According to the Tables below, Şekerbank emerges as the highest risky bank for sample periods. The lowest risky bank seems to be the Yapı Kredi. It should be noted that the risk of banks may differ from one period to other. For instance, in the 2^{nd} period, Finansbank is the lowest risky bank whereas Yapı Kredi is less riskier than the other banks for the 1^{st} period. The remarkable thing is that for all the periods ISE-100 is the lowest risky portfolio, positive effect of diversification might be claimed as the reason.

As stated earlier, we used two different error distribution assumptions. However, assumption of normality and Student's *t* distribution does not produce too different VaR results. Student's *t* estimates are slightly higher then those for normal distribution. For instance, in the 1^{st} period, Sekerbank's VaR is 14.97 % under Student's *t* distribution whereas, 14.31% with normal distribution. Or, ISE-100 has 4.85 % under Student's *t*, 4.73 % with normal distribution. Moreover, Yapı Kredi has 6.57 % and 6.07 % , respectively.

If one wants to analyse the highest risky period, s/he observes that third period is generally arise as the most risky one. Even the first period covers more shocks than those of third period, the effect of the shocks are smoothed by the time. Fresh affirmative news are weighted more than the former negative news. However, in the third period, a newly shock has been experienced and its effect does not diffuse in the time yet. Besides, fourth period, 07-06/07-07 is fairly stable, subsequently, it stands out as the safest interval.

The other noteworthy point is that all the forecasts are smaller than today's VaR numbers. It makes one to think that forward looking expectations about Turkey's general view of political, economic and social environment are positive.

Table 3 Estimation Results of GARCH with Norm. Dist. & VaR Figures for the 1st Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
07.1997 - 07. 2007 GARCH(1,1) - Norm. Dist.						1%	7.99%	7.39%
	Akbank	0.000*	0.069*	0.918*	0.988	5%	5.70%	5.17%
						1%	6.32%	5.82%
	Yapı Kredi	0.000*	0.076*	0.918*	0.994	5%	4.51%	4.01%
						1%	14.31%	11.62%
	Sekerbank	0.000*	0.364*	0.446*	0.810	5%	10.17%	8.16%
						1%	7.05%	6.63%
	ISC	0.000*	0.065*	0.920*	0.986	5%	5.02%	4.65%
						1%	-	-
	Finansbank	0.000*	0.111*	0.889*	1.001	5%	-	-
						1%	-	-
	Alternatifbank	0.000*	0.157*	0.856*	1.013	5%	-	-
						1%	7.35%	6.9%
	Garanti	0.000*	0.110*	0.870*	0.980	5%	5.24%	4.83%
						1%	4.73%	3.76%
	ISE 100	0.000*	0.094*	0.902*	0.996	5%	3.38%	2.46%
						1%	5.17%	4.8%
	ISE 30	0.000*	0.088*	0.908*	0.997	5%	3.69%	3.36%
						1%	6.07%	5.58%
	Bank Index	0.000*	0.075*	0.919*	0.994	5%	4.33%	4.03%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 4 Estimation Results of GARCH with Norm. Dist. & VaR Figures for the 2nd Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
01.2003 – 07.2007 GARCH(1,1) - Norm. Dist.						1%	7.38%	6.78%
	Akbank	0.000*	0.055*	0.912*	0.968	5%	5.28%	4.74%
						1%	6.07%	5.49%
	Yapı Kredi	0.000*	0.057*	0.913*	0.971	5%	4.34%	3.84%
						1%	11.51%	10.18%
	Sekerbank	0.000*	0.208*	0.640*	0.848	5%	8.19%	7.14%
						1%	6.94%	6.34%
	ISC	0.000*	0.069*	0.876*	0.946	5%	4.96%	4.45%
						1%	5.63%	4.95%
	Finansbank	0.000*	0.121*	0.873*	0.995	5%	4.05%	3.43%
						1%	-	-
	Alternatifbank	0.000*	0.213*	0.817*	1.030	5%	-	-
						1%	6.40%	5.93%
	Garanti	0.000**	0.022*	0.971*	0.993	5%	4.59%	4.13%
						1%	4.52%	4.06%
	ISE 100	0.000*	0.080*	0.888*	0.968	5%	3.24%	2.82%
						1%	4.87%	4.43%
	ISE 30	0.000*	0.071*	0.898*	0.969	5%	3.49%	3.08%
						1%	5.62%	5.16%
	Bank Index	0.000*	0.054*	0.917*	0.971	5%	4.03%	3.59%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 5 Estimation Results of GARCH with Norm. Dist. & VaR Figures for the 3rd Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
04.2006 - 07.2007 GARCH(1,1) - Norm. Dist.	**Akbank**	0.000***	0.139*	0.840*	0.979	1%	9.42%	8.46%
						5%	6.70%	5.95%
	Yapı Kredi	0.000***	0.141*	0.645*	0.787	1%	7.20%	6.64%
						5%	5.12%	4.67%
	Sekerbank	0.000*	0.347*	0.470*	0.817	1%	13.60%	10.86%
						5%	9.72%	7.57%
	ISC	0.000	0.085*	0.799*	0.884	1%	7.08%	6.74%
						5%	5.01%	4.77%
	Finansbank	0.000*	0.815*	0.232*	1.048	1%	-	-
						5%	-	-
	Alternatifbank	0.000***	0.279*	0.791*	1.070	1%	-	-
						5%	-	-
	Garanti	0.000	0.060*	0.828*	0.889	1%	6.66%	6.20%
						5%	4.76%	4.33%
	ISE 100	0.000***	0.151*	0.772*	0.923	1%	4.98%	4.37%
						5%	3.57%	3.05%
	ISE 30	0.000	0.130**	0.790*	0.920	1%	5.29%	4.75%
						5%	3.78%	3.32%
	Bank Index	0.000	0.116***	0.803*	0.919	1%	6.25%	5.75%
						5%	4.44%	4.03%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 6 Estimation Results of GARCH with Norm. Dist. & VaR Figures for the 4th Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
07.2006 - 07.2007 GARCH(1,1) - Norm. Dist.	**Akbank**	0.000	0.083*	0.865*	0.949	1%	7.87%	7.14%
						5%	5.61%	5.01%
	Yapı Kredi	0.000	0.073	0.779*	0.853	1%	6.23%	5.88%
						5%	4.45%	4.12%
	Sekerbank	0.000***	0.088**	0.815*	0.903	1%	9.15%	8.42%
						5%	6.55%	5.87%
	ISC	0.000	0.059	0.827*	0.887	1%	6.63%	6.21%
						5%	4.72%	4.37%
	Finansbank	0.000*	0.389*	0.580*	0.970	1%	5.80%	4.69%
						5%	4.13%	3.29%
	Alternatifbank	0.000	0.265*	0.789*	1.054	1%	-	-
						5%	-	-
	Garanti	0.000*	-0.028*	1.009*	0.980	1%	-	-
						5%	-	-
	ISE 100	0.000	0.105	0.716*	0.822	1%	4.50%	3.84%
						5%	3.23%	2.67%
	ISE 30	0.000	0.104	0.736*	0.840	1%	4.91%	4.27%
						5%	3.52%	2.97%
	Bank Index	0.000	0.127	0.739*	0.867	1%	6.18%	5.45%
						5%	4.42%	3.81%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 7 Estimation Results of GARCH with S's T Dist. & VaR Figures for the 1st Period

07.1997 - 07. 2007 GARCH(1,1) - Student-t Dist.		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
						1%	8.52%	7.95%
	Akbank	0.000*	0.084*	0.898*	0.982	5%	6.05%	5.59%
						1%	6.78%	6.63%
	Yapı Kredi	0.000*	0.098*	0.894*	0.993	5%	4.82%	4.48%
						1%	14.97%	12.98%
	Sekerbank	0.000*	0.398*	0.567*	0.965	5%	10.58%	9.18%
						1%	7.40%	6.99%
	ISC	0.000*	0.077*	0.899*	0.977	5%	5.29%	4.91%
						1%	-	-
	Finansbank	0.000**	0.115*	0.897*	1.013	5%	-	-
						1%	-	-
	Alternatifbank	0.000**	0.132**	0.889**	1.021	5%	-	-
						1%	7.27%	6.84%
	Garanti	0.000*	0.107**	0.880*	0.988	5%	5.18%	4.78%
						1%	4.85%	4.35%
	ISE 100	0.000*	0.099*	0.891*	0.991	5%	3.48%	3.03%
						1%	5.18%	4.74%
	ISE 30	0.000*	0.084*	0.906*	0.991	5%	3.71%	3.30%
						1%	6.22%	5.70%
	Bank Index	0.000*	0.080*	0.910*	0.991	5%	4.44%	3.96%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 8 Estimation Results of GARCH with S's T Dist. & VaR Figures for the 2nd Period

01.2003 – 07.2007 GARCH(1,1) - Student-t Dist.		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
						1%	8.64%	7.77%
	Akbank	0.000*	0.099*	0.832*	0.931	5%	6.15%	5.45%
						1%	6.54%	5.97%
	Yapı Kredi	0.000*	0.075*	0.867*	0.942	5%	4.65%	4.19%
						1%	14.22%	12.36%
	Sekerbank	0.000*	0.366*	0.585*	0.952	5%	10.05%	8.73%
						1%	7.40%	6.99%
	ISC	0.000**	0.071*	0.853*	0.925	5%	5.01%	4.49%
						1%	-	-
	Finansbank	0.000**	0.127*	0.883*	1.010	5%	-	-
						1%	-	-
	Alternatifbank	0.000**	0.160*	0.859*	1.020	5%	-	-
						1%	6.67%	6.14%
	Garanti	0.000***	0.062*	0.868*	0.949	5%	4.77%	4.27%
						1%	4.57%	4.03%
	ISE 100	0.000*	0.081*	0.866*	0.948	5%	3.29%	2.79%
						1%	4.94%	4.43%
	ISE 30	0.000**	0.074*	0.877*	0.951	5%	3.55%	3.07%
						1%	5.89%	5.35%
	Bank Index	0.000**	0.068*	0.884*	0.952	5%	4.23%	3.72%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 9 Estimation Results of GARCH with S's T Dist. & VaR Figures for the 3rd Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
04.2006 - 07.2007 GARCH(1,1) - Student-t Dist.	**Akbank**	0.000	0.147*	0.821*	0.968	1%	9.57%	8.52%
						5%	6.79%	5.99%
	Yapı Kredi	0.000	0.116	0.665*	0.781	1%	6.92%	6.58%
						5%	4.90%	4.64%
	Sekerbank	0.000***	0.303**	0.649*	0.953	1%	13.49%	12.20%
						5%	9.54%	8.63%
	ISC	0.000	0.086	0.817*	0.904	1%	7.09%	6.72%
						5%	5.01%	4.75%
	Finansbank	0.000**	0.463*	0.529*	0.992	1%	5.73%	4.51%
						5%	4.05%	3.15%
	Alternatifbank	0.000***	0.242*	0.779*	1.022	1%	-	-
						5%	-	-
	Garanti	0.000	0.053	0.827*	0.880	1%	6.63%	6.22%
						5%	4.74%	4.34%
	ISE 100	0.000	0.124	0.795*	0.920	1%	4.79%	4.25%
						5%	3.43%	2.96%
	ISE 30	0.000	0.112**	0.806*	0.919	1%	5.15%	4.67%
						5%	3.68%	3.33%
	Bank Index	0.000	0.113	0.805	0.919	1%	6.19%	5.72%
						5%	4.41%	4.01%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Table 10 Estimation Results of GARCH with S's T Dist. & VaR Figures for the 4th Period

		ω	α_1	β_1	Volatility Persistence	c.i.	VaR_t	VaR_{t+1}
07.2006 - 07.2007 GARCH(1,1) - Student-t Dist.	**Akbank**	0.000	0.110***	0.804*	0.914	1%	8.53%	7.50%
						5%	6.07%	5.25%
	Yapı Kredi	0.000	0.078	0.765*	0.844	1%	6.28%	6.00%
						5%	4.47%	4.21%
	Sekerbank	0.000	0.124	0.817*	0.941	1%	9.99%	9.73%
						5%	7.05%	6.89%
	ISC	0.000*	-0.045*	1.016*	0.970	1%	-	-
						5%	-	-
	Finansbank	0.000***	0.129***	0.816*	0.945	1%	5.12%	4.80%
						5%	3.62%	3.39%
	Alternatifbank	0.000**	0.158*	0.791*	0.949	1%	2.20%	2.50%
						5%	1.54%	1.66%
	Garanti	0.000	0.042	0.778***	0.820	1%	5.91%	6.46%
						5%	4.64%	4.10%
	ISE 100	0.000	0.101***	0.709*	0.811	1%	4.47%	3.81%
						5%	3.21%	2.64%
	ISE 30	0.000	0.099	0.729*	0.829	1%	4.87%	4.24%
						5%	3.49%	2.95%
	Bank Index	0.000	0.126	0.738*	0.864	1%	6.17%	5.44%
						5%	4.41%	3.80%

*Note: *, **, *** denotes significance level at %1, %5, %10, respectively.*

Simultaneously, below graphics can be consulted as an illustration of the model's ability to capture the changes in the stock prices.[5] The graphics are drawn upon daily VaR numbers with normal distribution assumption. The series in the middle represents the log return series. Two series surrounding the return series are VaR numbers for positive and negative volatility. The model, irrespective of the sample size chosen, understate the true one-day 5% confidence interval VaR estimate, however, 1% c.i. estimates are capture better the VaR (For the 5% c.i. graphical illustrations, please refer to Appendix II). However, VaR fails to capture seven points. These specific points are well-known economic and politic shocks. These shocks are in 1997, 1998, 2001, 2003, 2006, and 2007 successively.

In 1997, Asian economic crisis broke out. This crisis emerged in the second half of the 1997. The reasons of the crisis are given as free capital flow (especially hedge funds), exaggerated optimistic opinions caused by the Asia's stunning economic performance, and structural deficiencies of financial sector. The crisis initially affected Thailand, Indonesia, Malaysia, Philippines, South Korea and Japan successively. Then, it spreads world trade and finance markets. This crisis has direct and indirect effects on Turkey. After the devaluation of Baht, Asia countries gain advantage of competition. Direct impact is the Asia's increased exports, the indirect impact was that exports of Turkey and other emerging countries decreased. While the world experiencing Asia shock, in 1998 Russia devalues the rubble and announced moratorium. Consequently, world trade volume decreased even more. Turkey's trade

[5] Graphics are drawn upon normal dist. Results. T-dist. is not considered, because it generates highly similar results and graphical illustrations are overlapped.

volume decreased about 5% in 1998. In the mean time, investors withdraw their money and searched for more confident countries' bonds. Capital flight and high interest rates led to slowdown of production. It was like a vicious circle, because, this situation caused to increase in problem loans. Economy started to shrink late of 1998. Such an environment gave rise to high deposit rate but low credit rates meaning unbalanced loans to deposit ratio. Banks' profitability decreased with the upwarding risk trend. Besides, holding banking grew and profit of the banks transferred to the subsidiaries. Consequently, banks did not fulfil their main function. Moreover, their liquid assets were decayed and vulnerability to liquidity crisis rose. In 1999, Turkey concluded an agreement with IMF aiming to decrease inflation. Positive developments have seen for a short time, but in November 2000 Turkish financial sector faced with increasing foreign exchange demand resulted from liquidity shortfall. This crisis temporarily circumvented by IMF loan, however low inflation programme wounded crucially. This help only covered for 3 months, in February 2001 another economic crisis broke out. After that previous economic policy left and floating exchange rate system were introduced. Financial institutions influenced very badly by the crisis, and lot of banks seized by TMSF.

In 2003, a negative shock came with the occupation of Iraq by the United States of America. However, there is a positive shock in the October 2003. This period had political news about new cabinet election.

In May/June 2006, expectation of FED's interest rate increase waved the financial markets. The expectation based on fast growing of US economy and inflationary pressures. As a result of expectations many hedge funds started to lower their risk in the emerging markets. Especially in Turkey, this movement has felt, stock market decreased substantially.

The other and last shock is occurred in July 2007. It is emerged by the announcements of cabinet election. The expectation of one party cabinet affects the markets positively. However, GARCH model is not able to capture this positive shock.

Figure 6 Return vs VaR on ISE 100 with Norm Dist - 99 c.i. for 1st Period

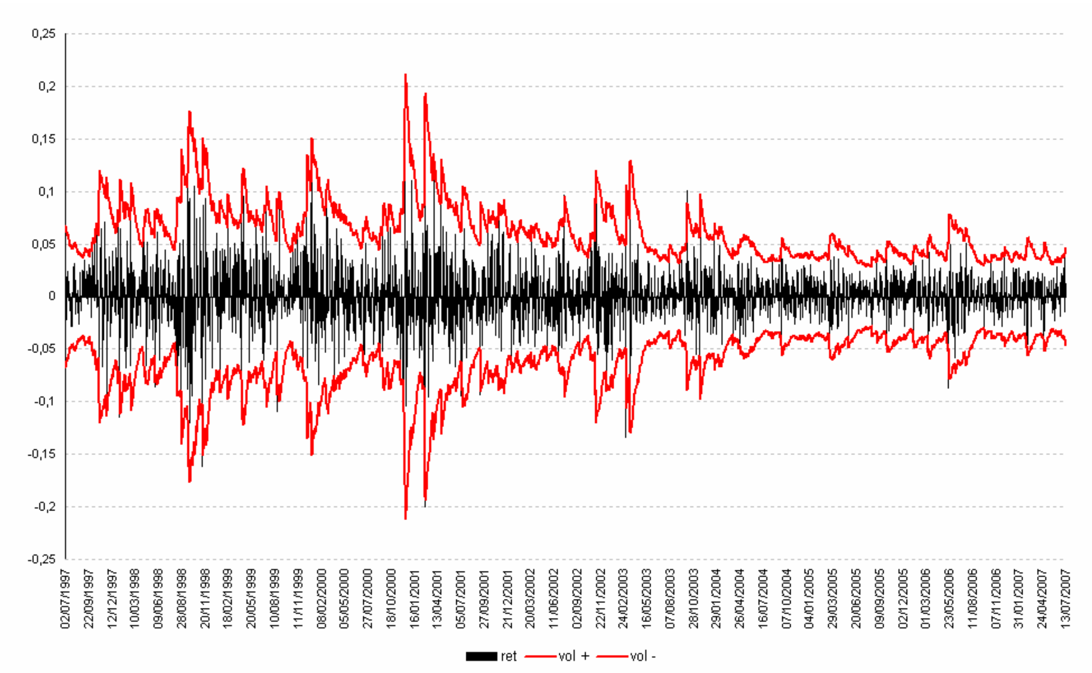


Figure 7 Return vs VaR on ISE 100 with Norm Dist. - 99 c.i. for 2nd Pperiod

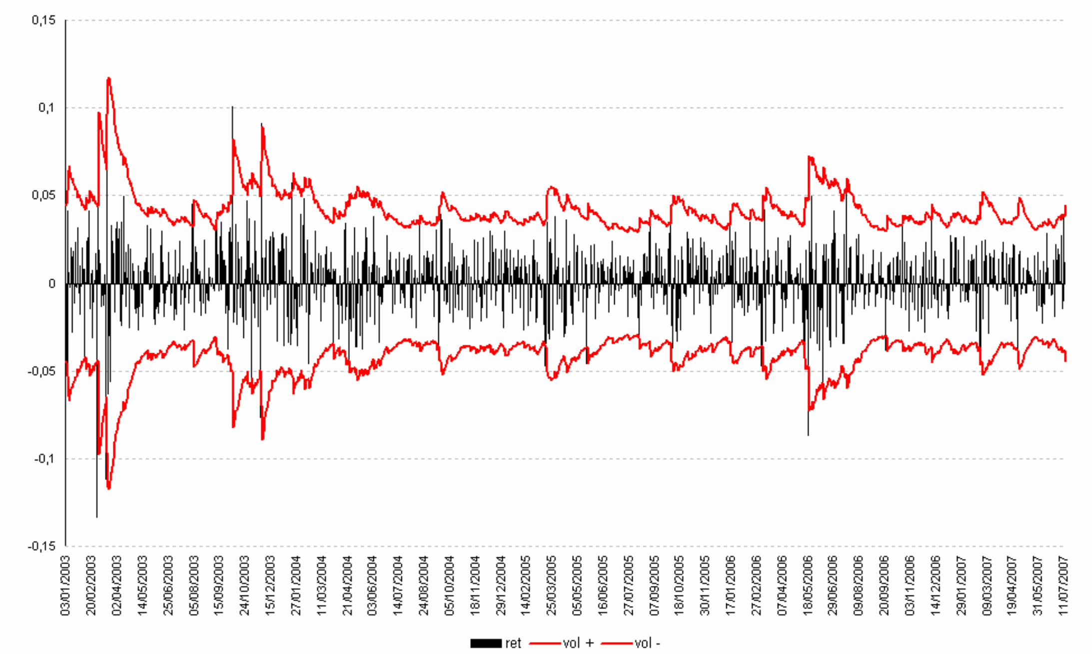


Figure 8 Return vs VaR on ISE 100 with Norm Dist. - 99 c.i. for 3rd Period

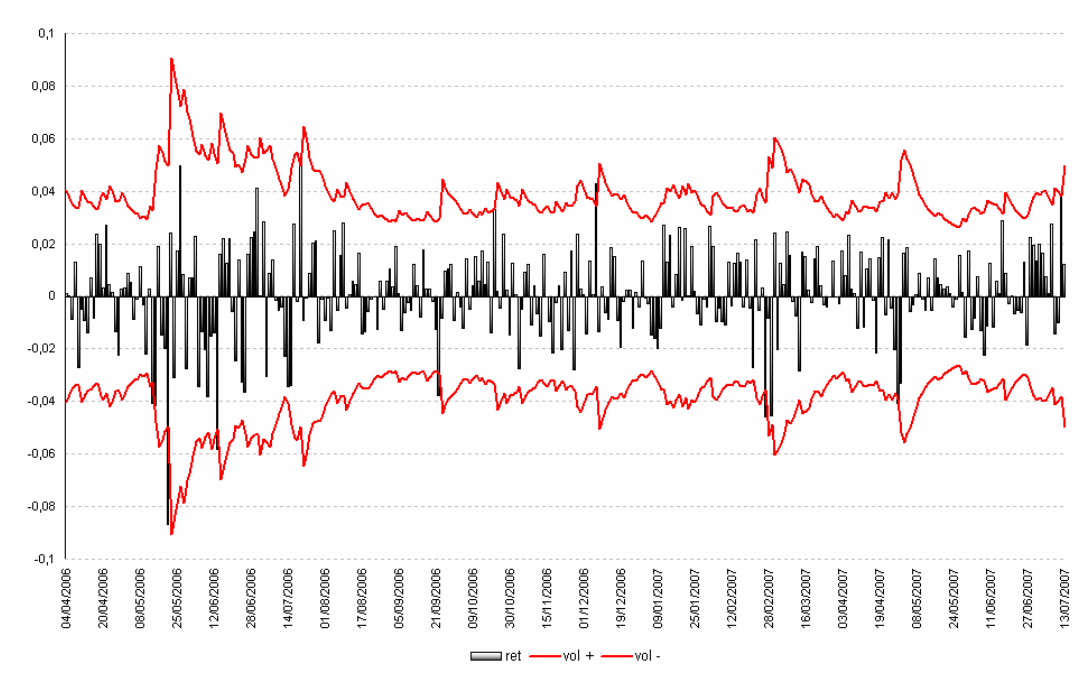


Figure 9 Return vs VaR on ISE 100 with Norm Dist . - 99 c.i. for 4th Period

Figure 10 Return vs VaR on ISE 30 with Norm Dist. - 99 c.i. for 1st Period

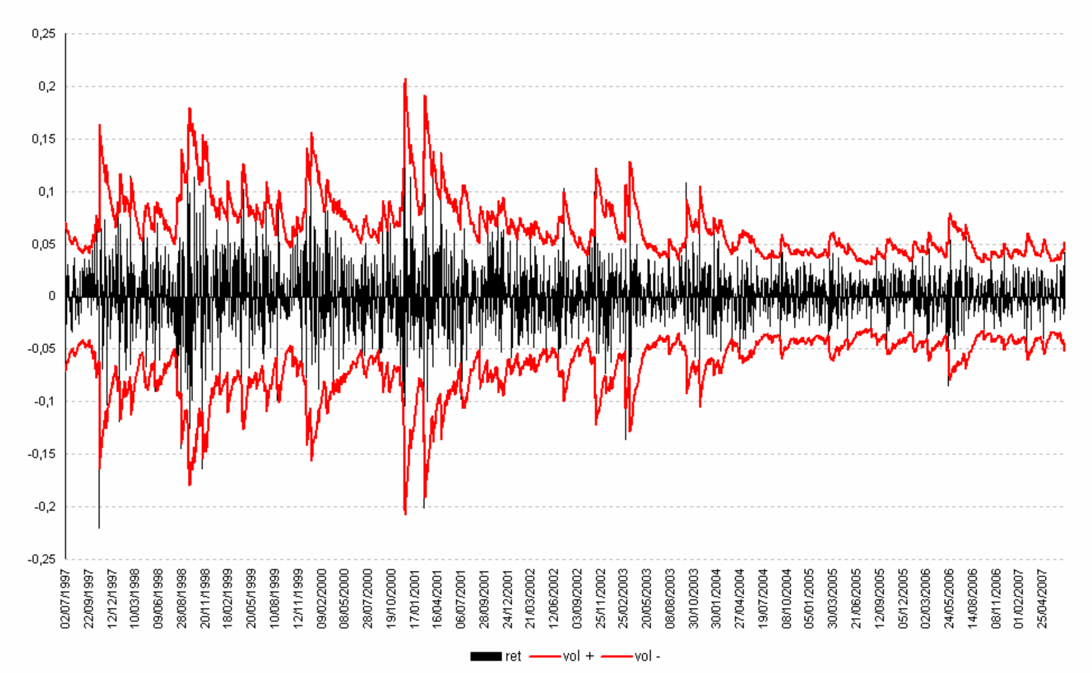


Figure 11 Return vs VaR on ISE 30 with Norm Dist . - 99 c.i. for 2nd Period

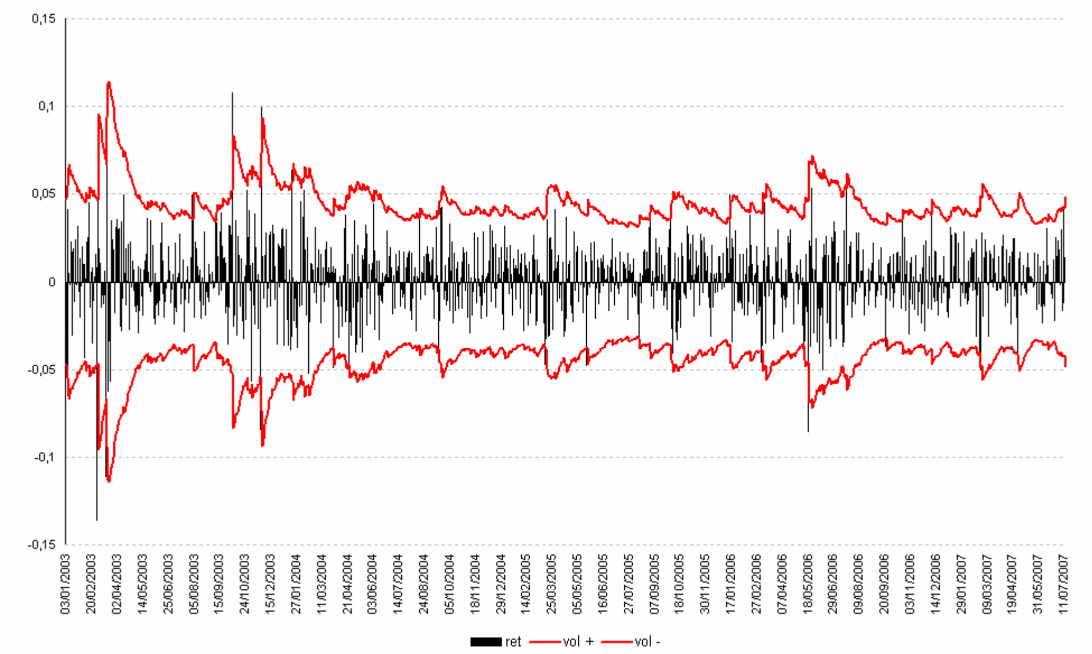


Figure 12 Return vs VaR on ISE 30 with Norm Dist. - 99 c.i. for 3rd Period

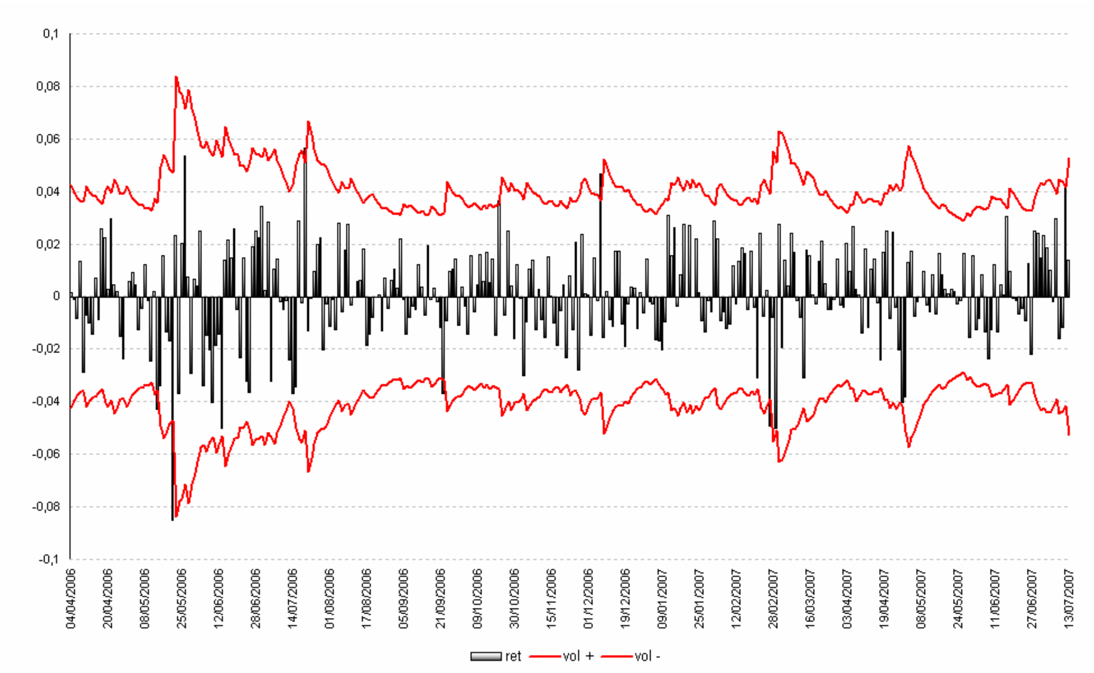


Figure 13 Return vs VaR on ISE 30 with Norm Dist. - 99 c.i. for 4th Period

Figure 14 Return vs VaR on Bank Index with Norm Dist. - 99 c.i. for 1st Period

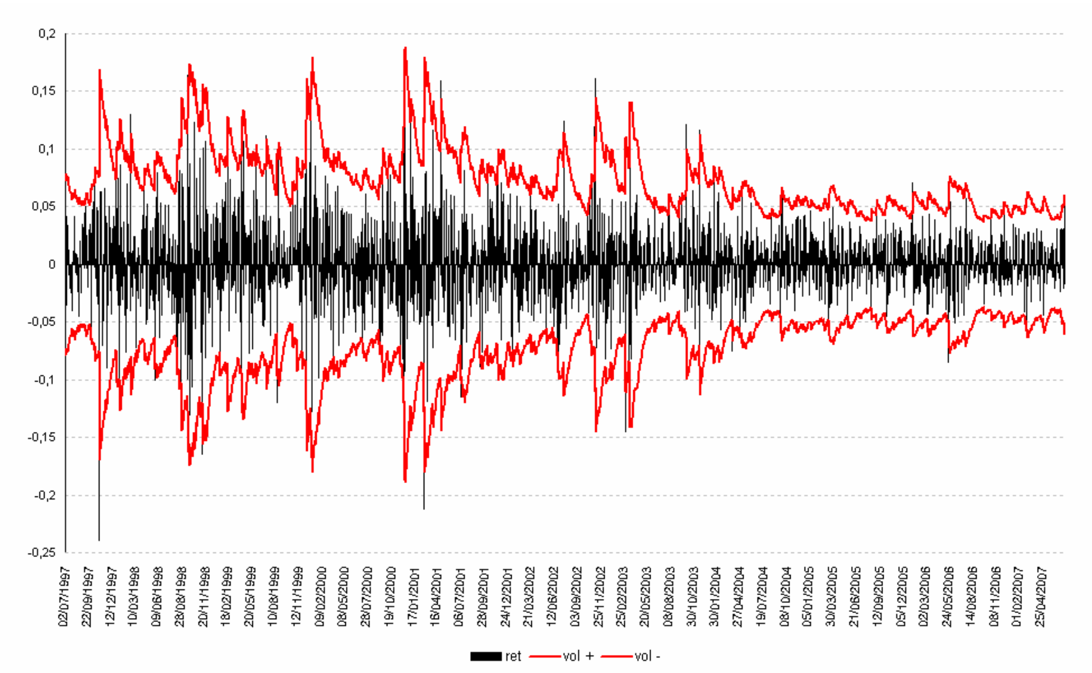


Figure 15 Return vs VaR on Bank Index with Norm Dist. - 99 c.i. for 2nd Period

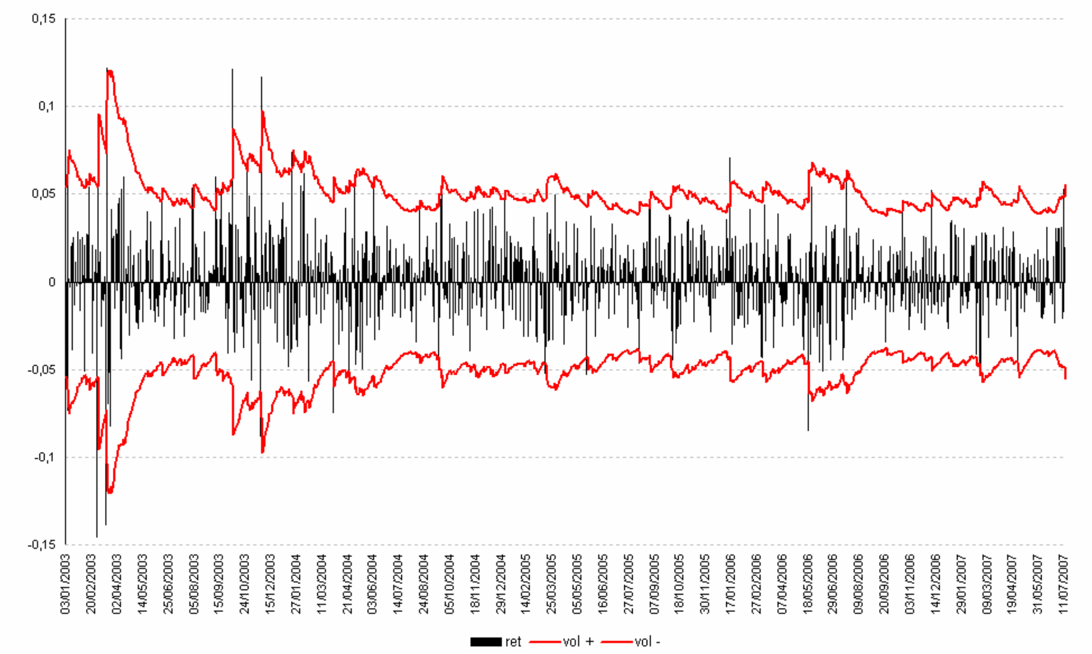


Figure 16 Return vs VaR on Bank Index with Norm Dist. - 99 c.i. for 3rd Period

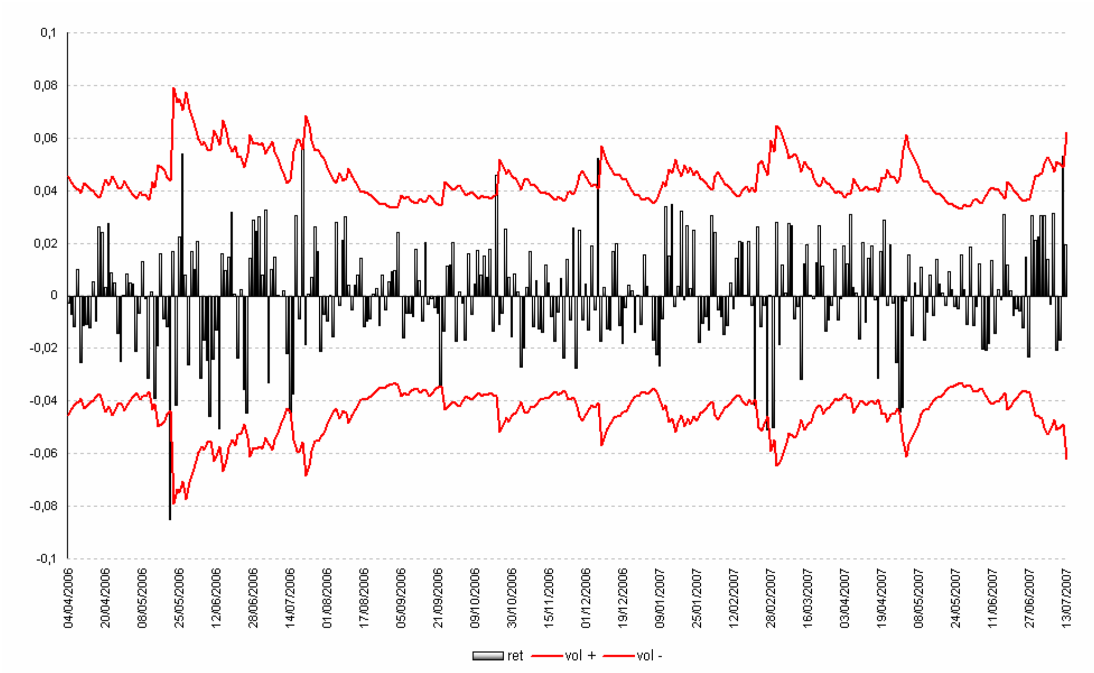


Figure 17 Return vs VaR on Bank Index with Norm Dist. - 99 c.i. for 4th Period

Figure 18 Return vs VaR on Akbank with Norm Dist. - 99 c.i. for 1st Period

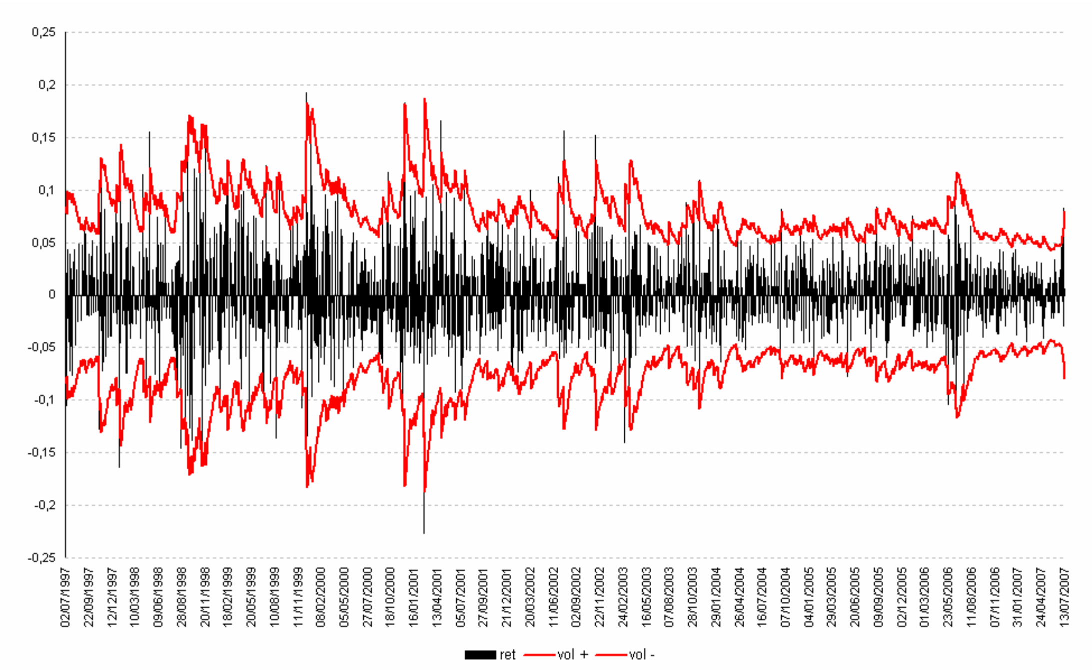


Figure 19 Return vs VaR on Akbank with Norm Dist. - 99 c.i. for 2nd Period

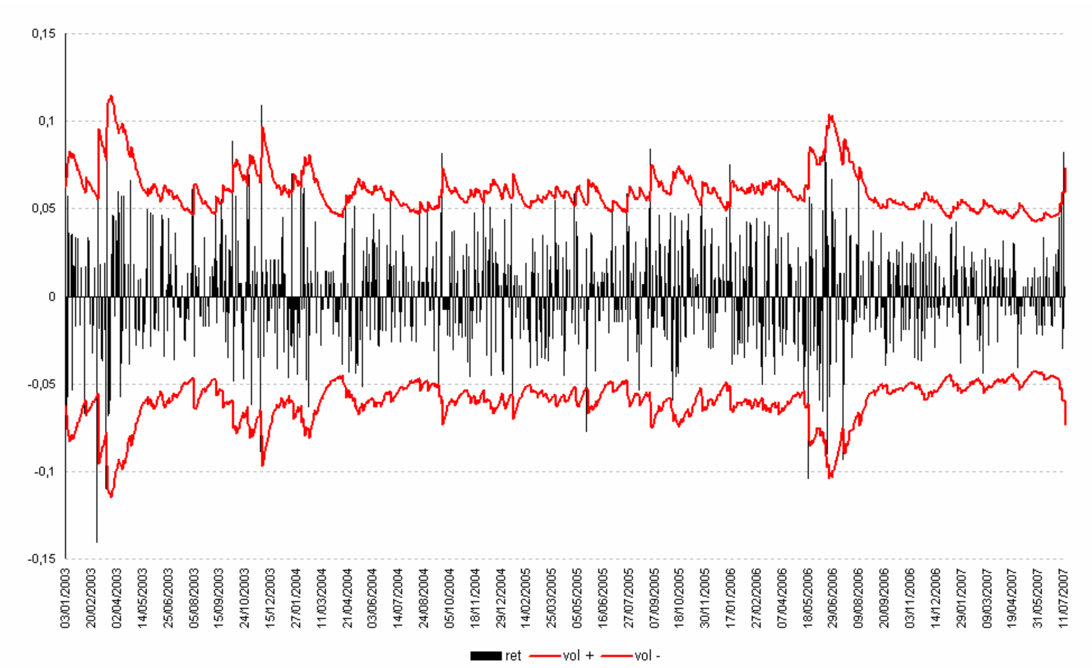


Figure 20 Return vs VaR on Akbank with Norm Dist. - 99 c.i. for 3rd Period

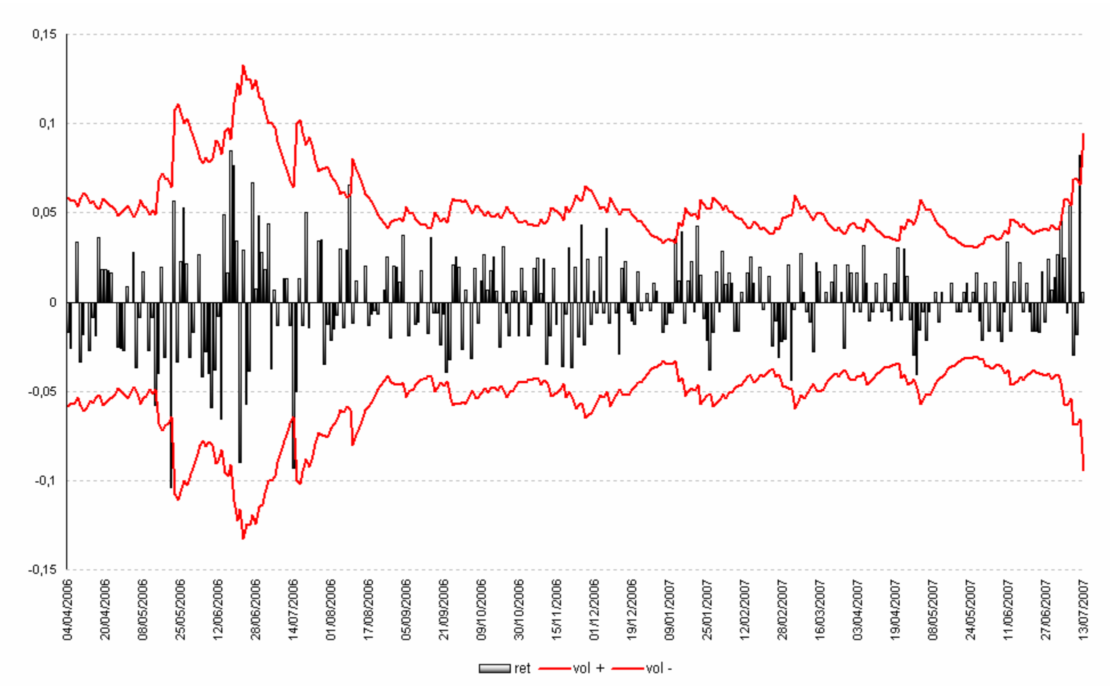
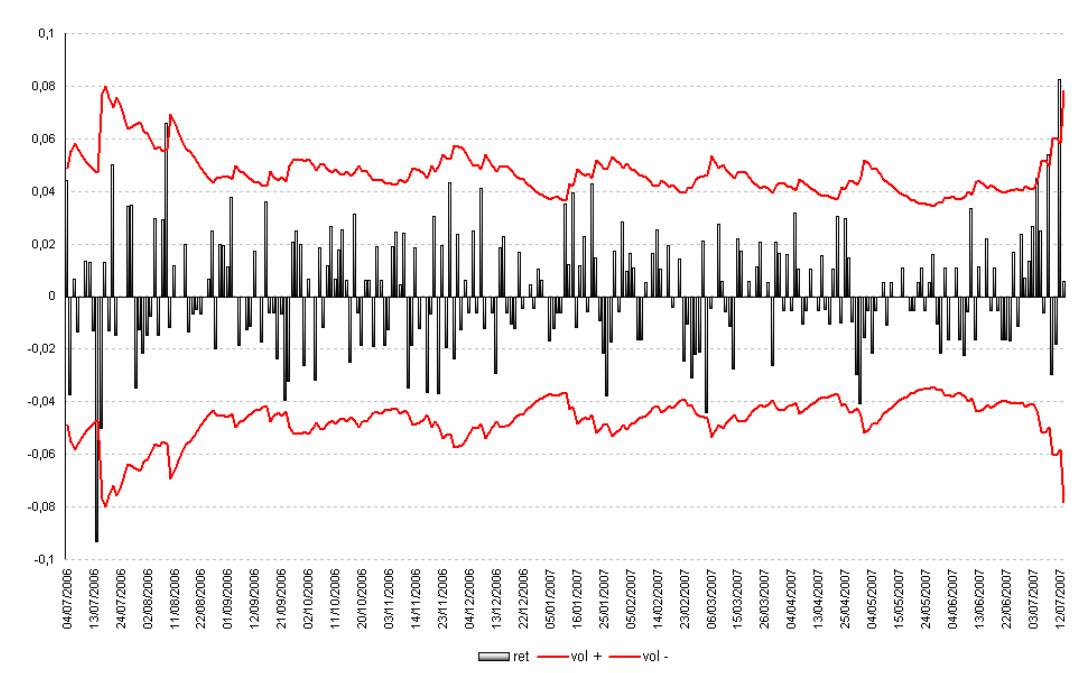


Figure 21 Return vs VaR on Akbank with Norm Dist. - 99 c.i. for 4th Period



CONCLUSION

The last decade has seen a remarkable growth in the development and trading of financial instruments. The growth of this activity has also generally increased awareness of risk exposures and has contributed to the development of more formal methods of risk management and risk measures such as value-at-risk (VaR). Indeed, the Bank for International Settlements (BIS) has suggested regulatory policies for setting capital requirements for banks that are closely related to the VaR methodology, and the system has been adopted by the European Community and by banking authorities elsewhere around the world.

Besides growing financial instruments, global investments are accelerated and spread all around the world with the improved technology and stock market liberalization. These developments lead to upward risk trend in the world financial markets. Consequently, it becomes a primary concern to measure of market risk. Volatility finds acceptance as a risk metric, because investors' expected profit are based on price movements.

Primarily, volatility is measured by the conventional methods (unconditional variance). This measure of the unconditional volatility does not take into account the predictable pattern in the stock market volatility. However, practices show that for the high frequency data, variance is not constant over time. Subsequently, Engel (1982) provides ARCH (autoregressive conditional heteroscedasticity) model which takes into account the financial return series characteristics. After Engel, Bollerslev (1986), treated time-varying conditional variance as function of moving averages of past squared residuals, and added this model the lagged values of the variance, consequently he suggested GARCH model which can capture the behaviour of the series.

Motivated by these events, this thesis looked into some important aspects of risks, and risk measures. In the thesis, we investigate the three indexes and seven banks equities volatility (ISE-100, ISE-30, Banking Index, Akbank, Alternatifbank, Finansbank, ISC, Şekerbank, Garantibank, Yapı Kredi) which is accepted as a metric of risk. The reason of choosing bank equities is that they are one of the most sensitive economic agents to macro news such as economic, political. Besides, shocks are primarily and profoundly affect the banks. The best example may be given as 2000-2001 Turkish economic crisis both the cause and the most affected part of the economy were banks. Furthermore, in relatively stable periods, many number of news about banks are announced. These news may be about new credit strategy, syndication credits, profits, changes in the executive management. In addition to bank equities we also studied three indexes. The reason behind this is to observe whether banks evolve with the indexes or they act separately from them.

We used the GARCH (1, 1) model with gauss and Student-t innovations distributions to examine volatility, because it is a well known fact that financial time series' variance is not constant, it evolves with time. GARCH models are able to capture this behaviour. Besides, there are more stylised facts about financial data GARCH is able to describe:

- Large and small values in a log return sample tend to occur in clusters, indicating that there is dependence in the tails. This characteristic is also called volatility clustering.

- Changes in stock prices tend to be negatively correlated with changes in volatility, i.e., volatility is higher after negative shocks than after positive shocks of same magnitude. This property is called the leverage effect.

- Long-range dependence in the data. Sample autocorrelations of the data are small whereas the sample autocorrelations of the absolute and squared values are significantly different from zero even for large lags. This behaviour suggests that there is some kind of long-range dependence in the data.

- Aggregational Gaussianity, i.e., the distribution of log-returns over larger periods of time (such as a month, half a year, a year) is closer to the normal distribution than for hourly or daily log-returns.

The empirical results may be summarized as follows:

- Both normal and student-t distribution assumptions are suitable to describe the stocks behaviour and almost generate the same results. Student-t distribution results slightly higher VaR figures floating around 0,05 – 0,01 %.

- However, in some cases contradictory results are obtained. Like Baillie and DeGennaro (1990), we found that conditional variance is not significant when the conditional distribution was a normal distribution rather than a t-distribution. This conflicting results is the picture for Garanti Bank in the last time period. The parameter estimations under normal distribution does not hold for Garanti Bank for the 4th period, however, for the same period student-t parameter estimation is valid for the model.

- The other finding is that GARCH cannot capture structural breaks and regime changes. We saw that shocks as economic crisis or global turbulences or drastic positive news are not captured. This result is parallel with Aiolfi and Timmerman’s (2004) study.

- When volatility starts to fall, VaR moves backward to its old degree. Consequently, GARCH performs well in the short term. As we stated earlier, for the third period we are most likely to see the shock effect, however, for the first and the longest time period it seems that shocks effect relatively smoothed and languished. Hendry and Clements (2002), found the same results that GARCH is temporarily affected from today's rising volatility.

- Some of the return series do not fulfill the adequate parameter constraints. Espacially, Altenatif Bank and Finansbank attract notice. Alternatif Bank gives satisfying results only for the 4th period and under student-t distribution assumption. Whereas, Finansbank's results differ according to period and assumption.

- The measure of volatility persistence $\alpha + \beta$ in the model shows that the tendency of the shock to persist meaning that series have long memory characteristics. This indicates that the mean return is slow.

- The results suggest that individual banks are evolved with the indexes, they have the same trend. However, GARCH model captures more data points in the indexes, whereas there are more data points are not captured by the model in the individual series. The reason may be claimed as bank-specific news are more effective on individual series, these news are felt more profoundly.

After specification of GARCH, we used Value at Risk model to convert GARCH figures to maximum possible loss amount. Value at risk (VaR) is a very popular risk management tool, because it is an easily understood and obviously relevant concept. It is simply the answer of "What is the most one can lose on a given investment?" This is a question that almost every investor who has invested or is considering investing in a risky asset asks at some point in time. So, in its most general form, VaR measures the potential loss in value of a risky asset or portfolio over a defined period for a given confidence interval. We used two different confidence intervals as 99 % and 95 %. The empirical results show that 99 % confidence interval outperforms the 95 %, it captures almost every realized stock return.

VaR results differ for each series, the most risky appears to be the Sekerbank, and the lowest risky one appears to be the ISE-100. However, one-step ahead VaR depicts unexceptionally for all the series have lower VaR number for tomorrow. The reason might be cited as positive expectations on Turkey.

As a result, this study shows that Turkey stock market has time-varying volatility, and long memory behaviour. According to these characteristics, GARCH (1,1) model captures fairly well the behaviour of daily stock returns.

REFERENCES

Aiolfi, M. and Timmermann A. (2006) “Persistence in Forecasting Performance and Conditional Combination Strategies”, *Journal of Econometrics,* Vol.135, pp. 31-53.

Akgül Işıl, Sayan Hülya. (2005) “IMKB-30 Hisse Senedi Getirilerinde Volatilitenin Asimetrik Koşullu Değişen Varyans Modelleri ile Öngörüsü”. T.C. Marmara Üniversitesi Bankcılık ve Sigortacılık Yüksekokulu Geleneksel Finans Sempozyumu Tebliğleri

Alexander, Carol and Lazar, Emese. (2006) “Normal Mixture GARCH(1,1):Applications to Exchange Rate Modeling”. *Journal of Applied Econometrics*, Vol.21,No. 3, pp.307-336.

Andersen Torben G., Bollerslev Tim, Christoffersen Peter F., Diebold Francis X. (2005) “Practical Volatility and Correlation Modeling for Financial Market Risk Management. Risks of Financial Institutions”. CFS Working Paper No:2005/02

Angelidis, Timotheos and Degiannakis, Stavros. (2004) “VaR and Intra-Day Volatility Forecasting:The Case of the Athens Stock Exchange”, Technical Paper 209

Artan Seyfettin. (2006) “Türkiye’de Enflasyon, Enflasyon Belirsizliği ve Büyüme”, Türkiye Ekonomi Kurumu Tartışma Metni, 2006/14

Baillie, Richard T. and Bollerslev, Tim. (1989) “The Message in Daily Exchange Rates: A Conditional-Variance Tale”, *Journal of Business and Economic Statistics*, Vol.7, pp.297-305

Baillie, R. and R. DeGennaro. (1990) “Stock Returns and Volatility”, *Journal of Financial and Quantitative Analysis* ,Vol.25, pp. 203-214.

Balaban, Ercan, Bayar Aslı, Faff Robert. (2006). “Forecasting Stock Market Volatility:Further International Evidence”, *European Journal of Finance*, Vol.12, No. 2, pp.171-188

Bali, G., Turan, Peng, Lin. (2006) , “Is There a Risk-Return Tradeoff? Evidence from High-Frequency Data”, http://papers.ssrn.com

Berument, H., Inamlik, A., & Kiymaz, H. (2004). „Borsa degiskenliginde haftanin gun etkisi:Istanbul Menkul Kiymetler Borsasi.“ (The Day of the Week Effect on Stock Return andVolatility: The Case of Istanbul Stock Exchange [ISE].), *Iktisat Isletme ve Finans,* Vol.19, No.223, pp. 91-102.

Bildirici Melike, Oktay Sadiye, Aykaç Elçin (2007), “IMKB’de Getiri Değişkenliğinin Hesaplanmasında ARCH/GARCH Ailesi Modellerinin Kullanılması”, 8.Türkiye Ekonomi ve İstatistik Kongresi

Bollerslev, Tim. (1986), “Generalized Autoregressive Conditional Heteroskedasticity', *Journal of Econometrics*, Vol. 31,pp. 307-327

Bollerslev, Tim. (1987). “A Conditional Heteroskedasticity Time Series Model for Speculative Prices and Rates of Return”, *Review of Economic and Statistics*, Vol.69, pp.542-547

Bollerslev, Tim, Chou, Ray Y. and Kroner, Kenneth F. (1992). “ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence”, *Journal of Economics and Statistics*, Vol.69, pp.542-547

Burns, Patrick. (2002) , “The Quality of VaR via Univariate GARCH” , www.burns-stat.com

Choudhry, Taufig, (1996) “Stock market volatility and the crash of 1987: evidence from six emerging markets”, *Journal of International Money and Finance*, Vol. 15,pp. 969-981.

Chou, Ray Y. (1988) “Volatility Persistence and Stock Valuations: Some Empirical Evidence Using GARCH”, *Journal of Applied Econometrics*, Vol. 3,pp. 279-294.

Christoffersen, Peter F., and Jacobs, Kris. (2004). "Which Garch Model for Option Valuation?", *Management Science*, Vol.50, pp.1204-1221

Ding, Zhuanxin, Clive W. J. Granger, and Robert F. Engle (1993). "A Long Memory Property of Stock Market Returns and a New Model", *Journal of Empirical Finance*, Vol.1, pp.83–106.

Duran Serap, Şahin Asuman (2006), "IMKB Hizmetler, Mali, Sınai ve Teknoloji Endeksleri Arasındaki İlişkinin Belirlenmesi", *Sosyal Bilimler Araştırma Dergisi*,Vol. 1, pp. 57-70

Engle, R. F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation', *Econometrica*, Vol. 50, pp. 987-1007.

Engle, Robert and Tim, Bollerslev, (1986), "Modeling the Persistence of Conditional Variances", *Econometric Reviews*, Vol. 5, pp.1-50.

Engle, Robert and Ng, Victory K, (1993), "Measuring and Testing the Impact of News on Volatility", *Journal of Finance,* Vol. 48, pp.1749-1778

Fabozzi, J. Frank, Tunaru Radu and Wu Tony (2004), "Modelling Volatility for the Chinese Equity Markets" , *Analysis of Economic and Finance*, Vol.5, pp. 79-92

French, K., G. Schwert, and R. Stambaugh. (1987) "Expected Stock Returns and Volatility", *Journal of Financial Economics* , Vol.19, pp. 3-29.

Glosten, Lawrence R., Jagahannathan, Ravi, and Runkle, David E. (1993). "On the Relationship Between the Expected Value and The Volatility of the Nominal Excess Return on Stocks", *Journal of Finance*, Vol.48, pp. 1779-1801

Goyal Amit. (2000). "Predictability of Stock Return Volatility from GARCH Models", Anderson Graduate School of Management, UCLA, Working Paper.

Gökçe Atilla (2001), "İstanbul Menkul Kıymetler Borsası Getirilerindeki Volatilitenin ARCH Teknikleri ile Ölçülmesi", *G.Ü. I.I.B.F. Dergisi*,Vol.1, pp 35-38

Hendry, D.F. and Clements M.P. (2002), "Pooling of Forecasts", *Econometrics Journal*, Vol.5, pp. 1-26

Higgins, M.L. and A.K. Bera (1992), "A Class of Nonlinear ARCH Models," *International Economic Review*, Vol. 33, pp.137-158.

Hsieh, David A. (1989). "Modeling Heteroskedasticity in Daily Foreign Exchange Rates", *Journal of Business and Economic Statistics*, Vol.7, pp. 307-317

Jayasuriya, Shamila,Shambora, William, Rossiter, Rosemary. (2005). "Asymmetric Volatility in Mature and Emerging Markets", Ohio University, Working Paper.

Knight, Frank H. 1921. *Risk, Uncertainty, and Profit.* New York:Hart, Schaffner, and Marx.

Kutan M. Ali, Aksoy Tansu (2004), "Public Information Arrival and Emerging Markets Returns and Volatility", *Multinational Finance Journal*, Vol.8, pp 227-245

Lane Christel, Quack Sigrid. (1990). "The Social Dimensions of Risk. Bank Financing of SMEs in Britain and Germany". *Organization Studies*, Vol. 20, No.6, pp.987-1010

Markowitz, Harry M. (1952). "Portfolio Selection", *Journal of Finance*, Vol.7, No.8, pp. 77-91

Mazıbaş Murat (2004), "IMKB Piyasasındaki Volatilitenin ve Asimetrik Fiyat Hareketlerinin Modellenmesi ve Öngörülmesi:GARCH Uygulaması", İTÜ 8.Ulusal Finans sempozyumu,İstanbul

Nelson, Daniel B. (1991). "Conditional Heteroskedasticity in Asset Returns: A New Approach", *Econometrica*, Vol.59, No.2, pp.347-370

Okay Nesin (1998), "Asymmetric Volatility Dynamics: Evidence from İstanbul Stock Exchange", Business Economics for the 21st Century International Conference

Palm, Franz. (1996). Garch Models of Volatility, in Handbook of Statistics, ed. By G.Maddala, and C.Rao, pp.209-240, Elsevier Science, Amsterdam

Palm, Franz, Vlaar Peter JG. (1997). "Simple Diagnostics Procedures for Modeling Financial Time Series", *Allgemeines Statistisches Archive,*Vol. 81,pp.85-101.

Pan, Hangyu, Zhiang Zhichao. (2006) " Forecasting Financial Volatility:Evidence From Chinese Stock Market", School of Economics, Finance and Business, University of Durham, Working Paper, 06/02.

Pagan, Adrian. (1996) "The Econometrics of Financial Markets", *Journal of Empirical Finance*, Vol.3, pp.15-102.

Shin Jaeun (2005), "Stock Returns and Volatility in Emerging Stock Markets", *International Journal of Business and Economics*,Vol. 4, No.1, pp 31-43

So, Mike K.P., Yu ,Philip L.H. (2006)."Empirical Analysis of GARCH Models in Value at Risk Estimation", *Journal of International Financial Markets, Institutions, and Money,* Vol.16, No.2,pp.180-197

Telatar Erdinç, Binay H. Soner (2002), "IMKB Endeksinin PARCH Modellemesi", *Akdeniz I.I.B.F. Dergisi*, Vol.3, pp 114-121

Turanlı Münevver, Özden H. Ünal, Vural Gökhan, "2002-2006 Döneminde IMKB Getiri Volatilitesinin Ekonometrik Analizi", 8.Türkiye Ekonomi ve İstatistik Kongresi

Tse, Kuen Y. (1998). "The Conditional Heteroscedasticity of the Yen-Dollar Exchange Rate", *Journal of Applied Econometrics*, Vol.193, pp.49-55

Varma, Jayanth R. (1999). "Value at Risk Models in the Indian Stock Market", Indian Institute of Management, Working Paper, No.99-07-05.

Wu, Goujun. (2001). "The Determinants of Asymmetric Volatility", *The Review of Financial Studies,*Vol.14, No.3, pp.837-859

Yu Jun (2002), “Forecasting Volatility in the New Zealand Stock Market”, *Applied Financial Economics*, Vol.12, pp. 193-202

Zakoian, Jean-Michel, (1994), “Threshold heteroskedascity Models”, *Journal of Economic Dynamics and Control*, Vol. 15, pp.931-955

APPENDIX I - DISTRIBUTION OF RETURN SERIES

Figure 22 Distribution of Return Series for Yapı Kredi

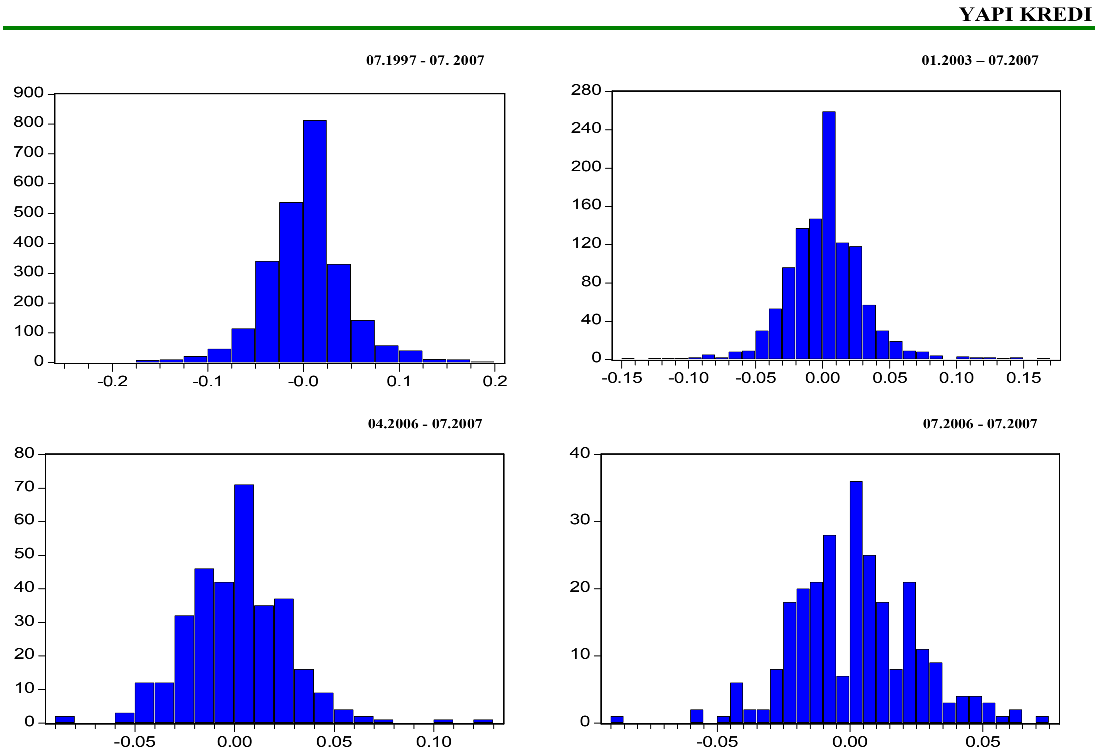


Figure 23 Distribution of Return Series for Sekerbank

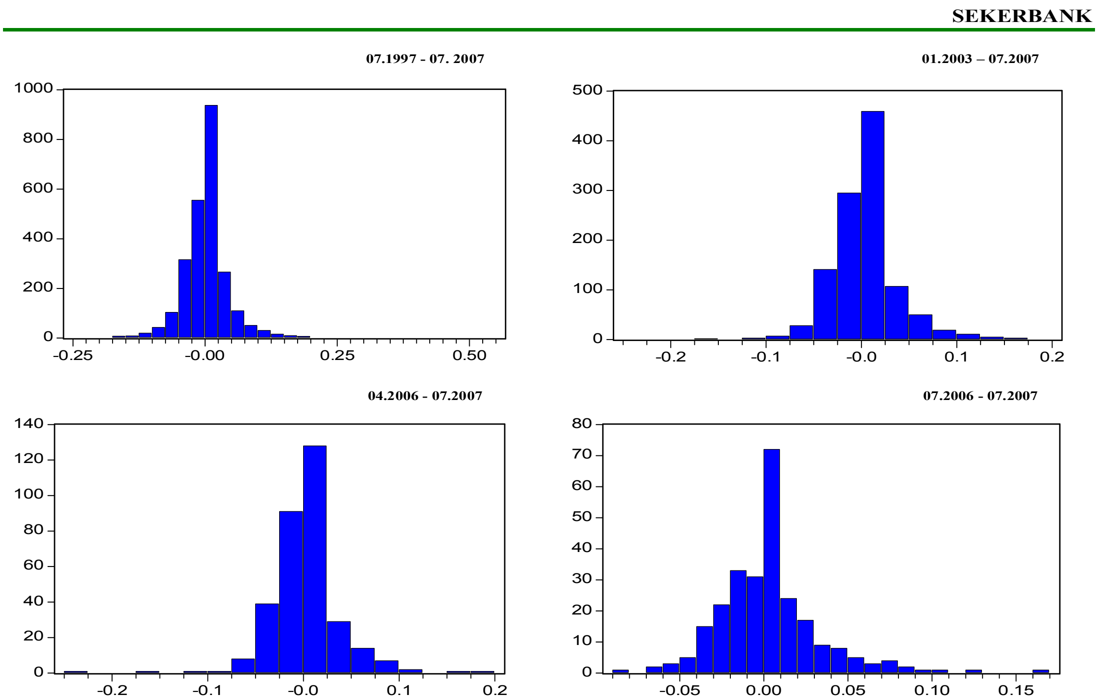


Figure 24 Distribution of Return Series for ISC

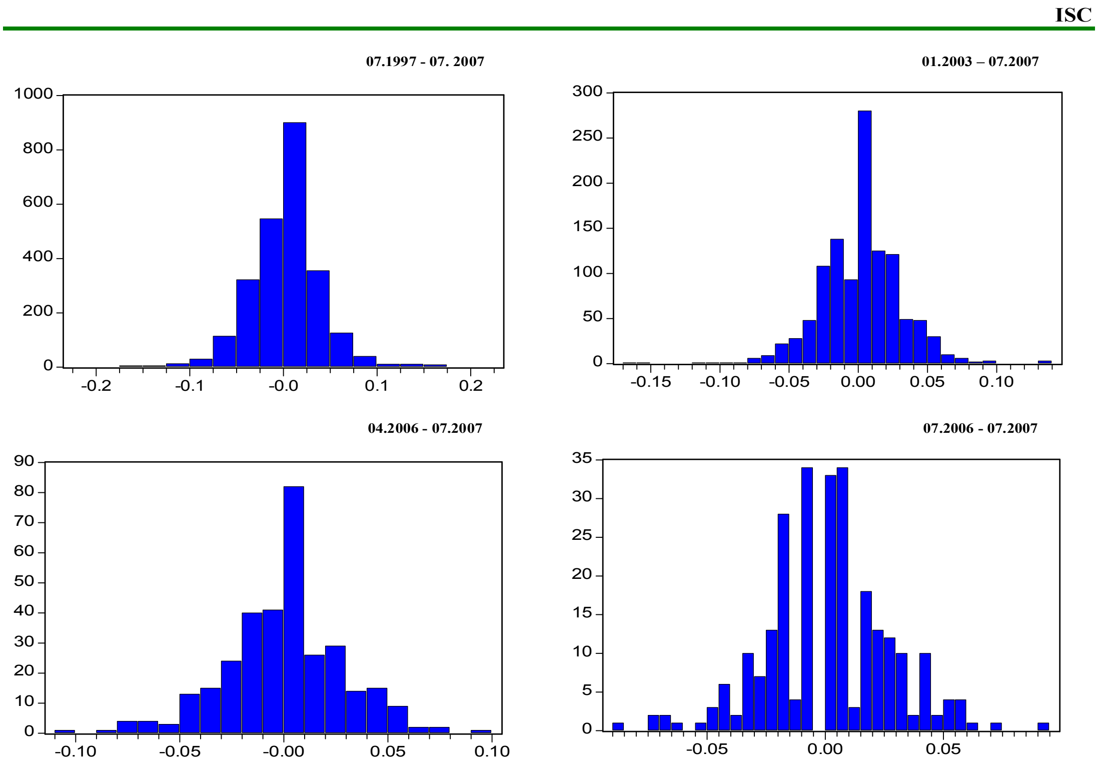


Figure 25 Distribution of Return Series for Finansbank

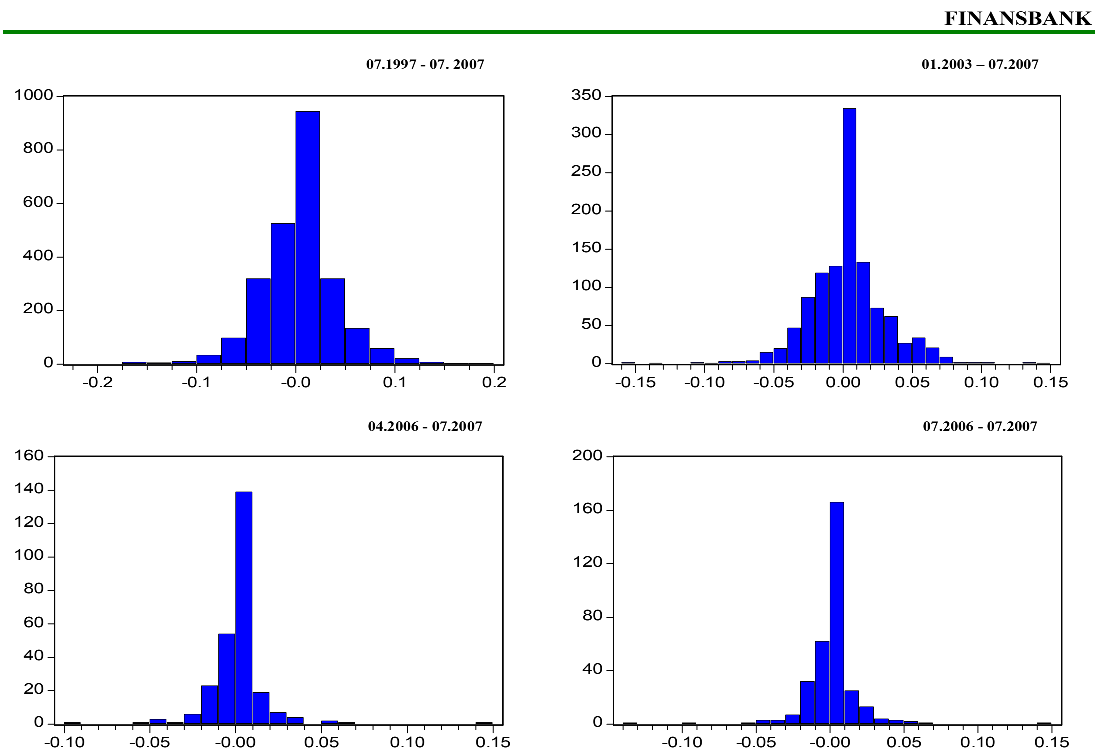


Figure 26 Distribution of Return Series for Alternatifbank

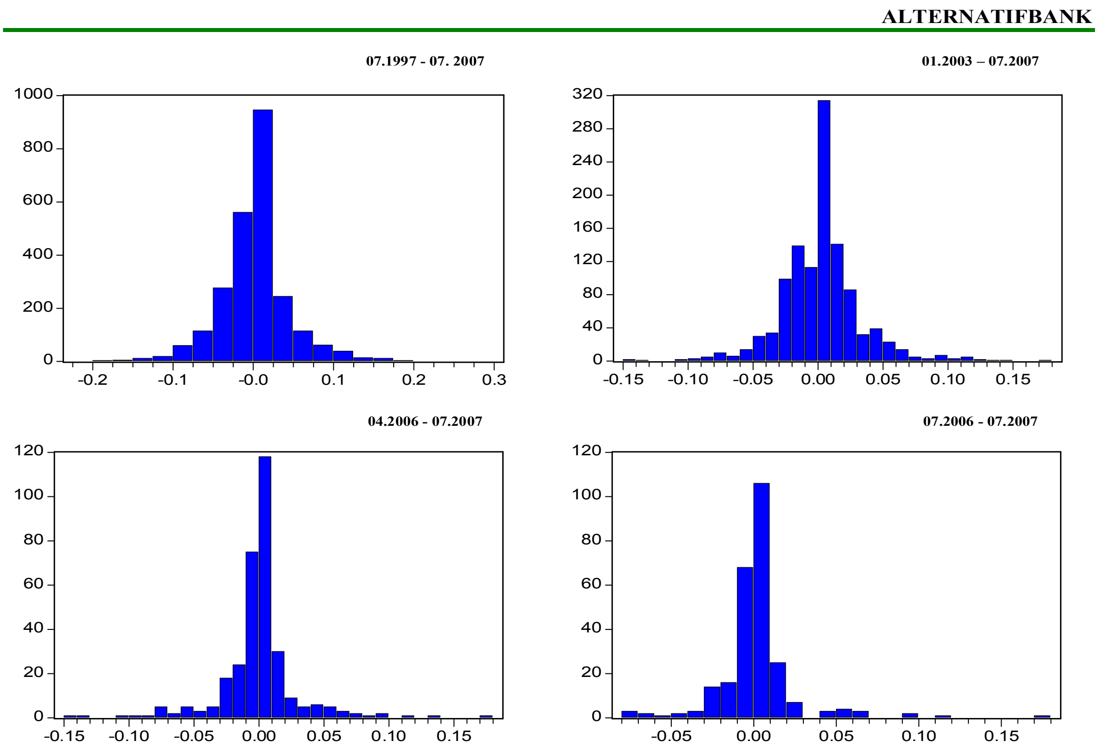
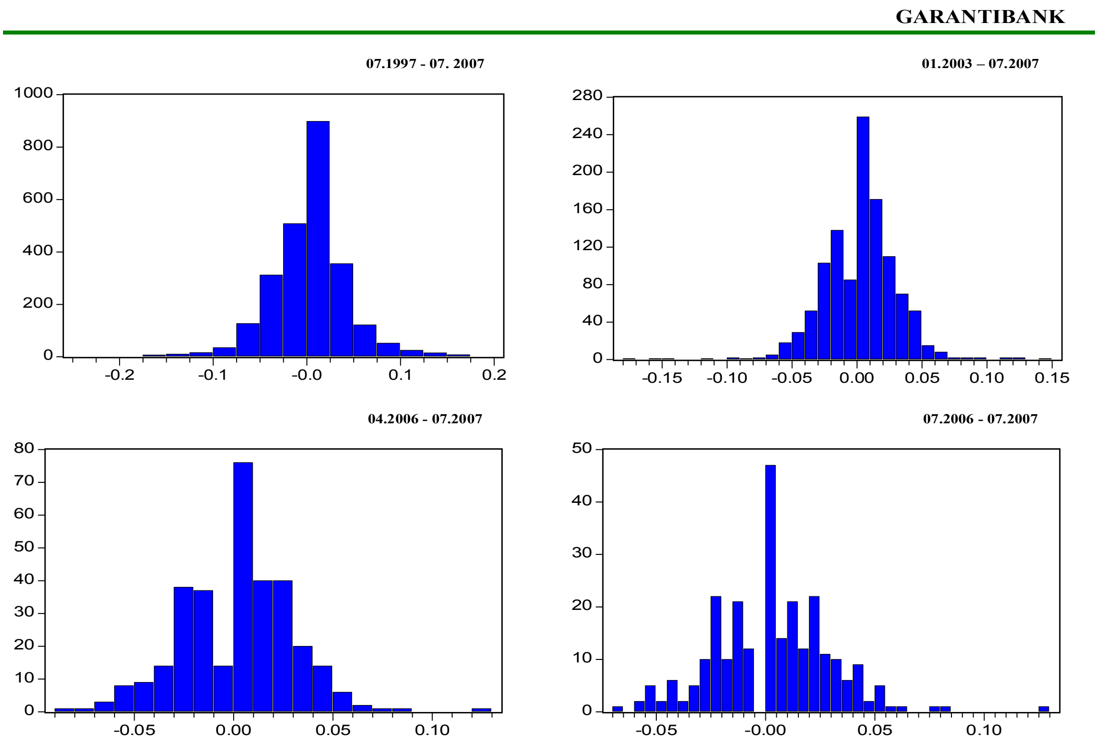


Figure 27 Distribution of Return Series for Garantibank



APPENDIX II – RETURN vs VALUE at RISK

Figure 28 Return vs VaR on ISE 100 with Norm Dist. - 95 c.i. for 1st Period

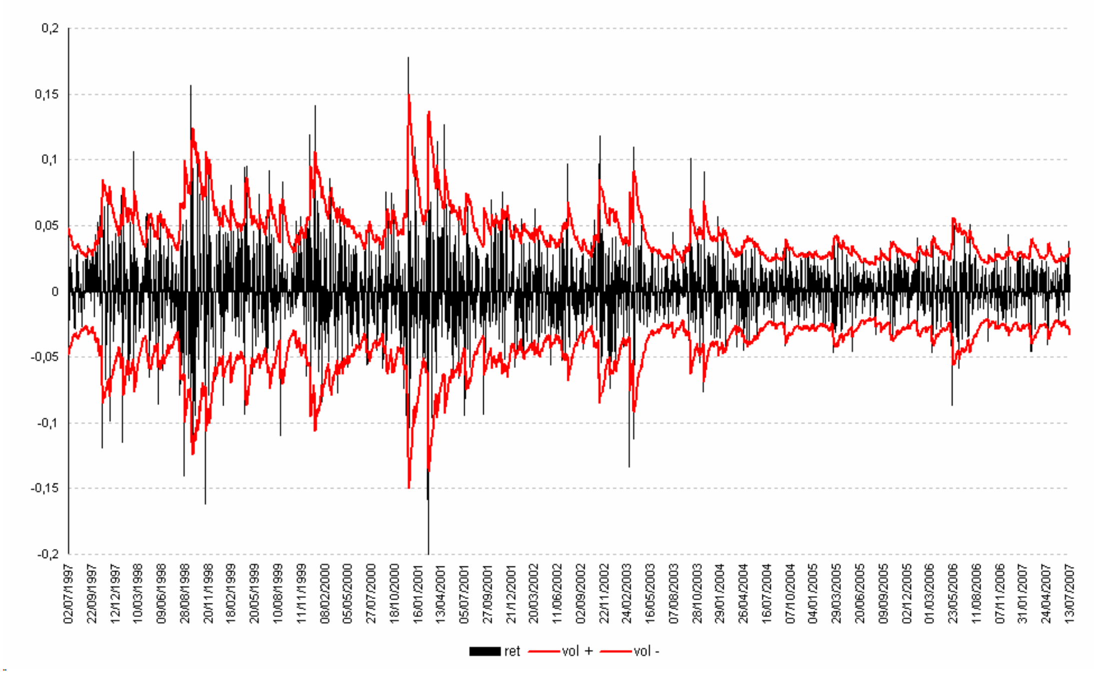


Figure 29 Return vs VaR on ISE 100 with Norm Dist. - 95 c.i. for 2nd Period

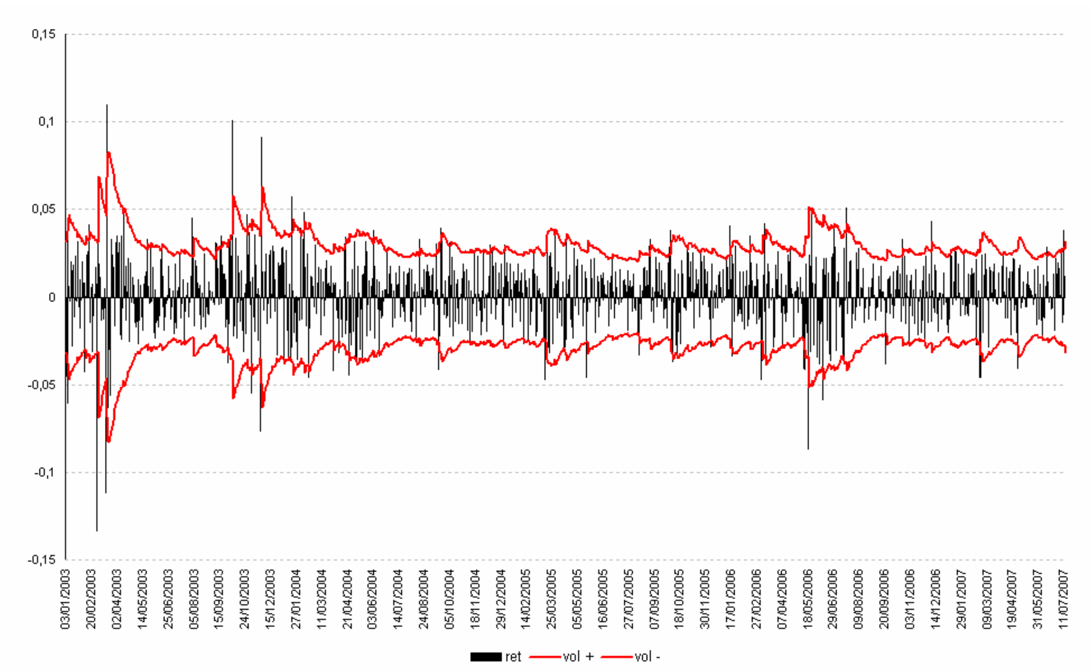


Figure 30 Return vs VaR on ISE 100 with Norm Dist. - 95 c.i. for 3rd Period

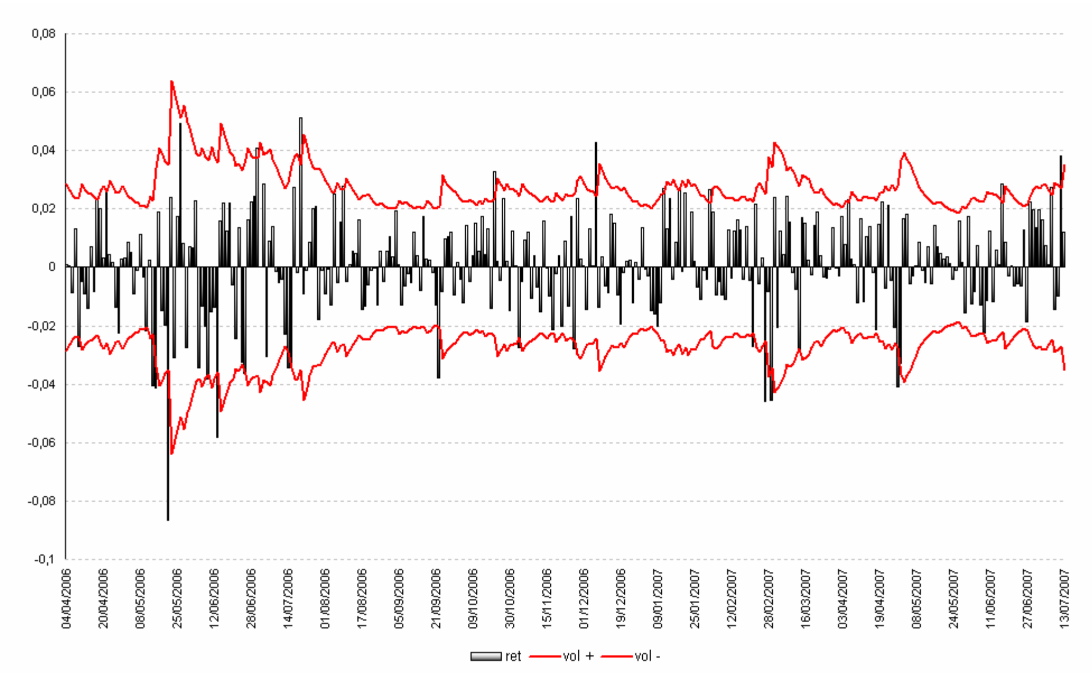


Figure 31 Return vs VaR on ISE 100 with Norm Dist. - 95 c.i. for 4th Period

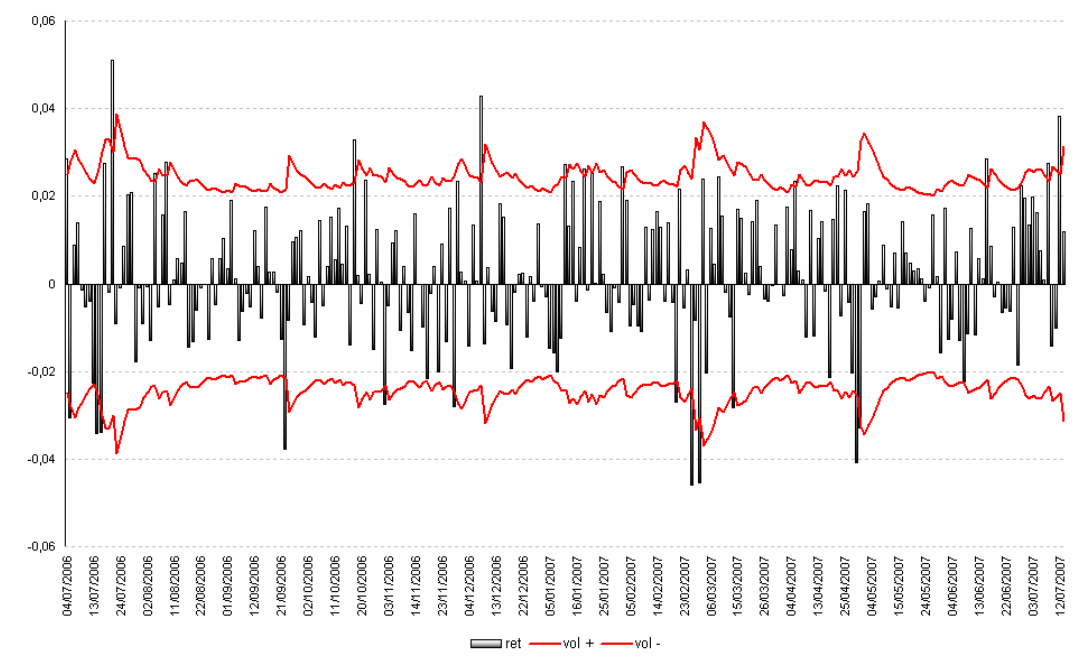


Figure 32 Return vs VaR on ISE 30 with Norm Dist. - 95 c.i. for 1st Period

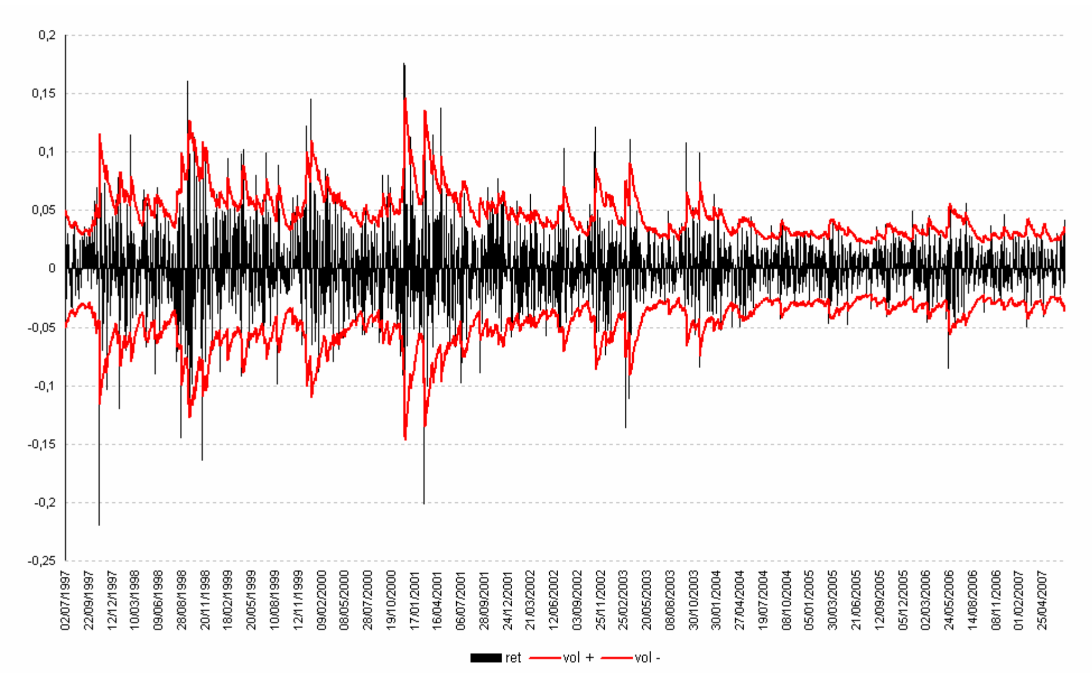


Figure 33 Return vs VaR on ISE 30 with Norm Dist. - 95 c.i. for 2nd Period

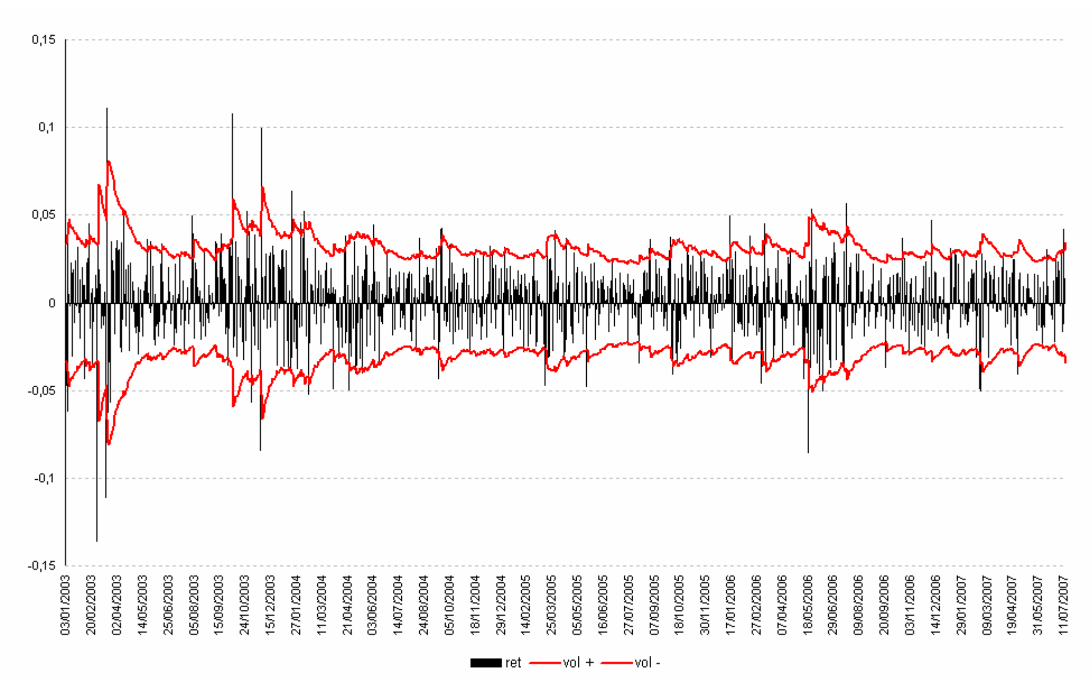


Figure 34 Return vs VaR on ISE 30 with Norm Dist. - 95 c.i. for 3rd Period

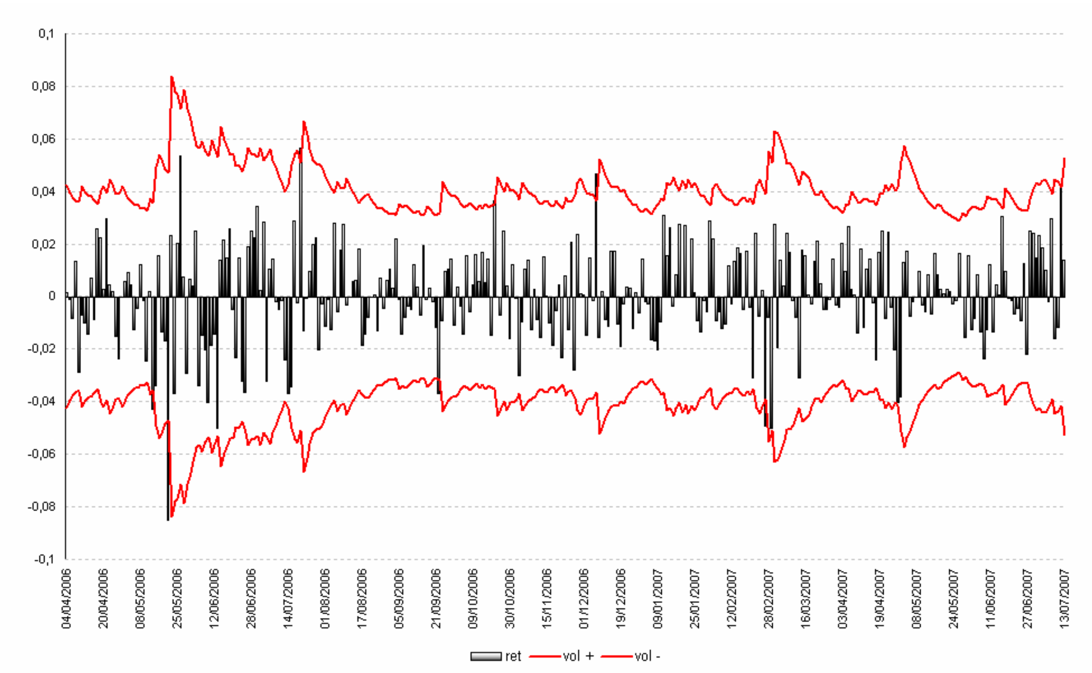


Figure 35 Return vs VaR on ISE 30 with Norm Dist. - 95 c.i. for 4th Period

Figure 36 Return vs VaR on Bank Index with Norm Dist. - 95 c.i. for 1st Period

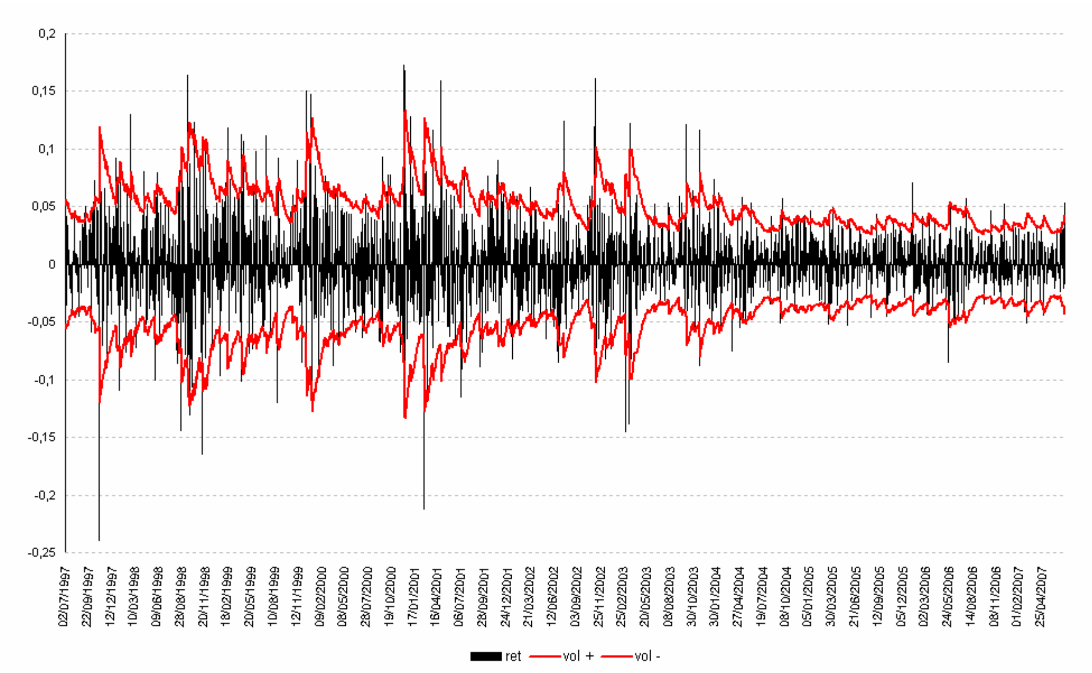


Figure 37 Return vs VaR on Bank Index with Norm Dist. - 95 c.i. for 2nd Period

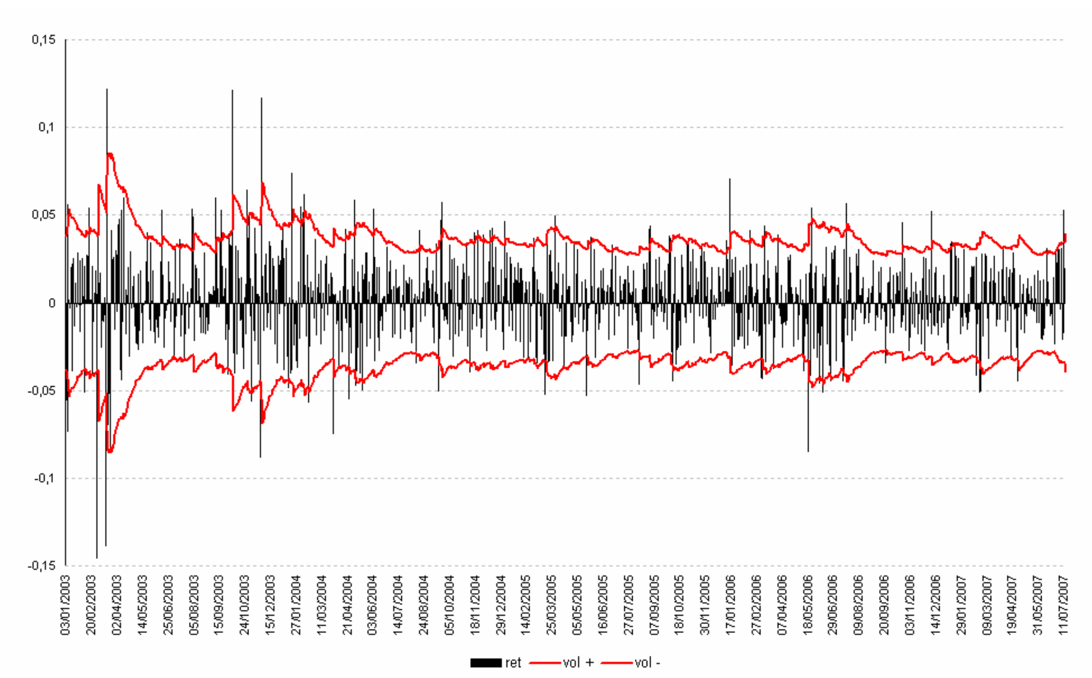


Figure 38 Return vs VaR on Bank Index with Norm Dist. - 95 c.i. for 3rd Period

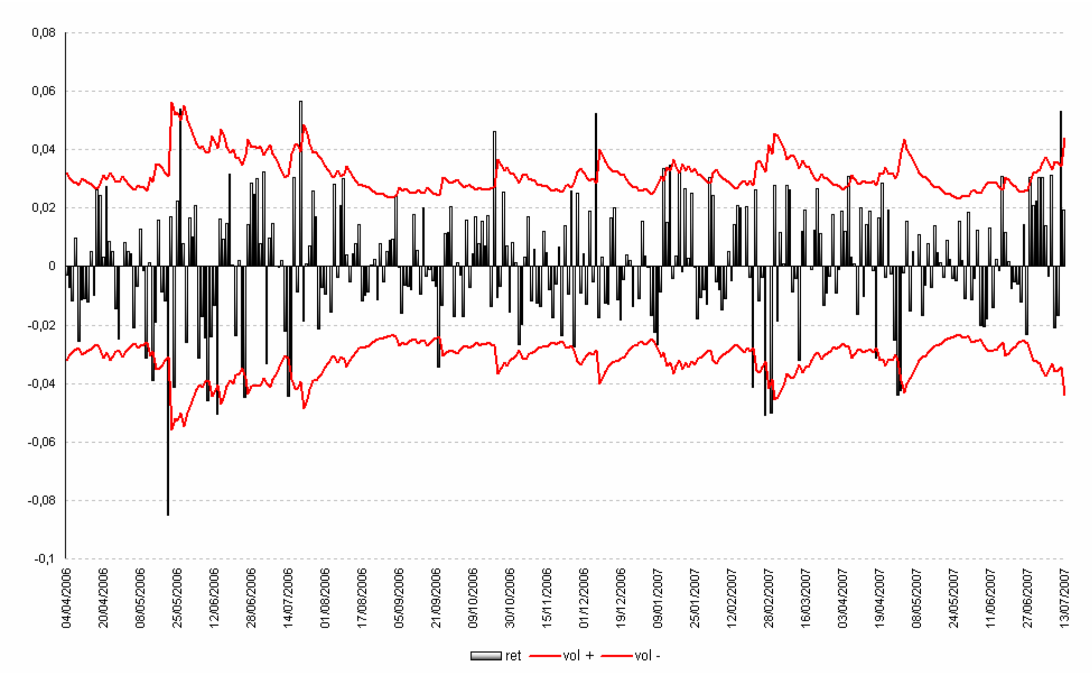


Figure 39 Return vs VaR on Bank Index with Norm Dist. - 95 c.i. for 4th Period

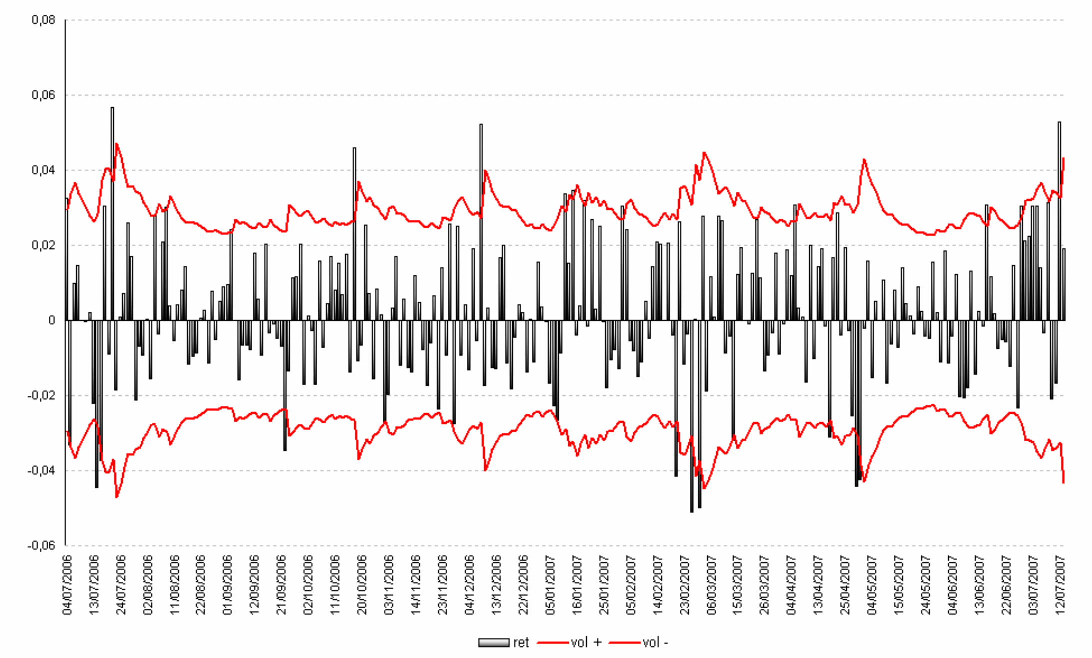


Figure 40 Return vs VaR on Akbank with Norm Dist. - 95 c.i. for 1st Period

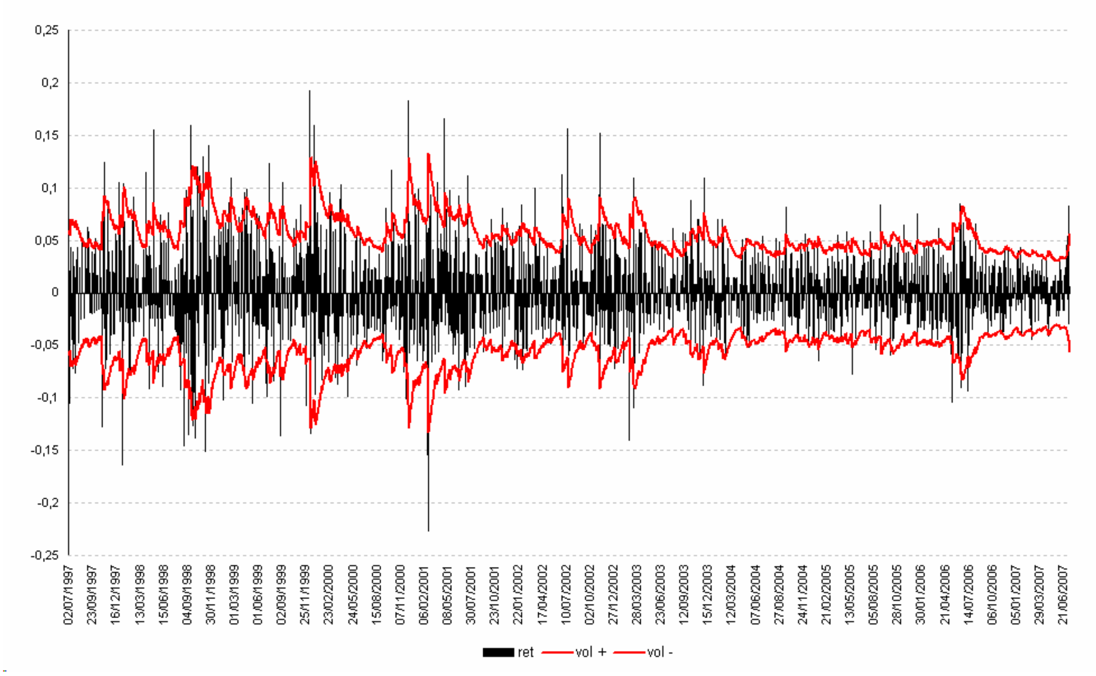


Figure 41 Return vs VaR on Akbank with Norm Dist. - 95 c.i. for 2nd Period

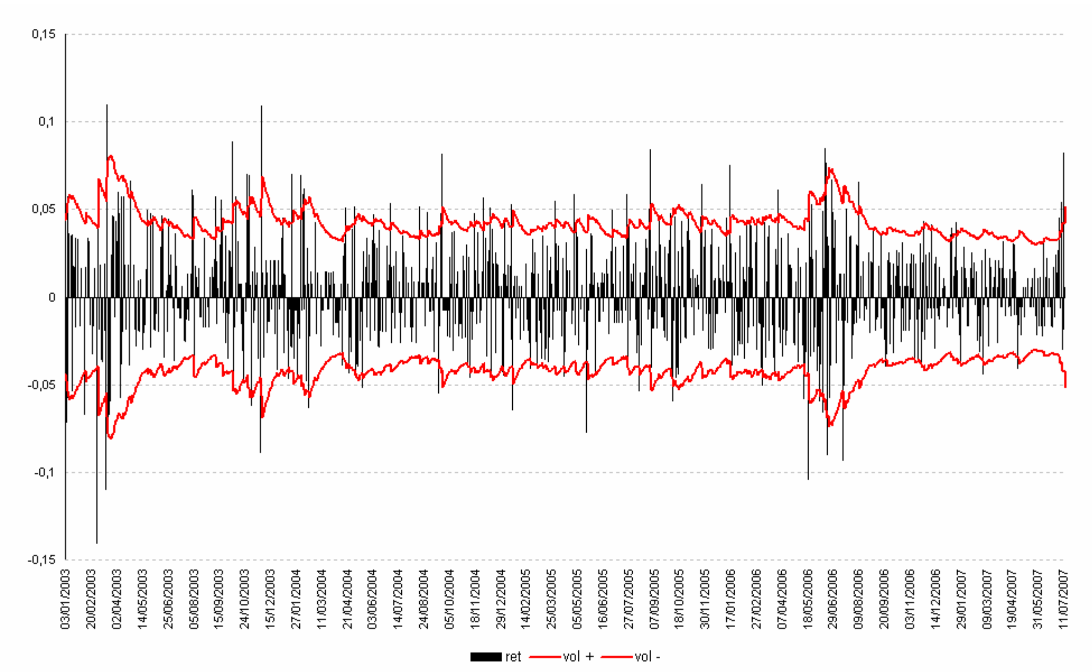


Figure 42 Return vs VaR on Akbank with Norm Dist. - 95 c.i. for 3rd Period

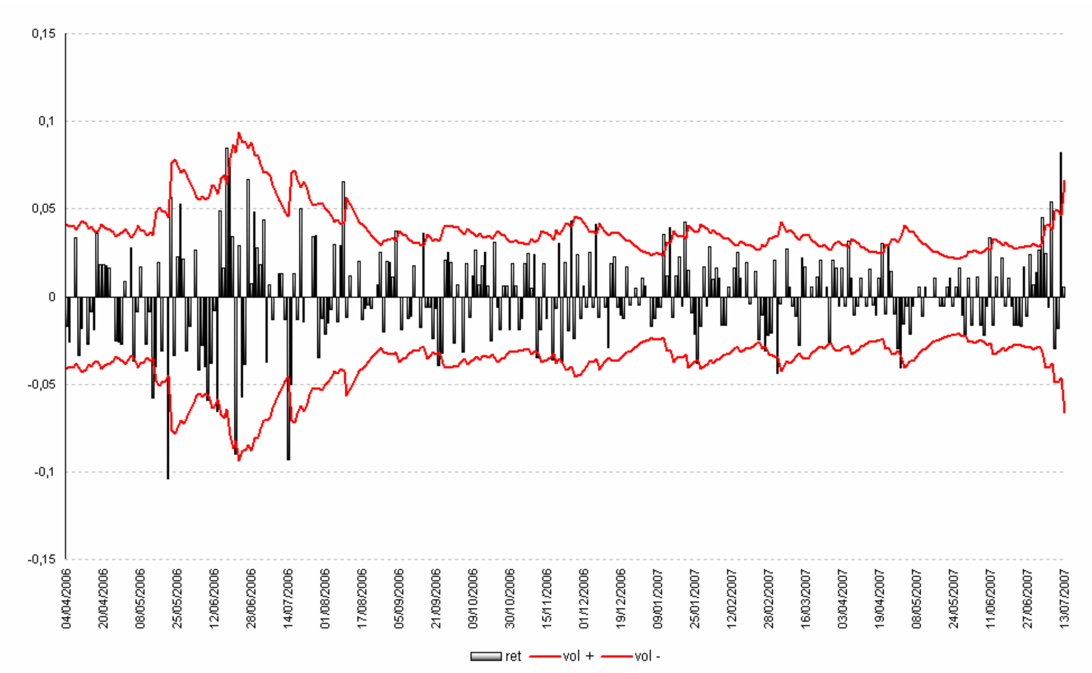


Figure 43 Return vs VaR on Akbank with Norm Dist. - 95 c.i. for 4th Period

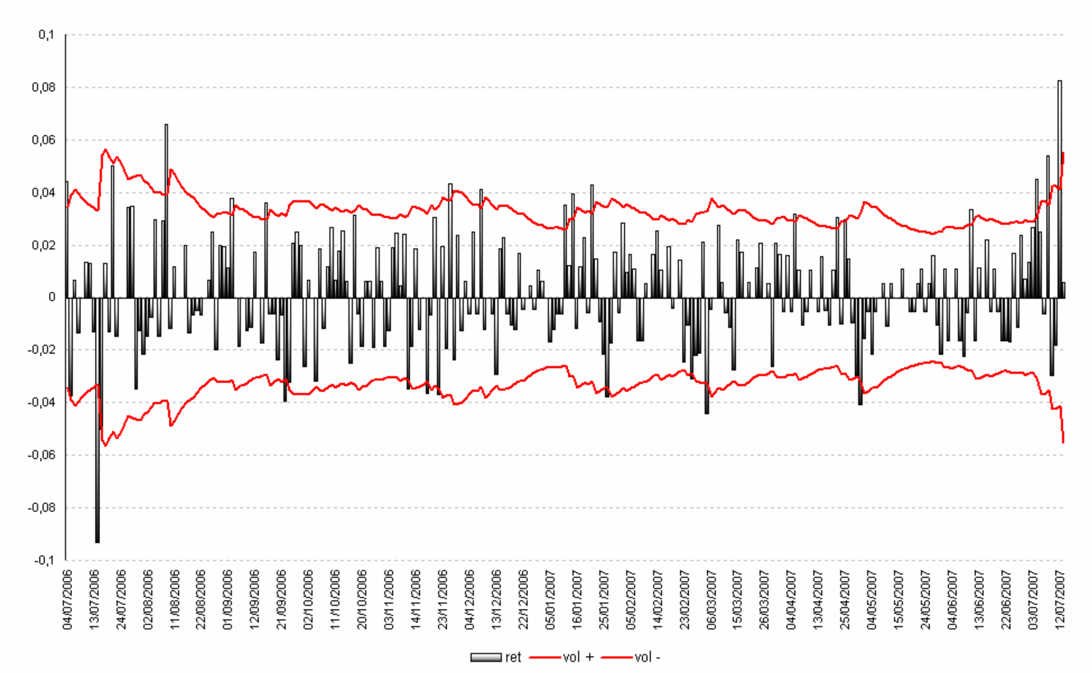


Figure 44 Return vs VaR on Yapı Kredi with Norm Dist. - 99 c.i. for 1st Period

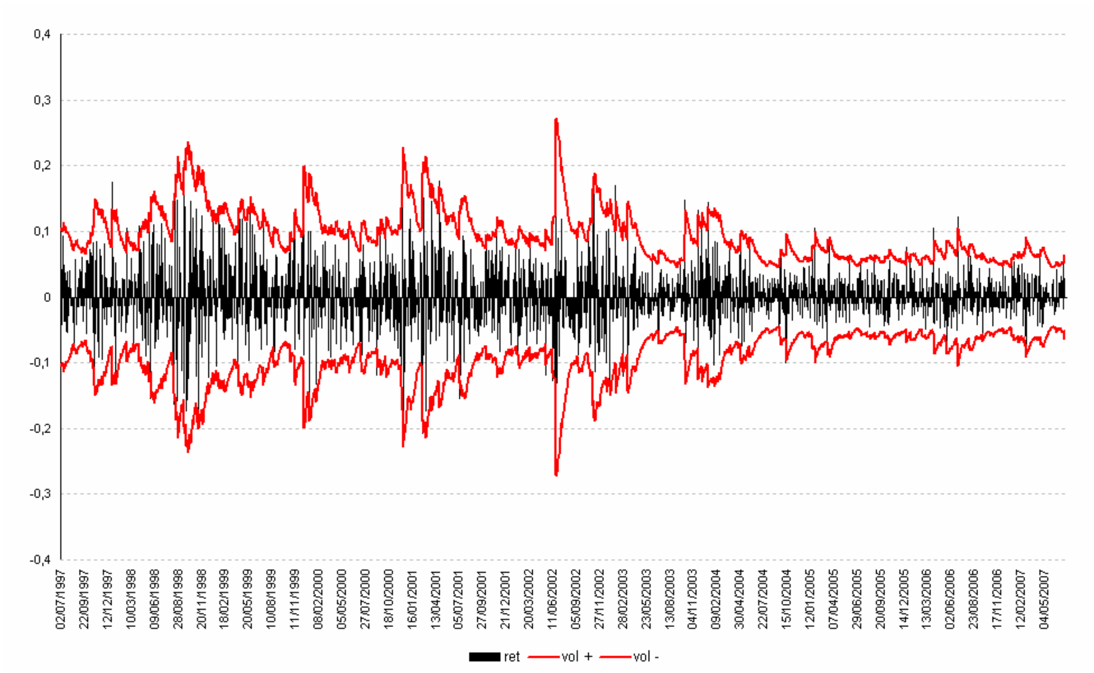


Figure 45 Return vs VaR on Yapı Kredi with Norm Dist. - 99 c.i. for 2nd Period

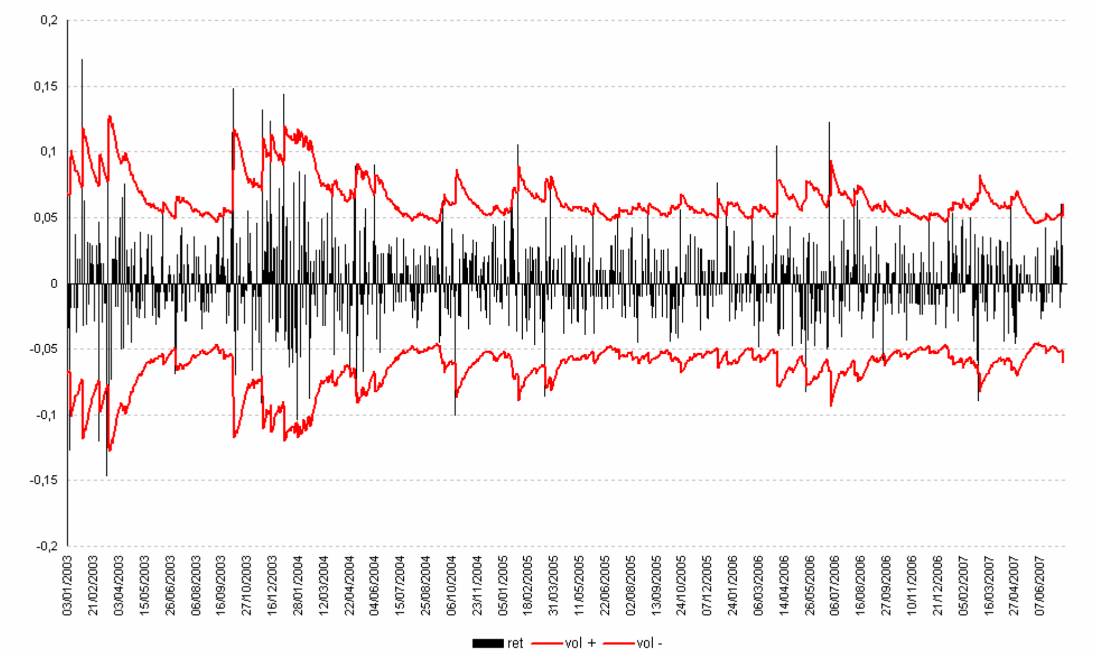


Figure 46 Return vs VaR on Yapı Kredi with Norm Dist. - 99 c.i. for 3rd Period

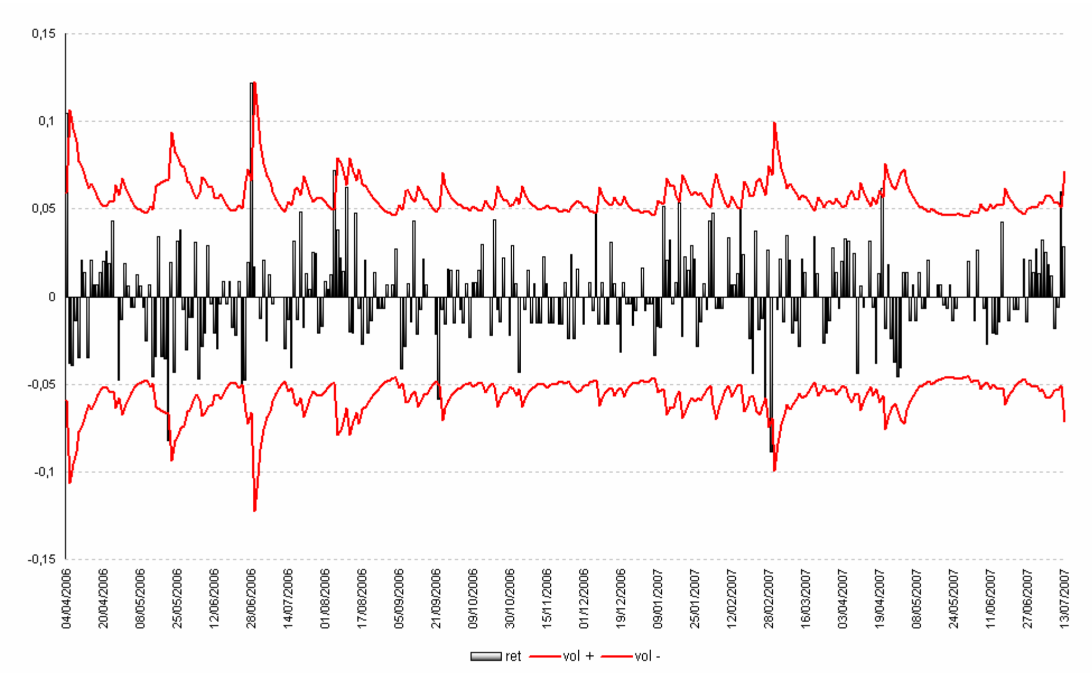


Figure 47 Return vs VaR on Yapı Kredi with Norm Dist. - 99 c.i. for 4th Period

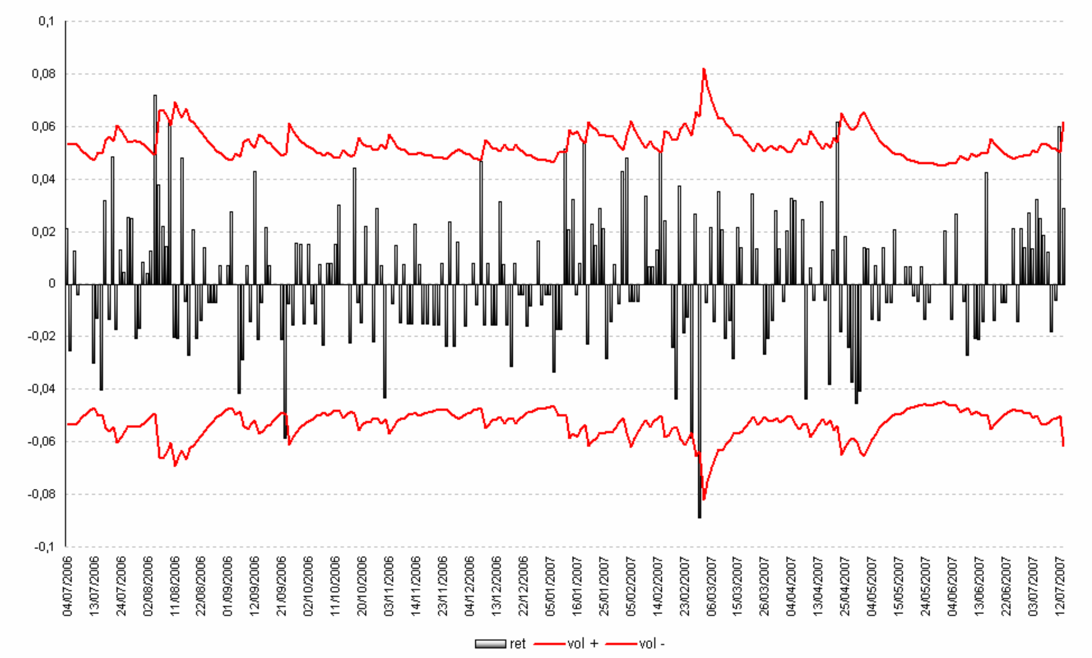


Figure 48 Return vs VaR on Yapı Kredi with Norm Dist. - 95 c.i. for 1st Period

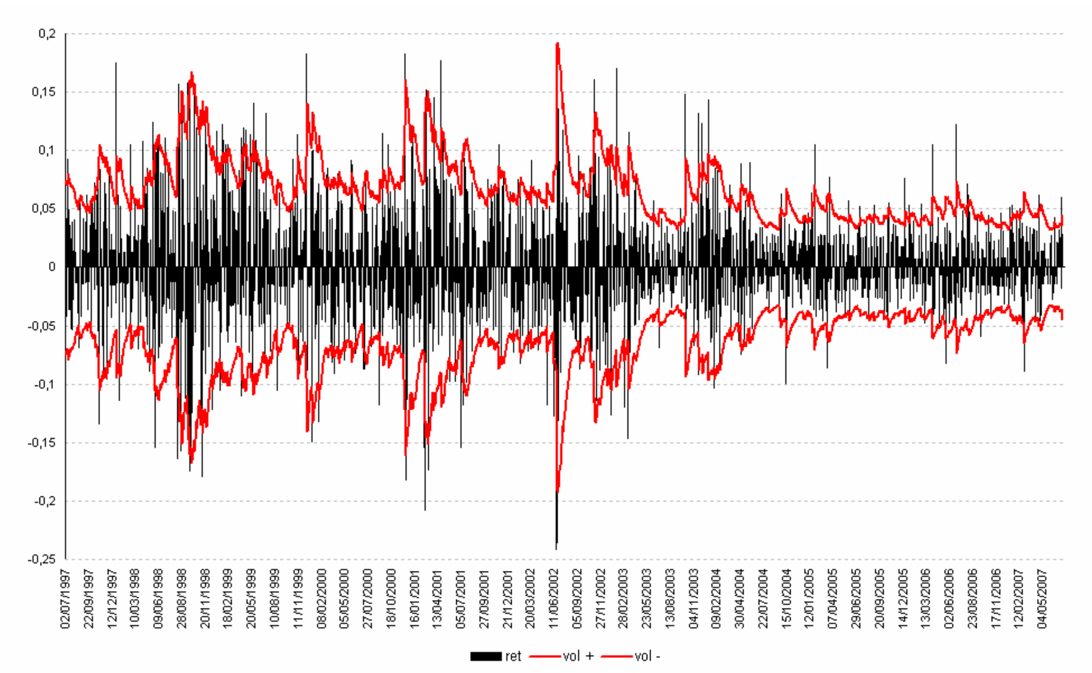


Figure 49 Return vs VaR on Yapı Kredi with Norm Dist. - 95 c.i. for 2nd Period

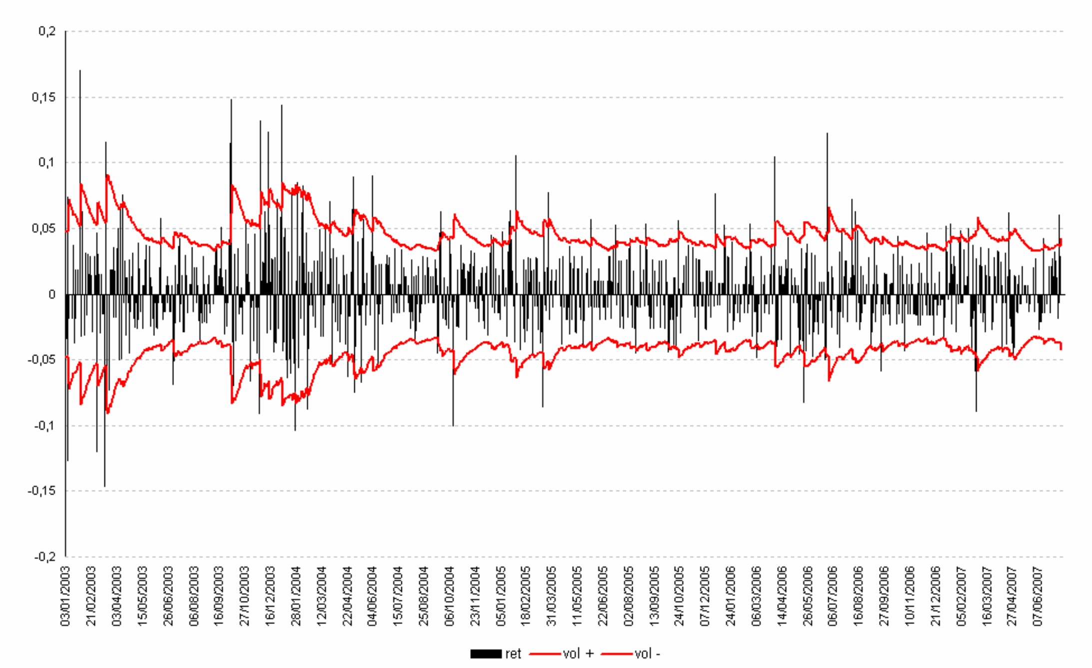


Figure 50 Return vs VaR on Yapı Kredi with Norm Dist. - 95 c.i. for 3rd Period

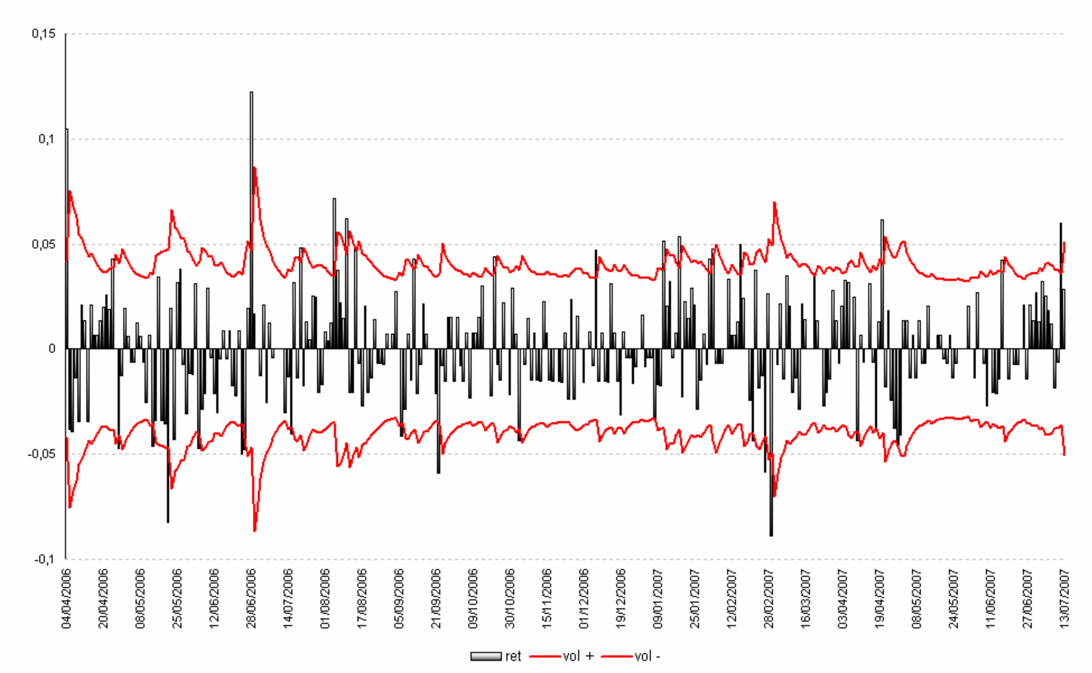


Figure 51 Return vs VaR on Yapı Kredi with Norm Dist. - 95 c.i. for 4th Period

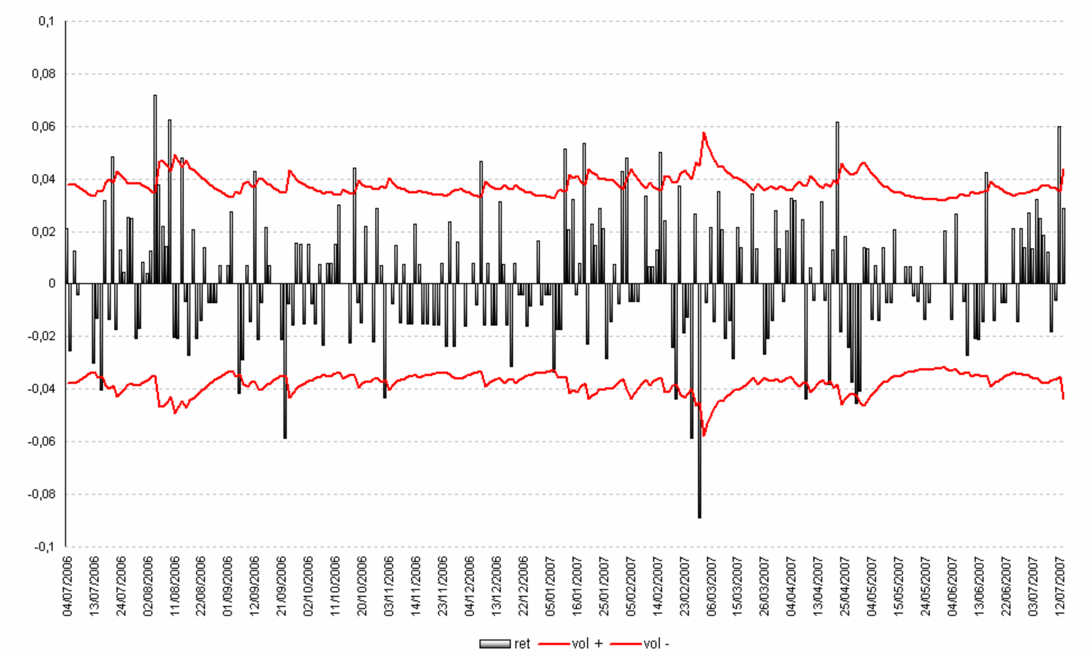


Figure 52 Return vs VaR on Sekerbank with Norm Dist. - 99 c.i. for 1st Period

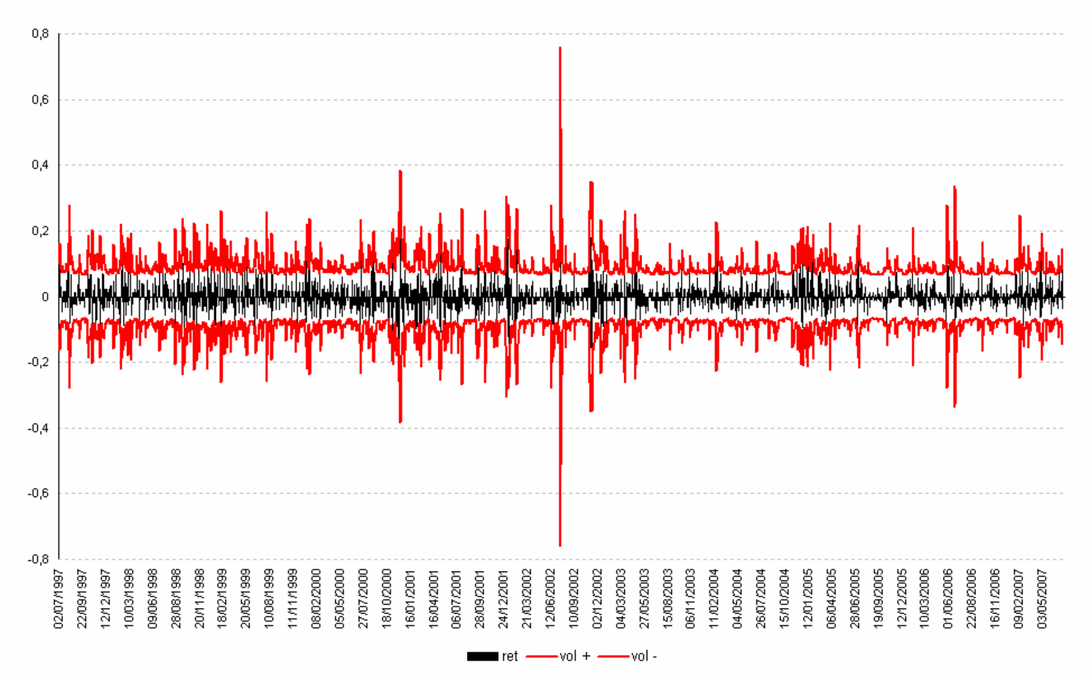


Figure 53 Return vs VaR on Sekerbank with Norm Dist. - 99 c.i. for 2nd Period

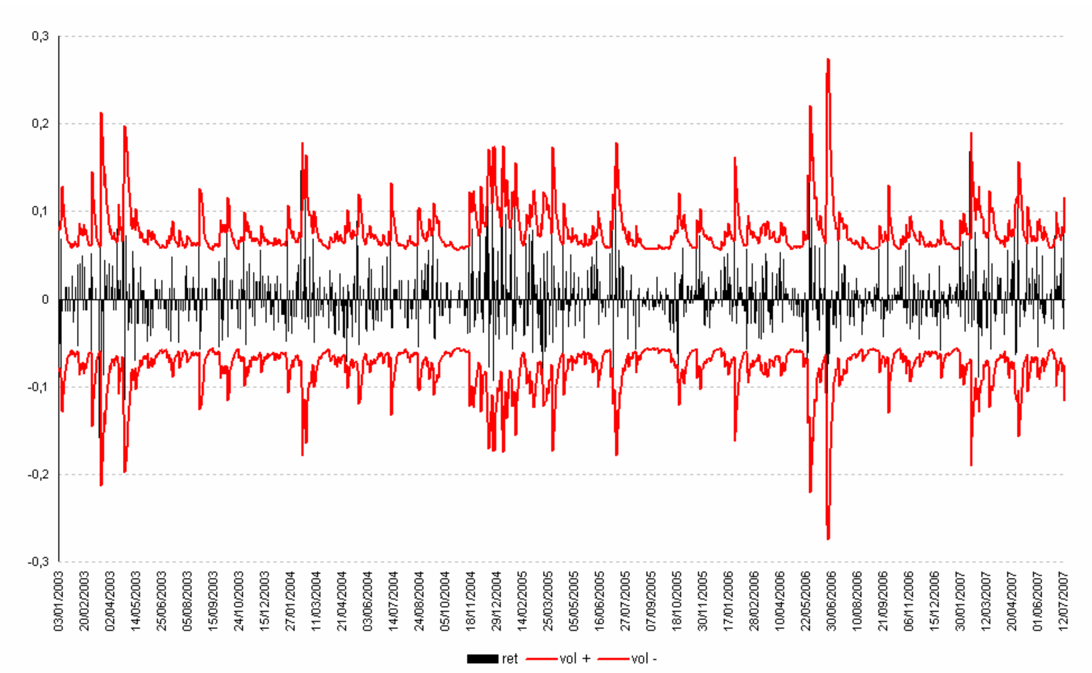


Figure 54 Return vs VaR on Sekerbank with Norm Dist. - 99 c.i. for 3rd Period

Figure 55 Return vs VaR on Sekerbank with Norm Dist. - 99 c.i. for 4th Period

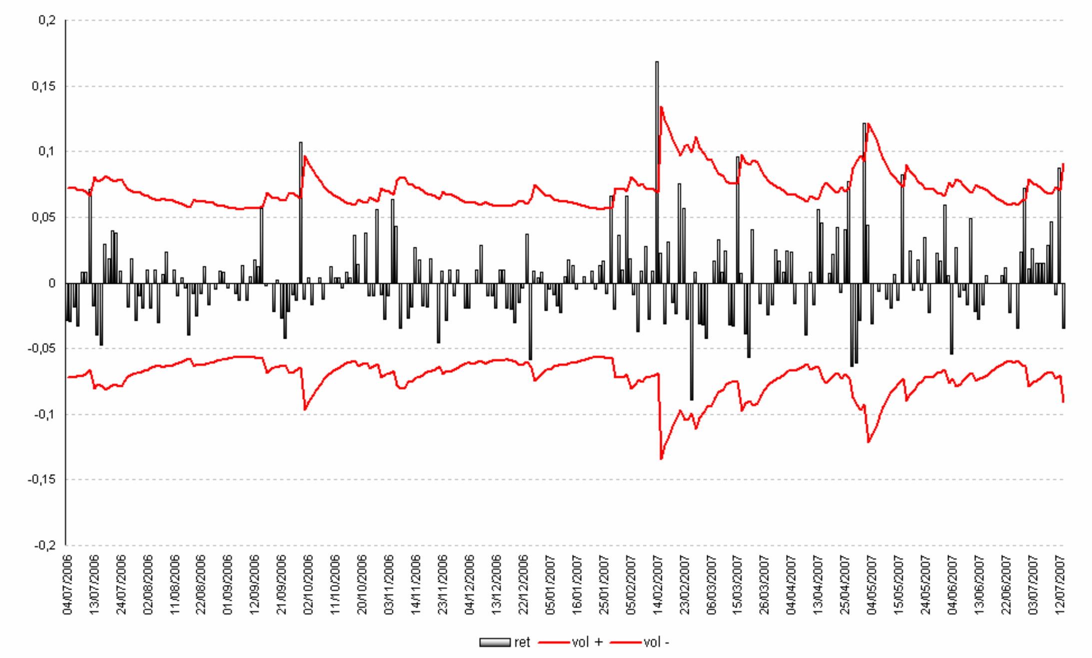


Figure 56 Return vs VaR on Sekerbank with Norm Dist. - 95 c.i. for 1st Period

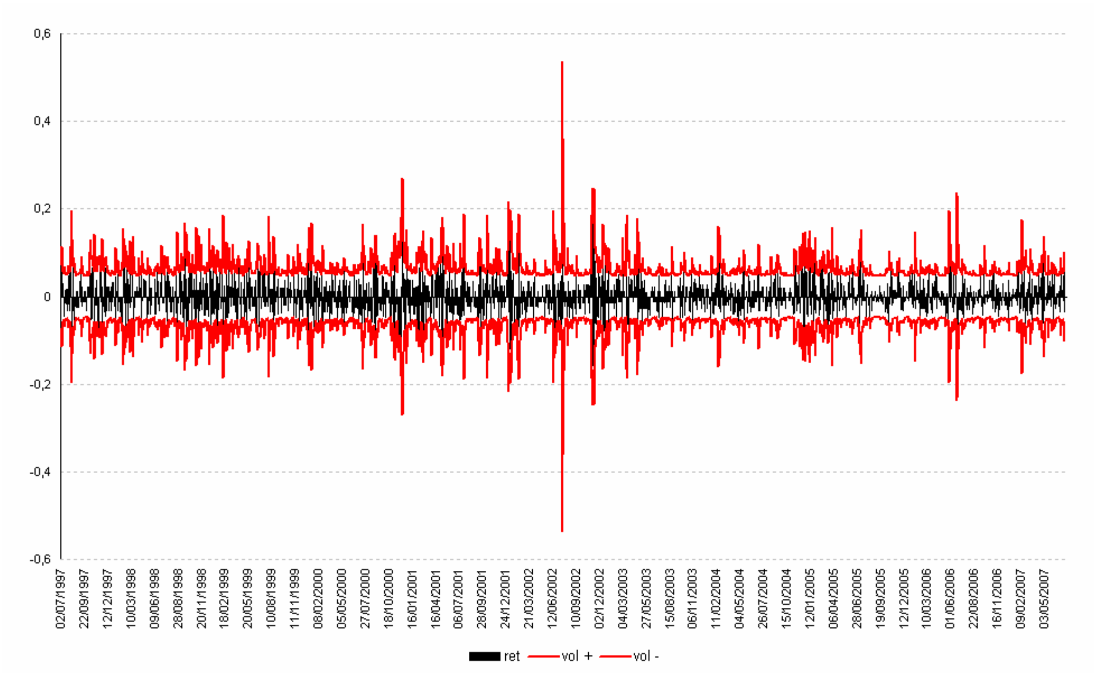


Figure 57 Return vs VaR on Sekerbank with Norm Dist. - 95 c.i. for 2nd Period

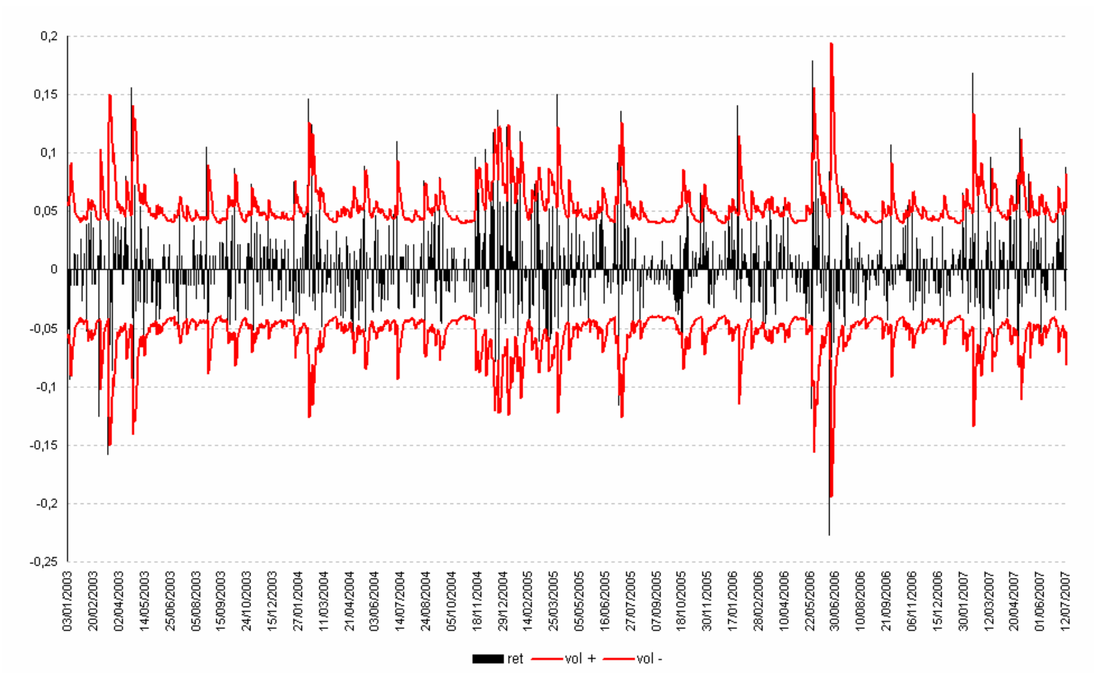


Figure 58 Return vs VaR on Sekerbank with Norm Dist. - 95 c.i. for 3rd Period

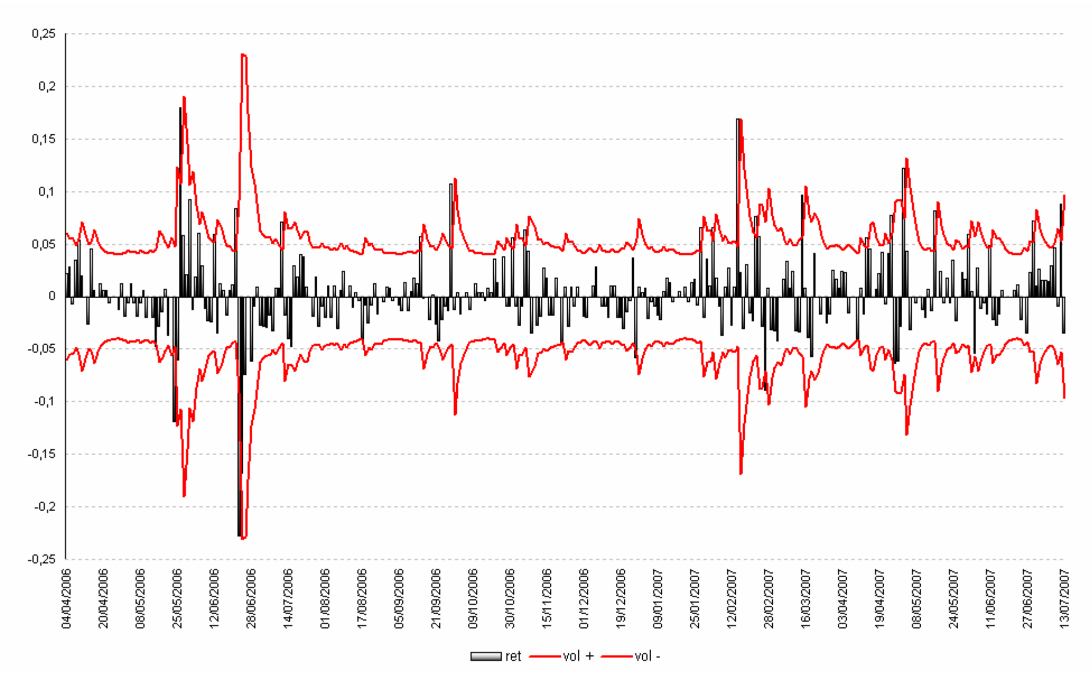


Figure 59 Return vs VaR on Sekerbank with Norm Dist. - 95 c.i. for 4th Period

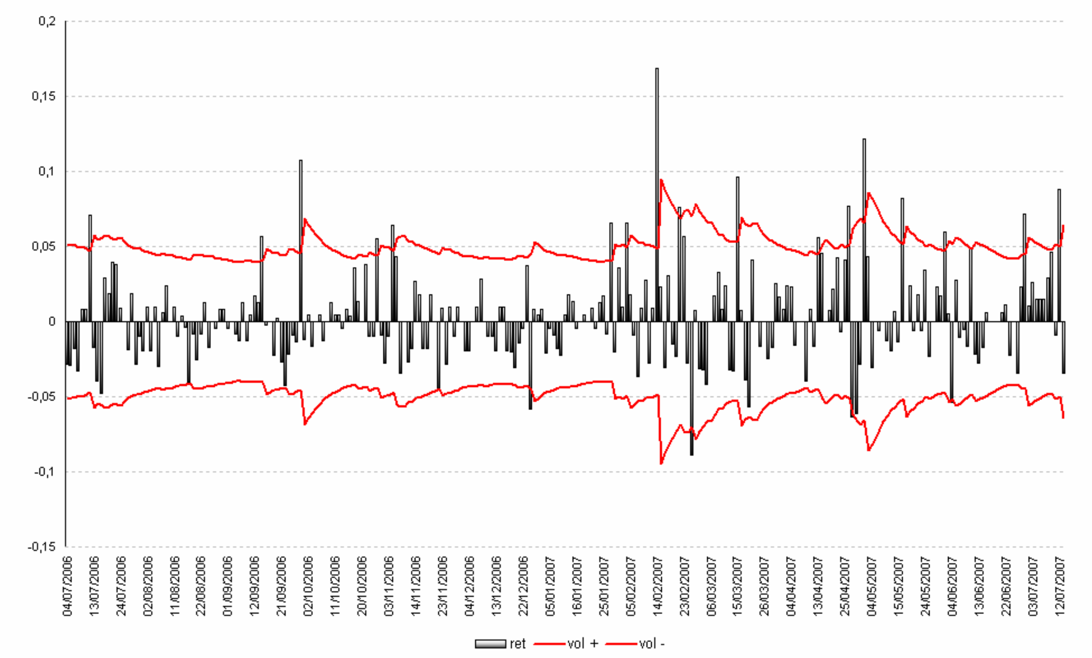


Figure 60 Return vs VaR on ISC with Norm Dist. - 99 c.i. for 1st Period

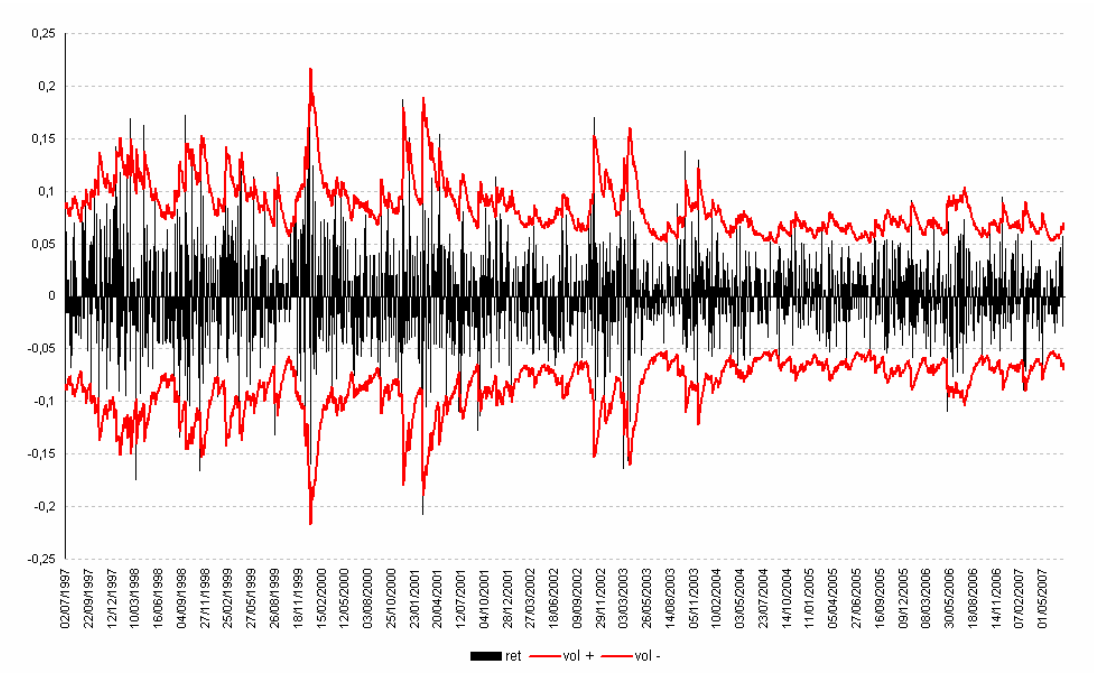


Figure 61 Return vs VaR on ISC with Norm Dist. - 99 c.i. for 2nd Period

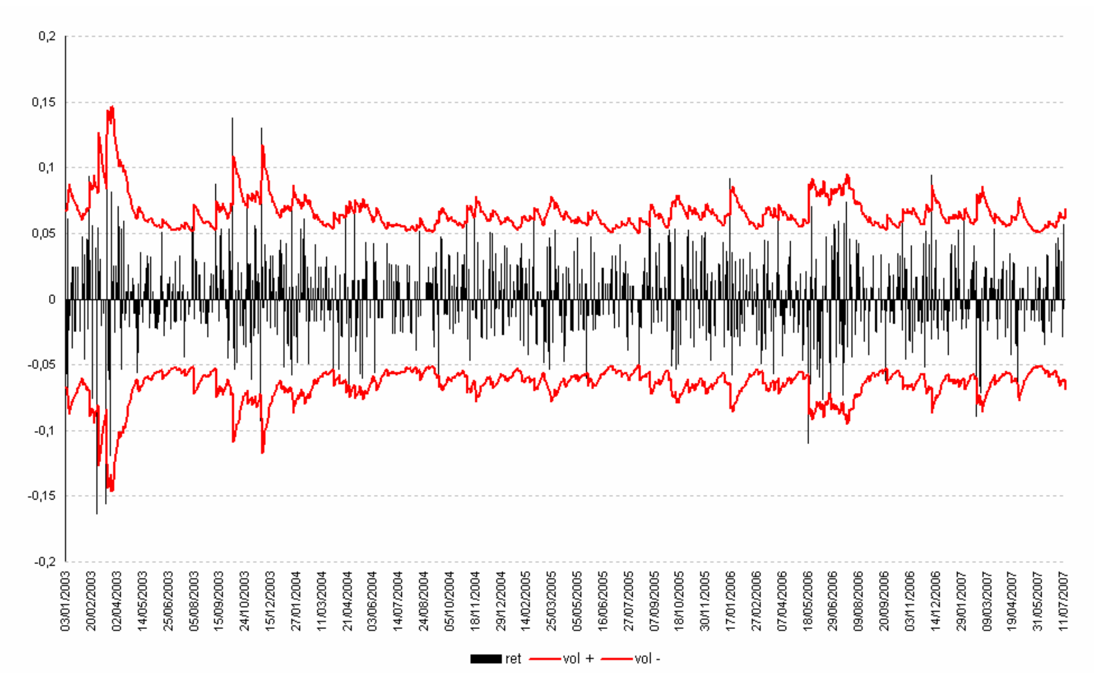


Figure 62 Return vs VaR on ISC with Norm Dist. - 99 c.i. for 3rd Period

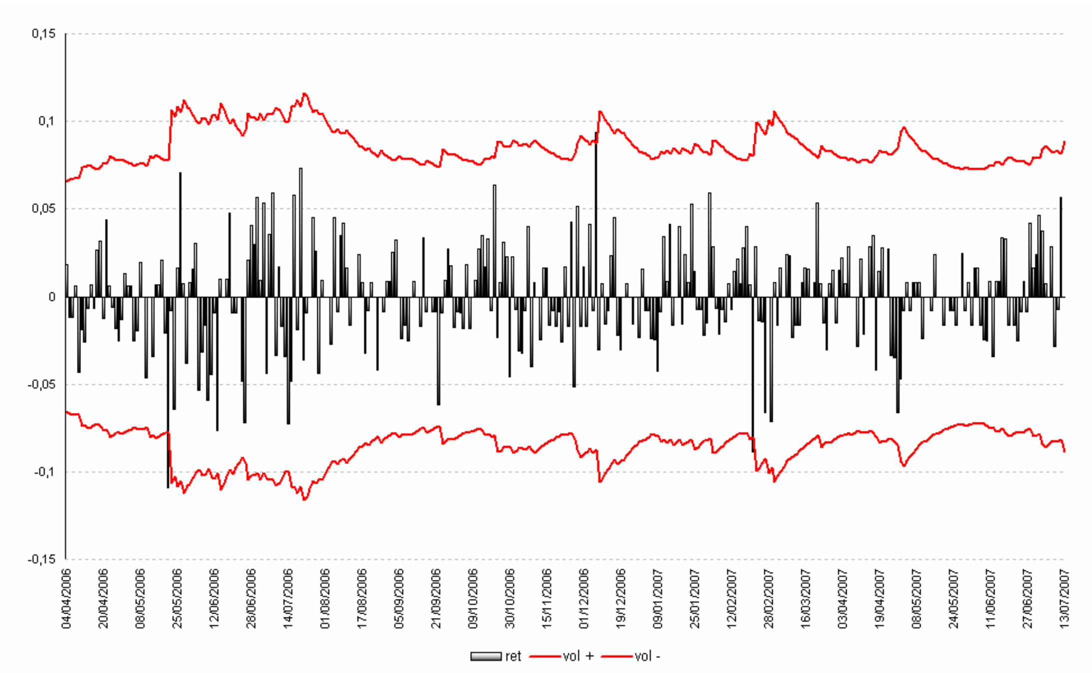


Figure 63 Return vs VaR on ISC with Norm Dist. - 99 c.i. for 4th Period

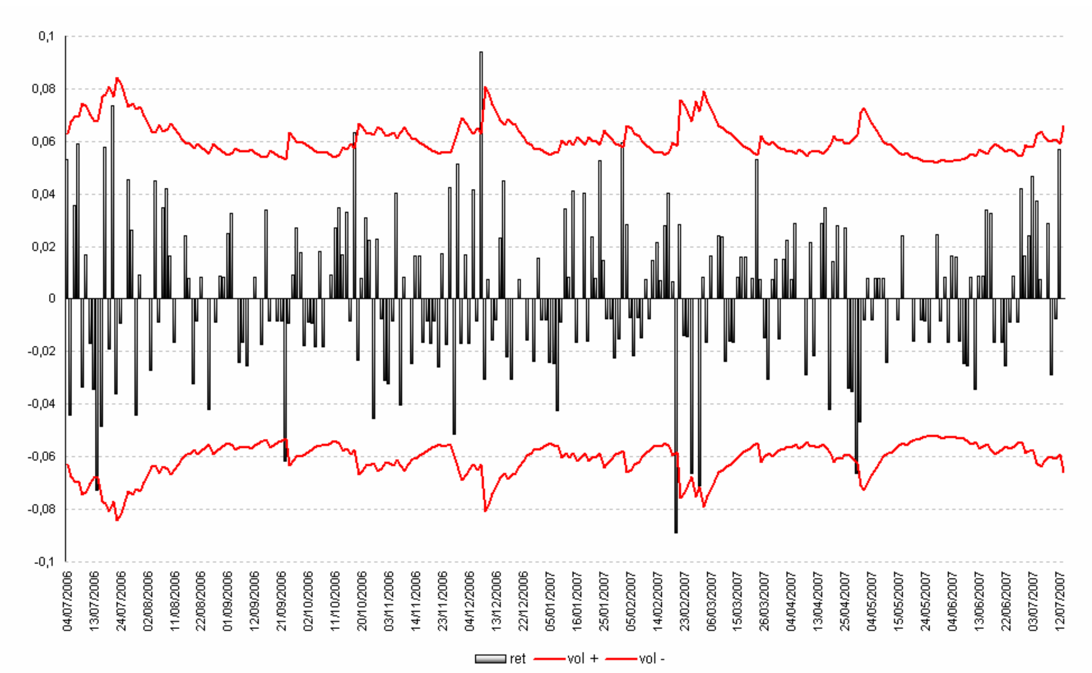


Figure 64 Return vs VaR on ISC with Norm Dist. - 95 c.i. for 1st Period

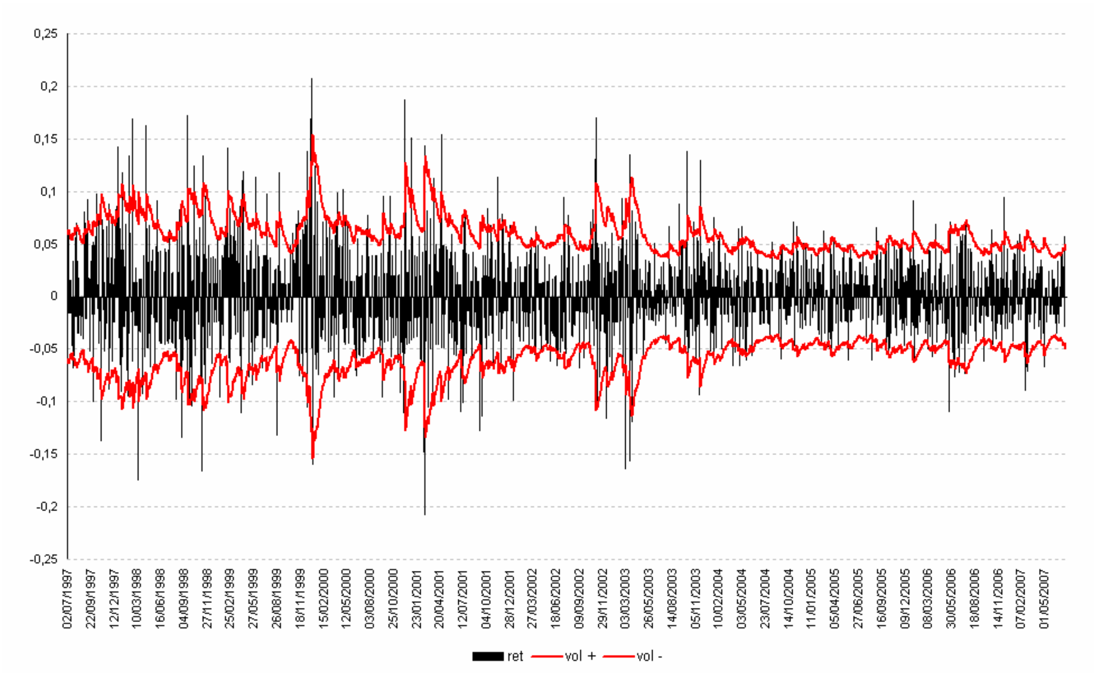


Figure 65 Return vs VaR on ISC with Norm Dist. - 95 c.i. for 2nd Period

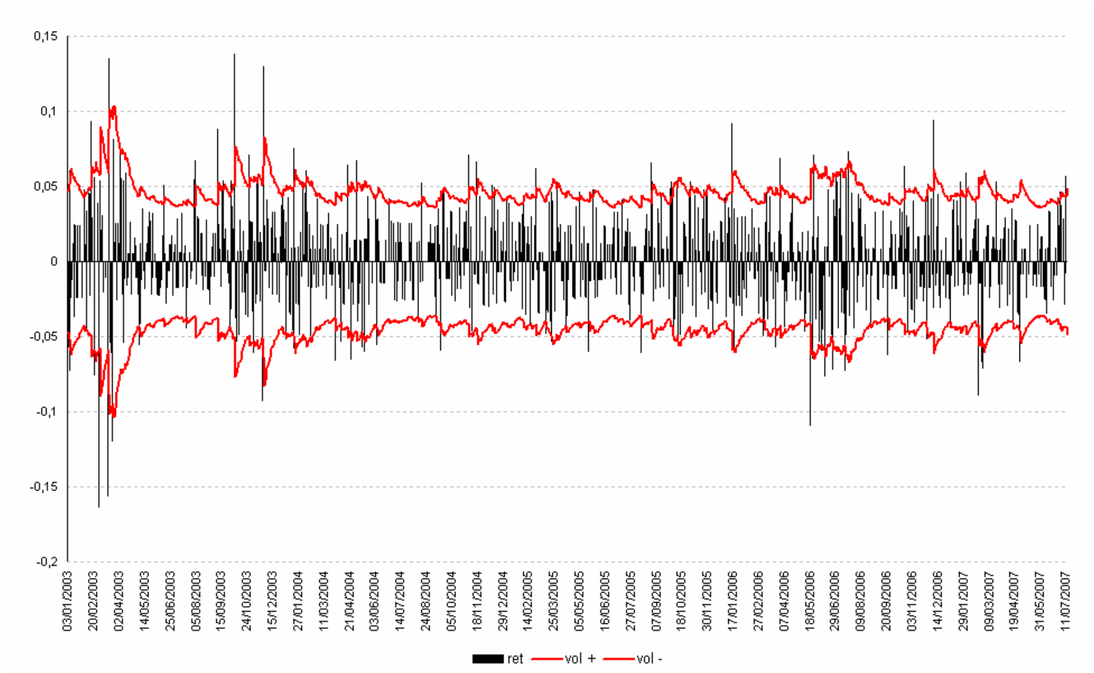


Figure 66 Return vs VaR on ISC with Norm Dist. - 95 c.i. for 3rd Period

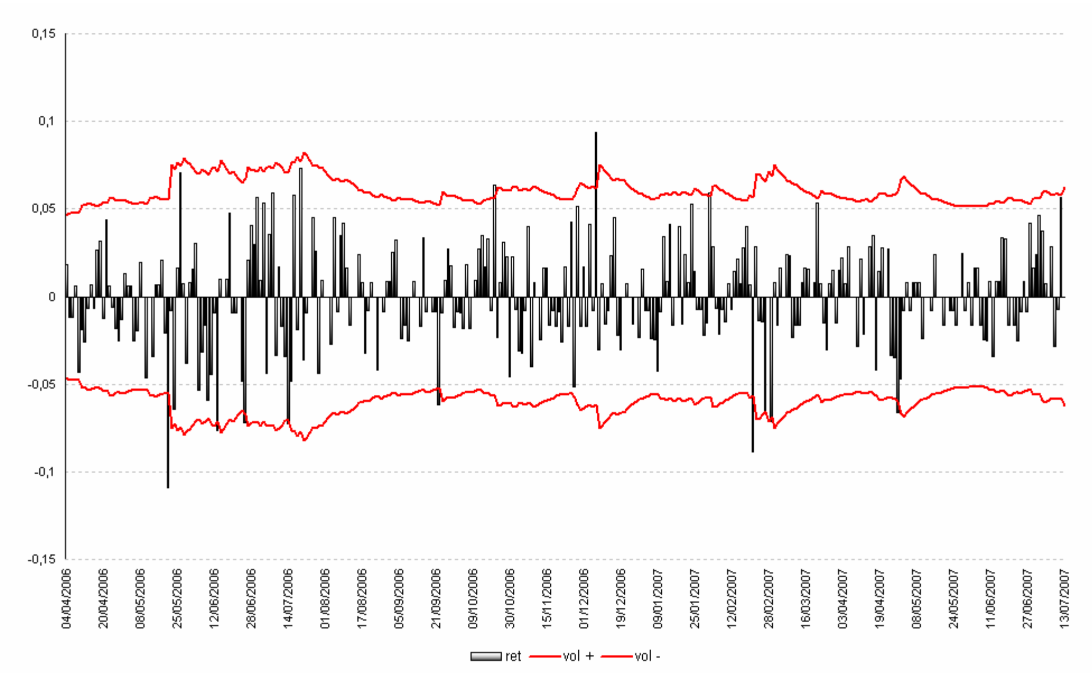


Figure 67 Return vs VaR on ISC with Norm Dist. - 95 c.i. for 4th Period

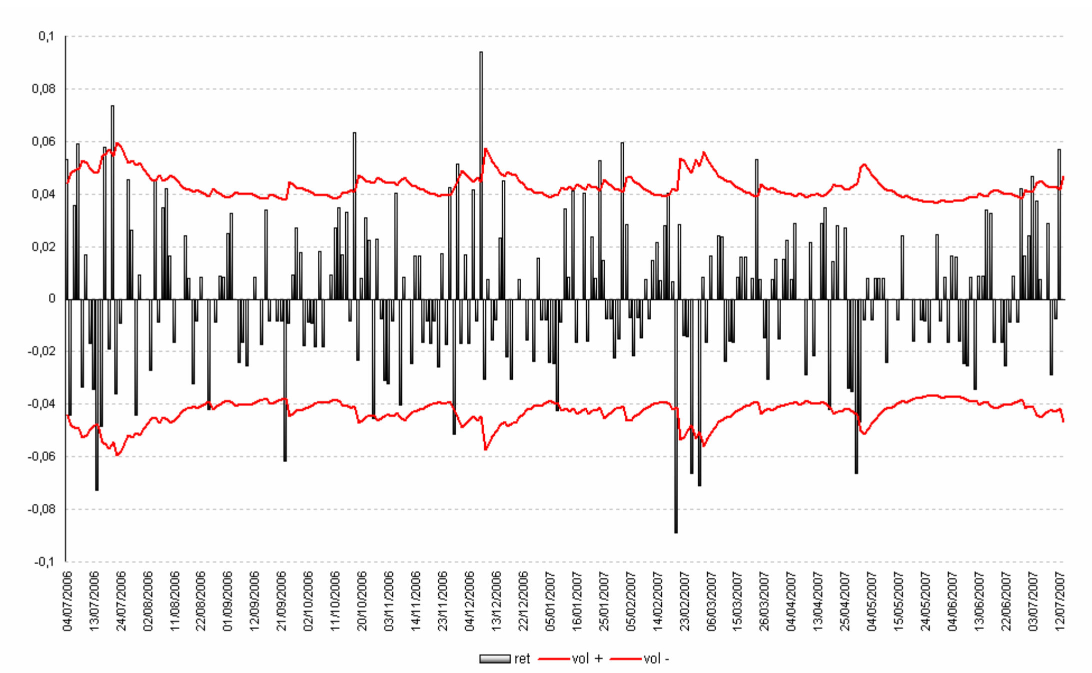


Figure 68 Return vs VaR on Finansbank with Norm Dist. - 99 c.i. for 1st Period

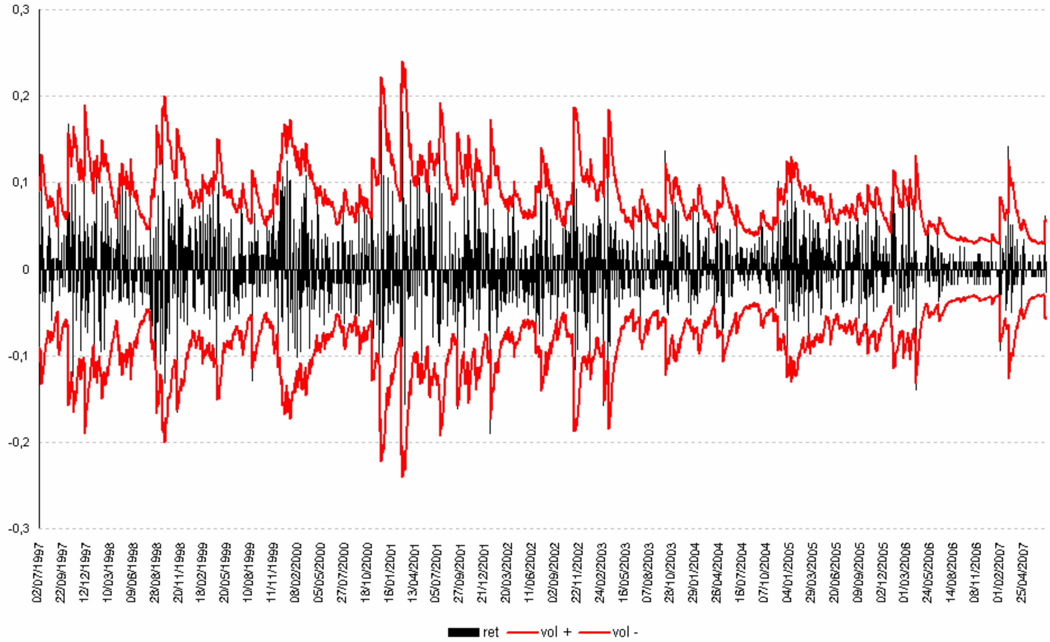


Figure 69 Return vs VaR on Finansbank with Norm Dist. - 99 c.i. for 2nd Period

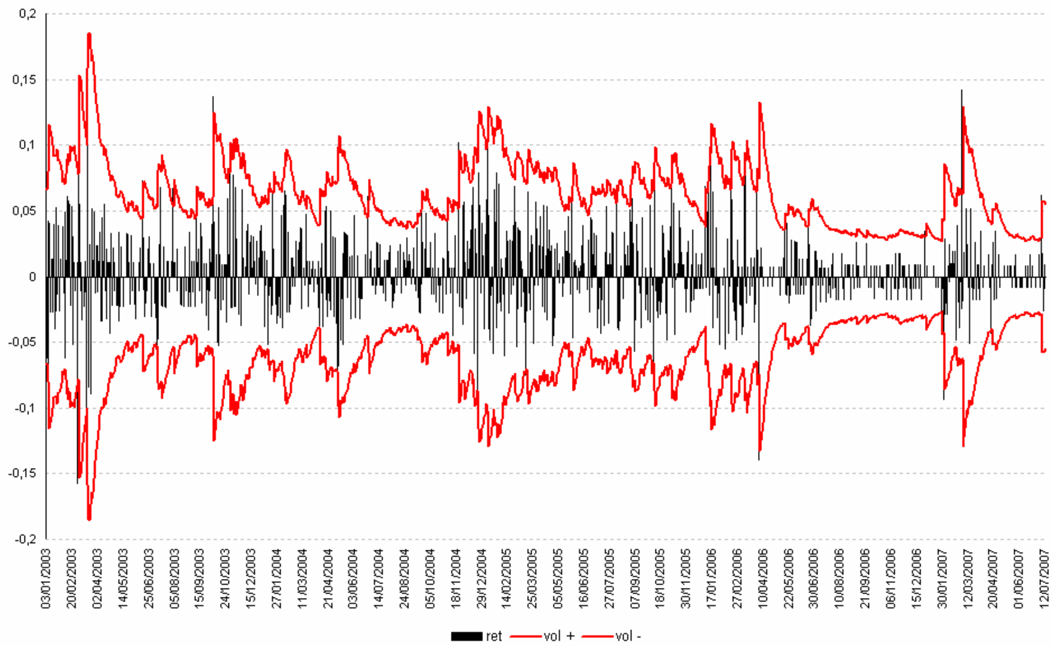


Figure 70 Return vs VaR on Finansbank with Norm Dist. - 99 c.i. for 3rd Period

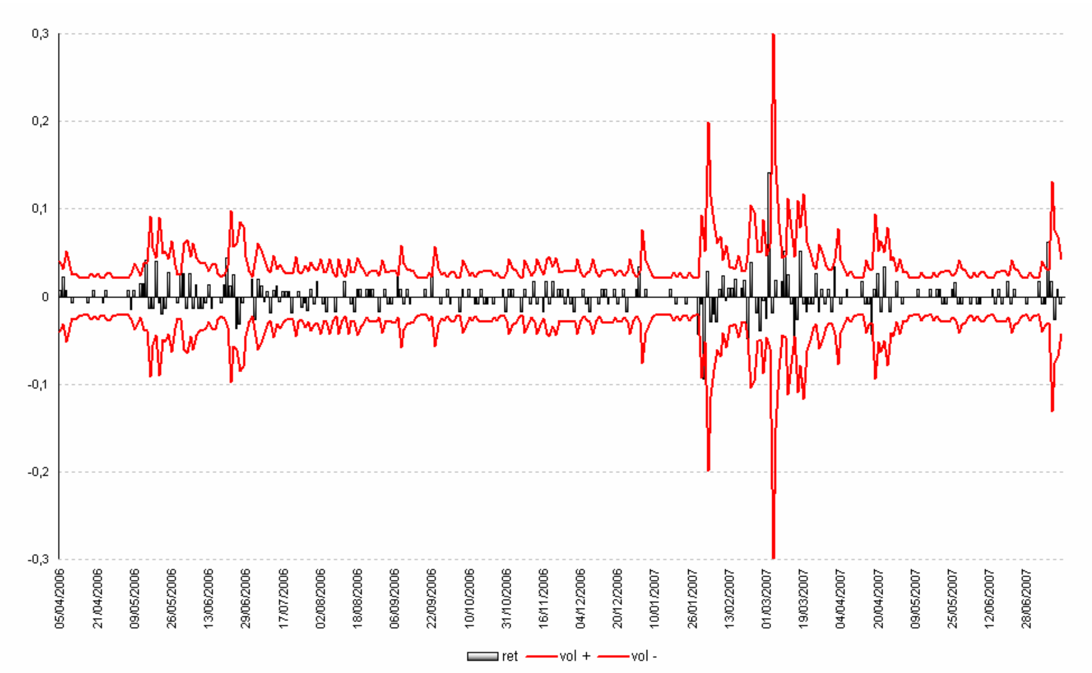


Figure 71 Return vs VaR on Finansbank with Norm Dist. - 99 c.i. for 4th Period

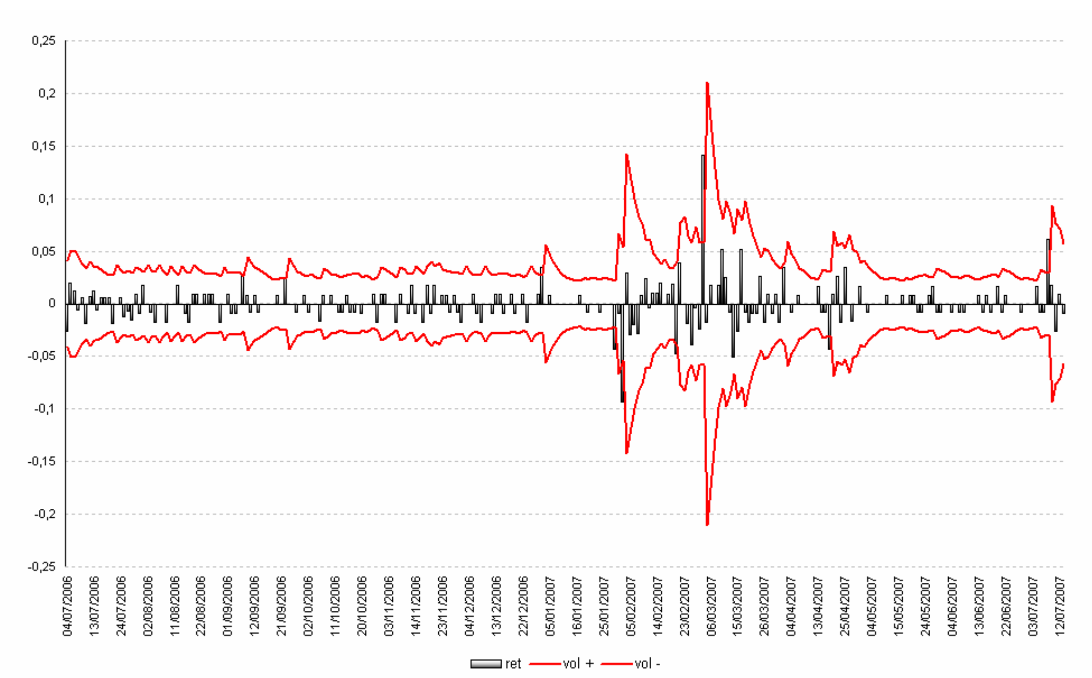


Figure 72 Return vs VaR on Finansbank with Norm Dist. - 95 c.i. for 1st Period

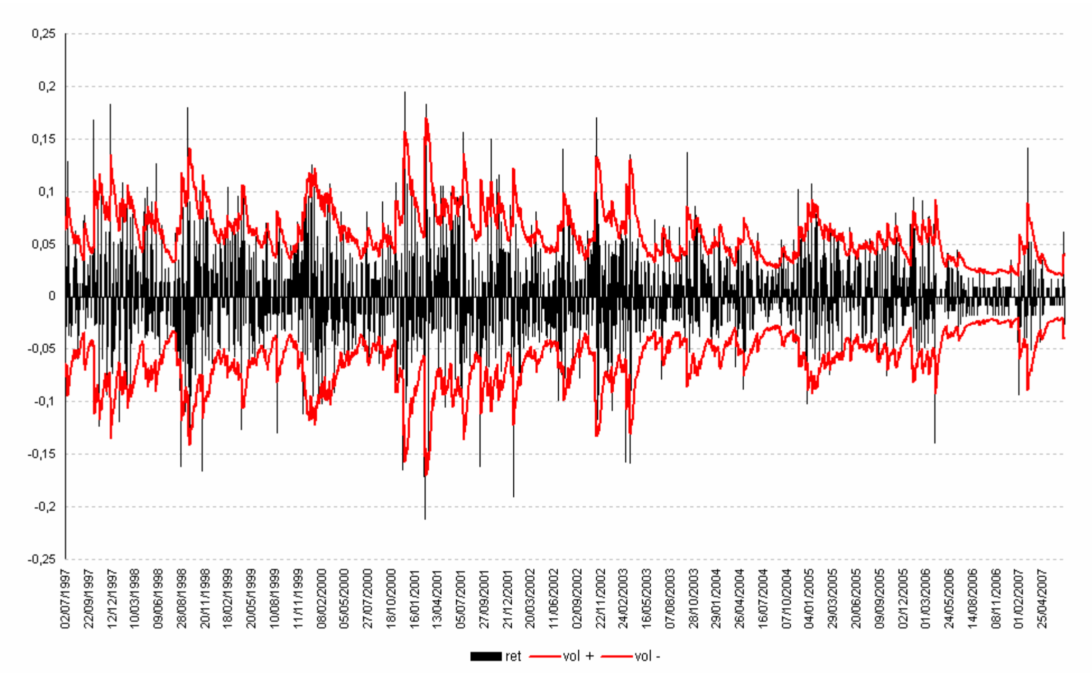


Figure 73 Return vs VaR on Finansbank with Norm Dist. - 95 c.i. for 2nd Period

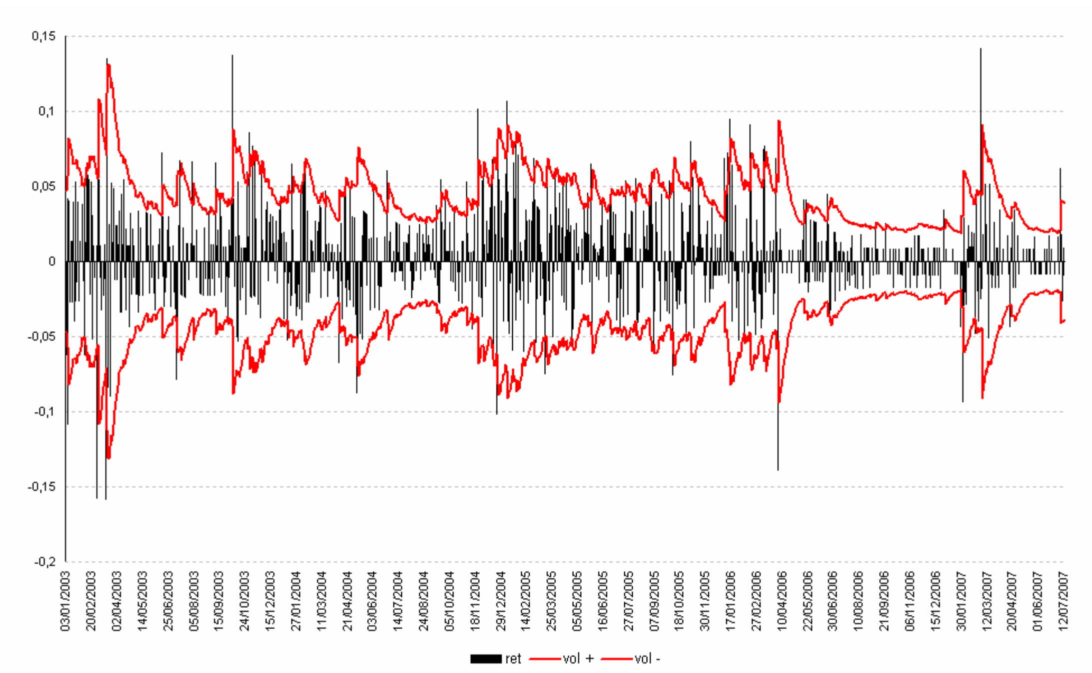


Figure 74 Return vs VaR on Finansbank with Norm Dist. - 95 c.i. for 3rd Period

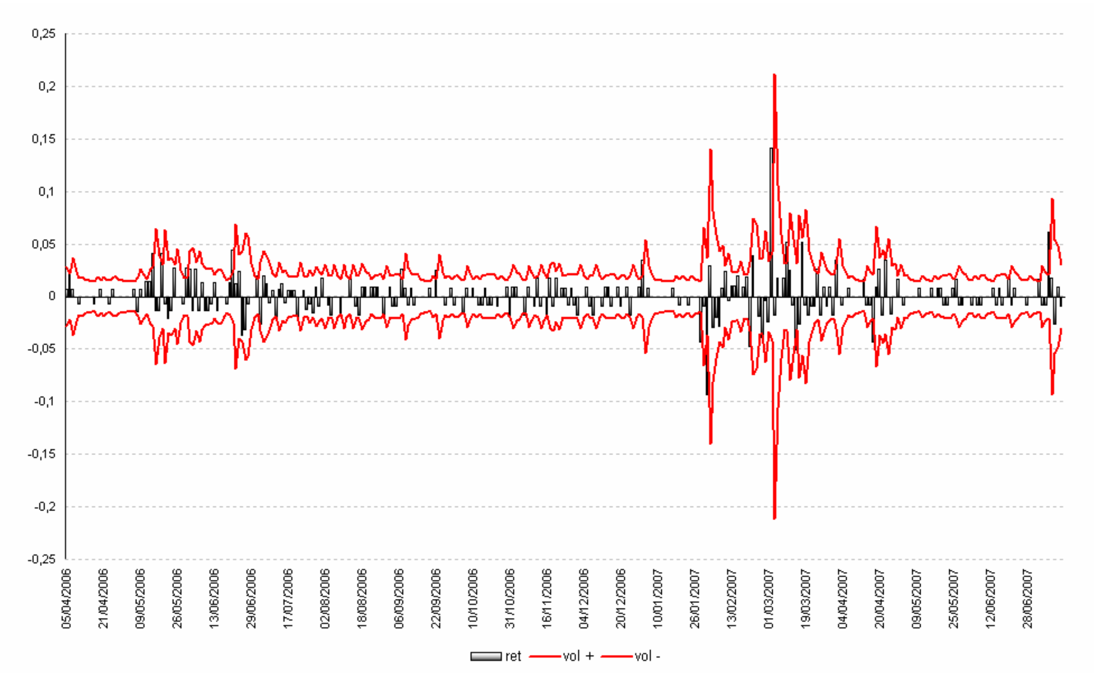


Figure 75 Return vs VaR on Finansbank with Norm Dist. - 95 c.i. for 4th Period

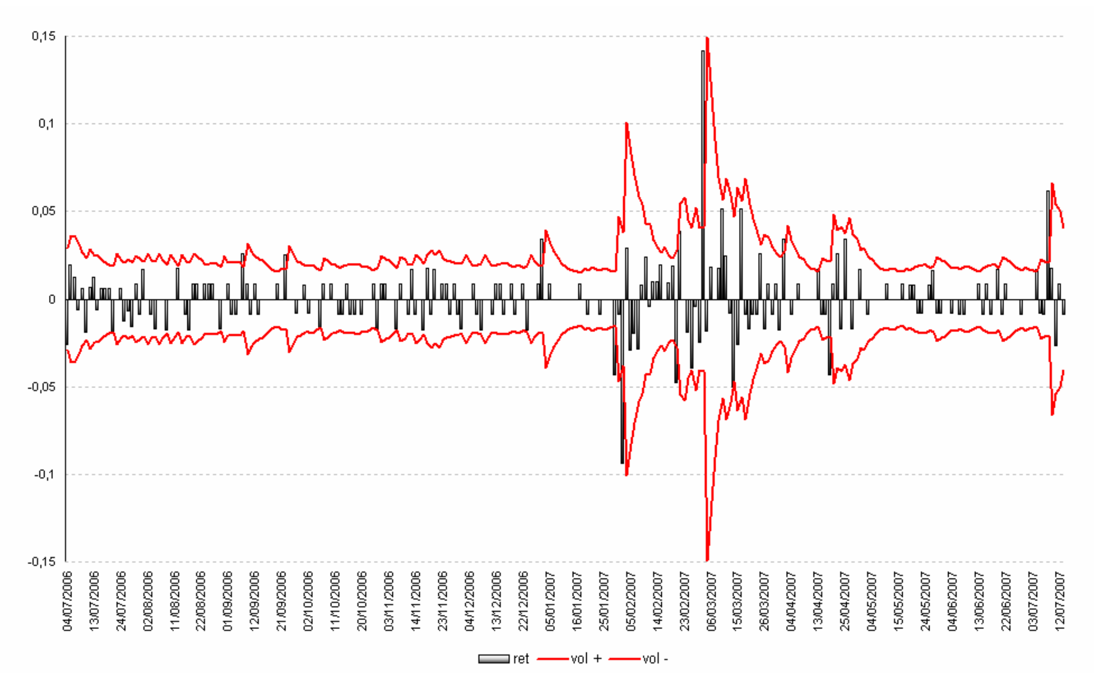


Figure 76 Return vs VaR on Alternatifbank with Norm Dist. - 99 c.i. for 1st Period

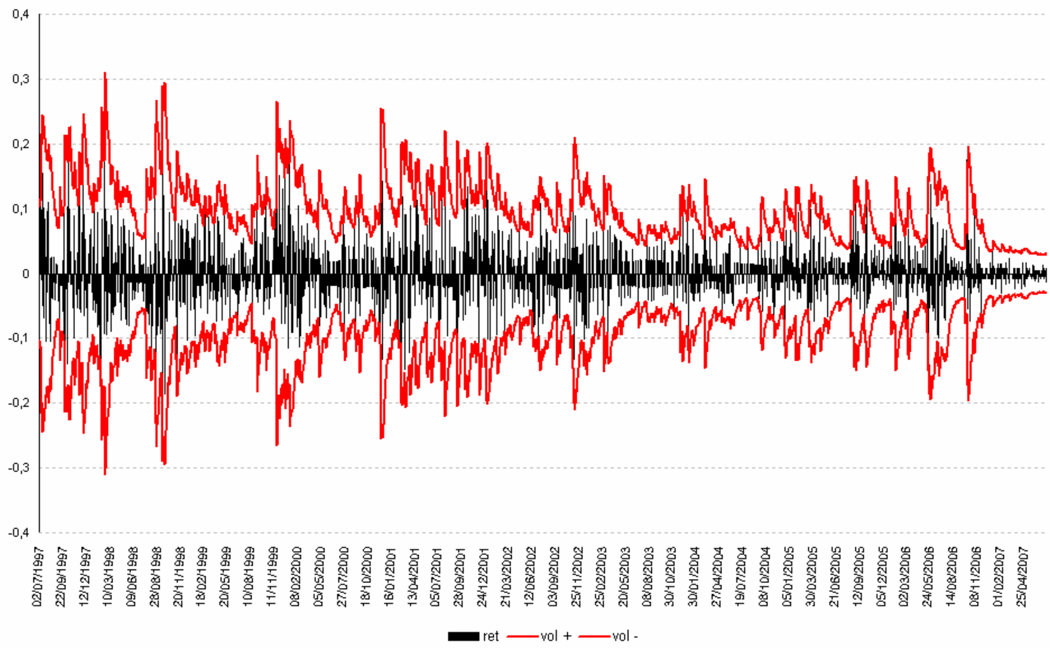


Figure 77 Return vs VaR on Alternatifbank with Norm Dist. - 99 c.i. for 2nd Period

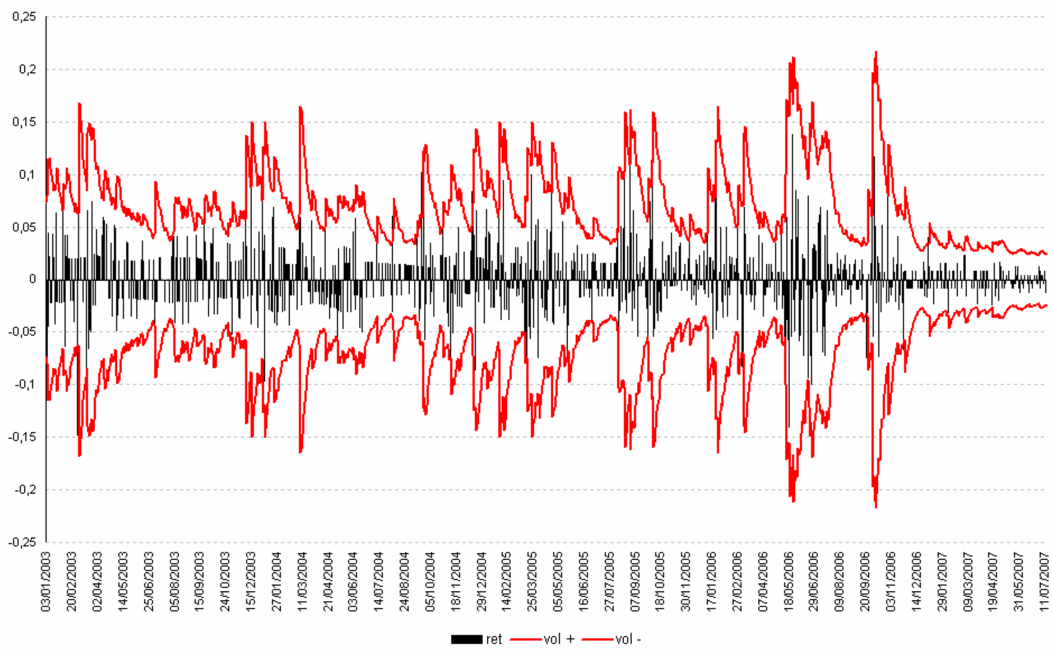


Figure 78 Return vs VaR on Alternatifbank with Norm Dist. - 99 c.i. for 3rd Period

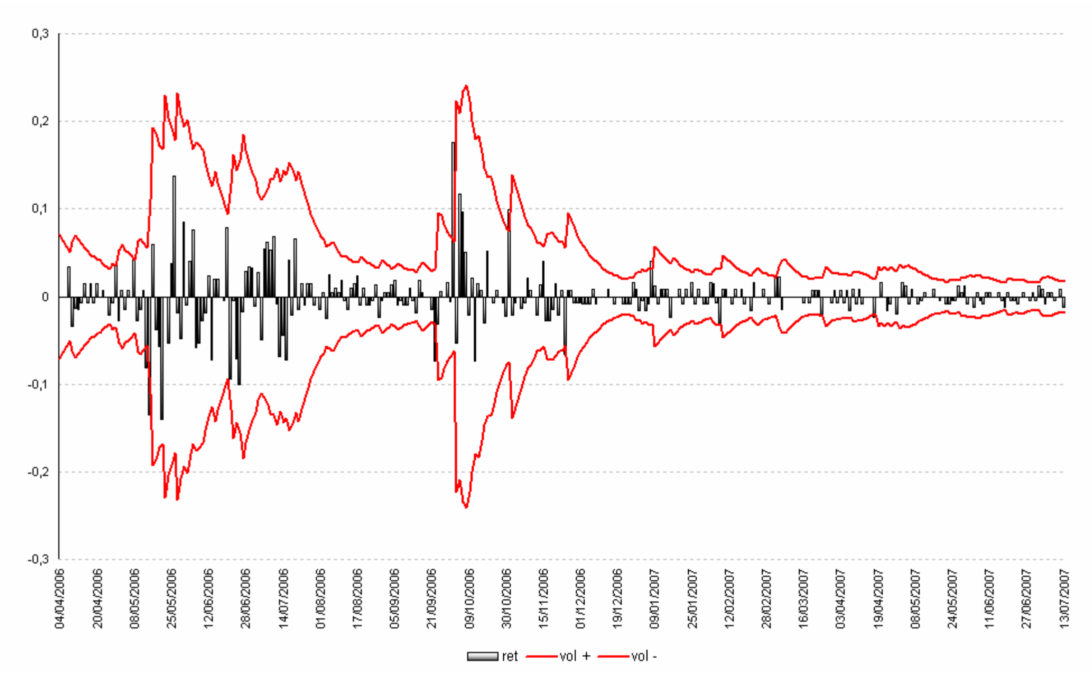


Figure 79 Return vs VaR on Alternatifbank with Norm Dist. - 99 c.i. for 4th Period

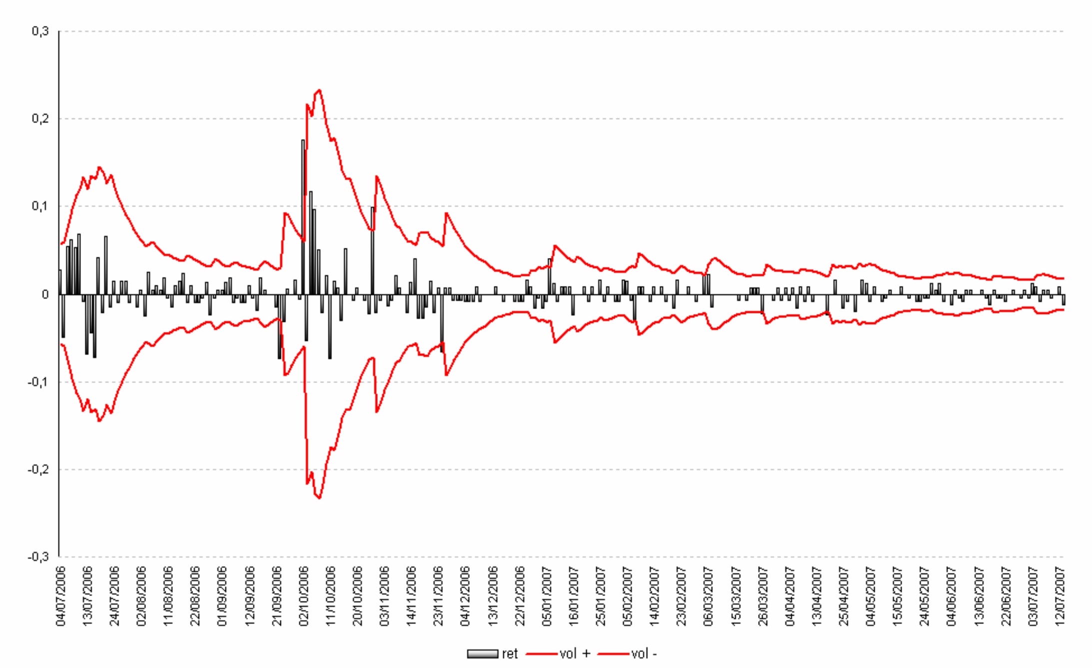


Figure 80 Return vs VaR on Alternatifbank with Norm Dist. - 95 c.i. for 1st Period

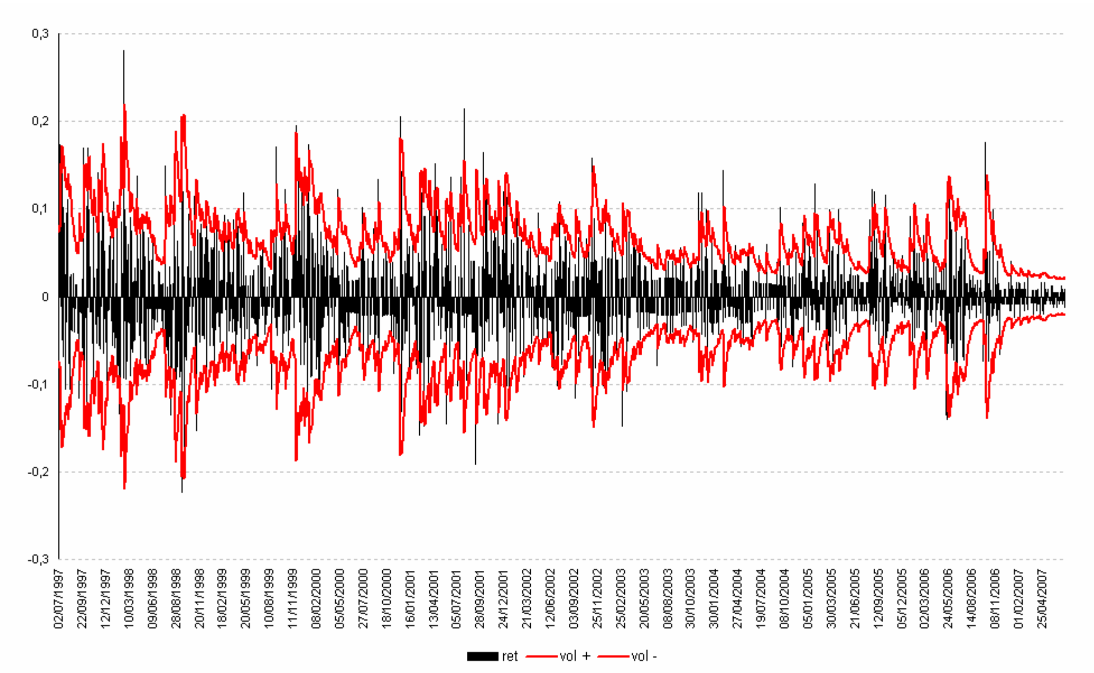


Figure 81 Return vs VaR on Alternatifbank with Norm Dist. - 95 c.i. for 2nd Period

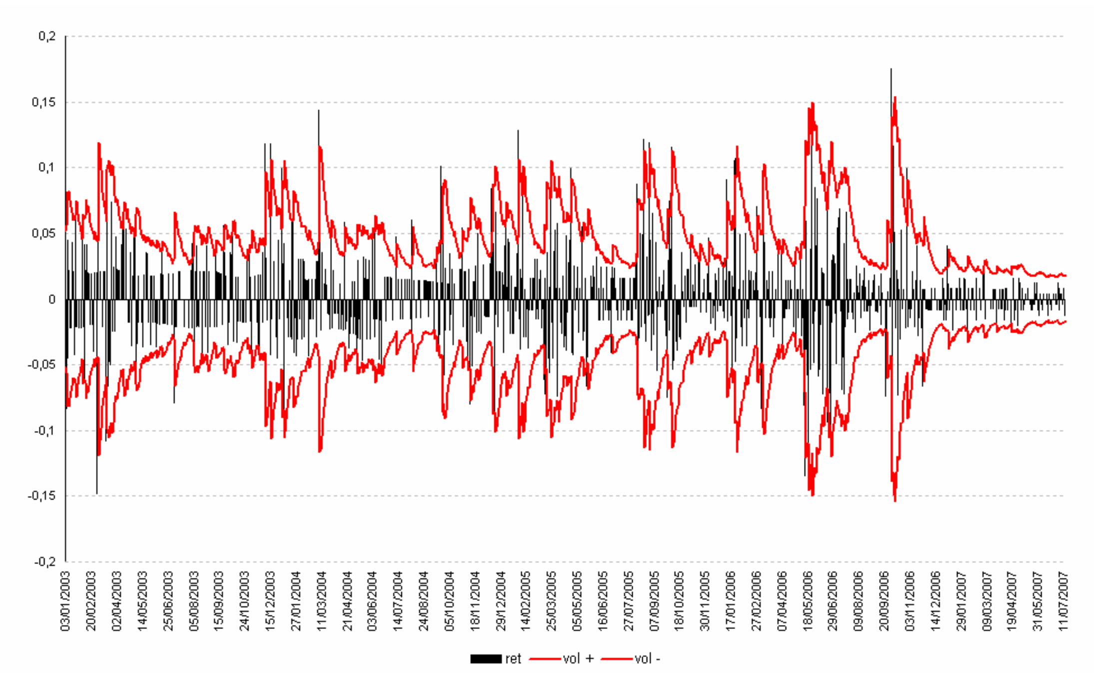


Figure 82 Return vs VaR on Alternatifbank with Norm Dist. - 95 c.i. for 3rd Period

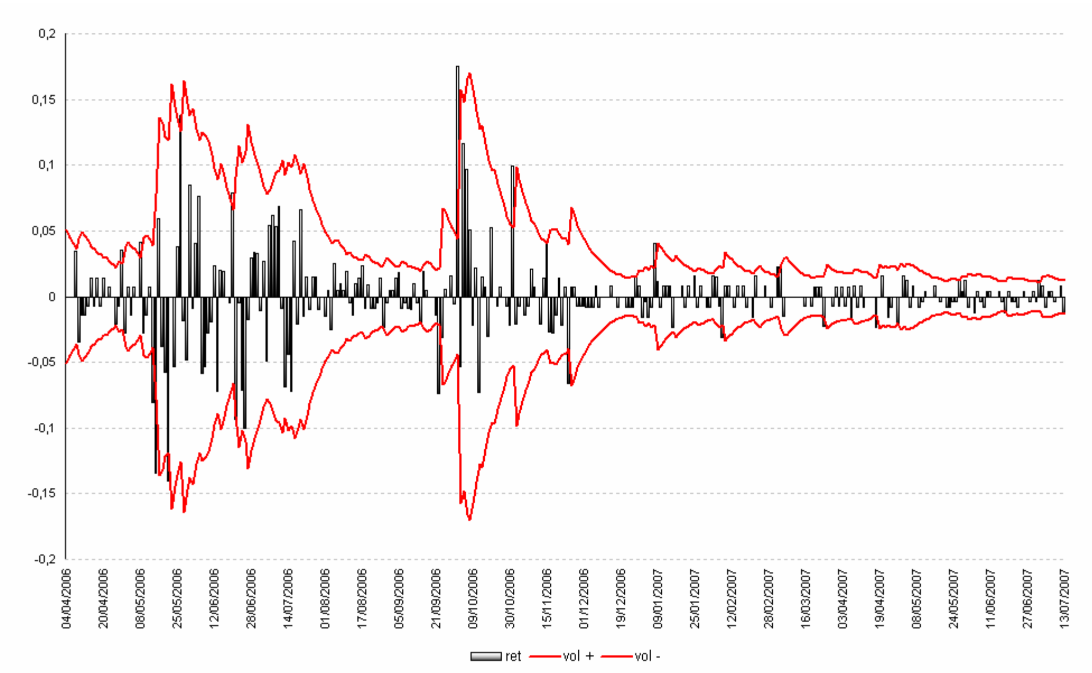


Figure 83 Return vs VaR on Alternatifbank with Norm Dist. - 95 c.i. for 4th Period

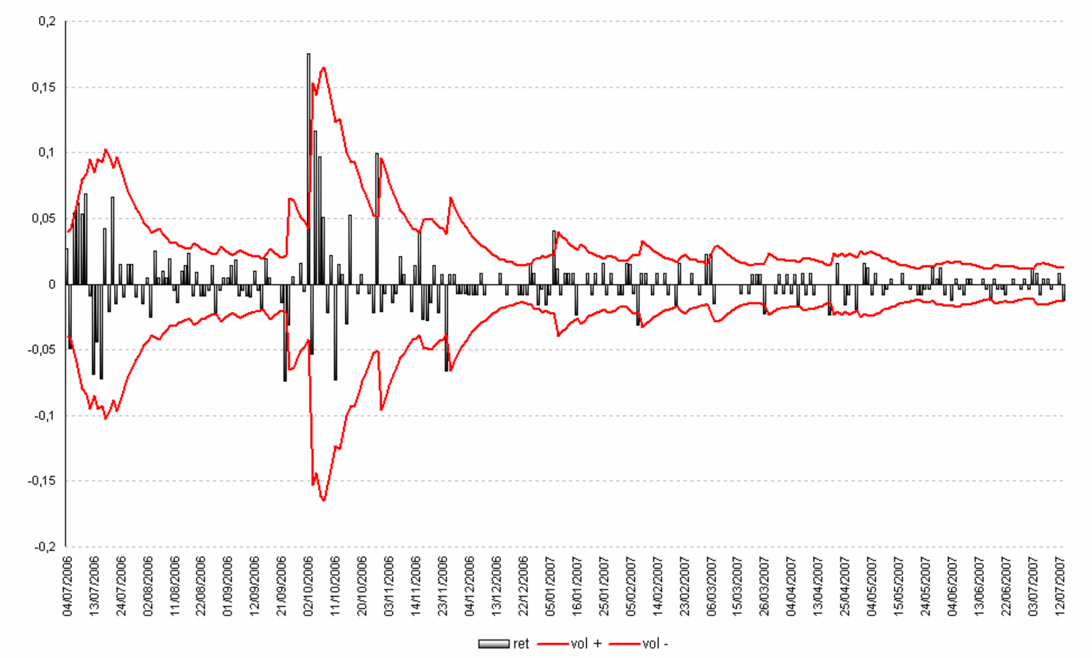


Figure 84 Return vs VaR on Garanti Bank with Norm Dist. - 99 c.i. for 1st Period

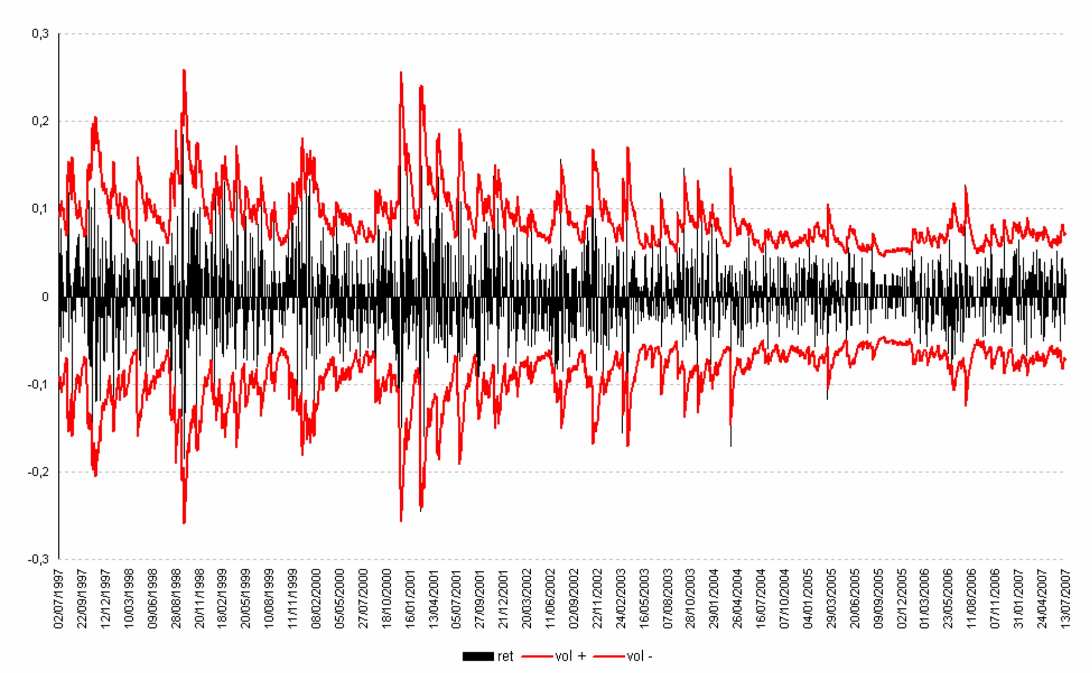


Figure 85 Return vs VaR on Garanti Bank with Norm Dist. - 99 c.i. for 2nd Period

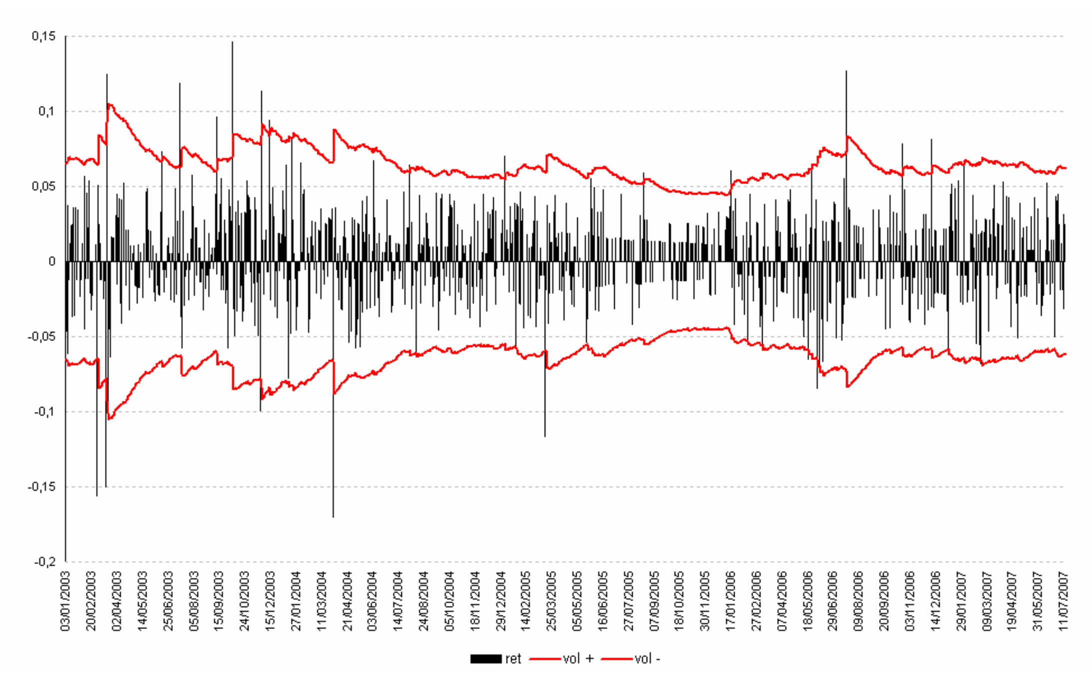


Figure 86 Return vs VaR on Garanti Bank with Norm Dist. - 99 c.i. for 3rd Period

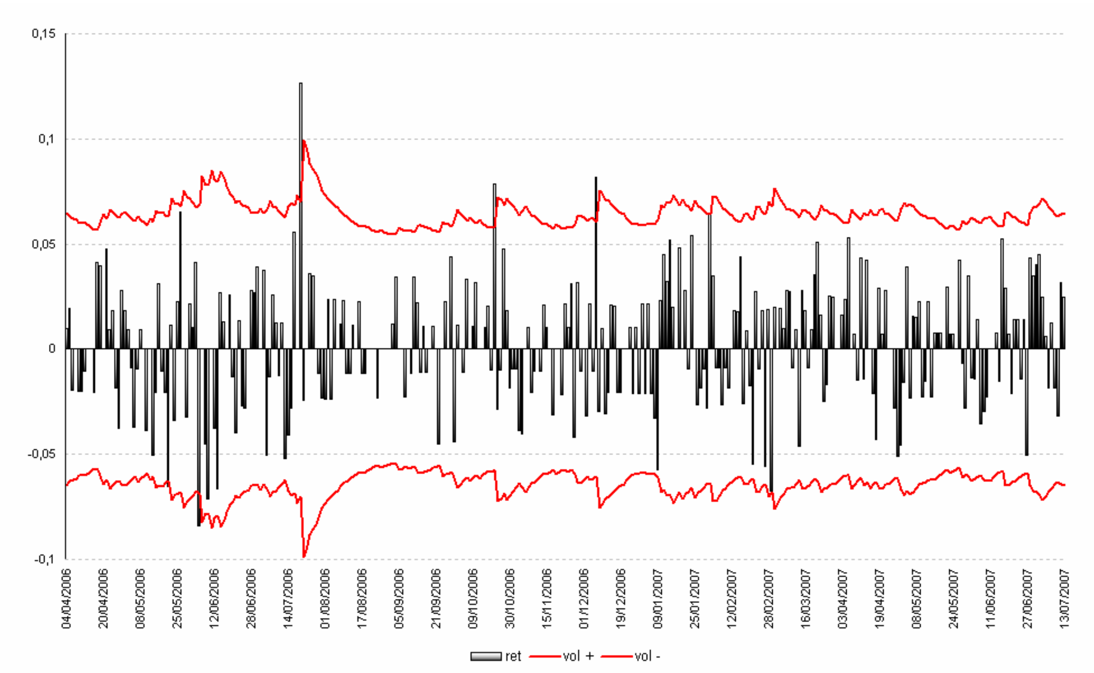


Figure 87 Return vs VaR on Garanti Bank with Norm Dist. - 99 c.i. for 4th Period

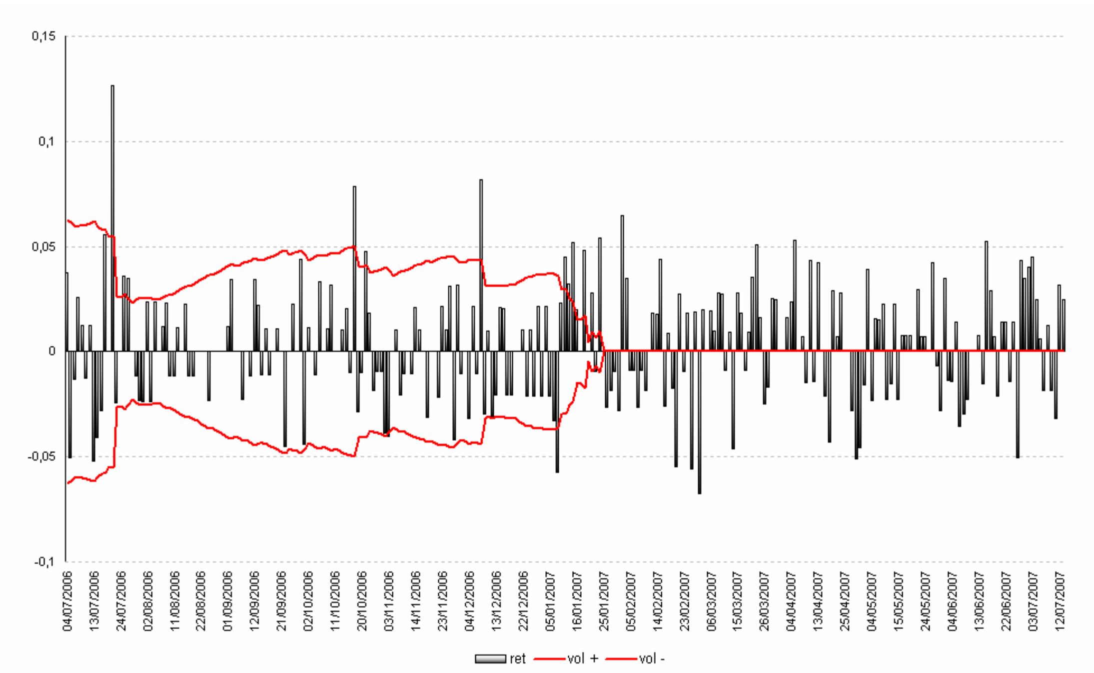


Figure 88 Return vs VaR on Garanti Bank with Norm Dist. - 95 c.i. for 1st Period

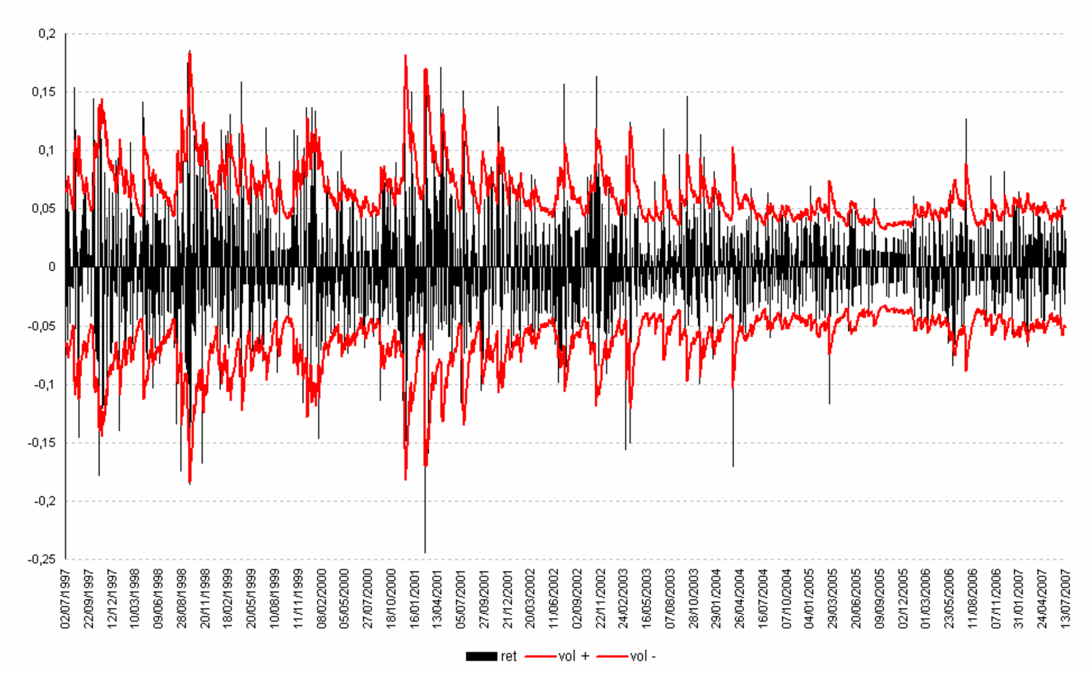


Figure 89 Return vs VaR on Garanti Bank with Norm Dist. - 95 c.i. for 2nd Period

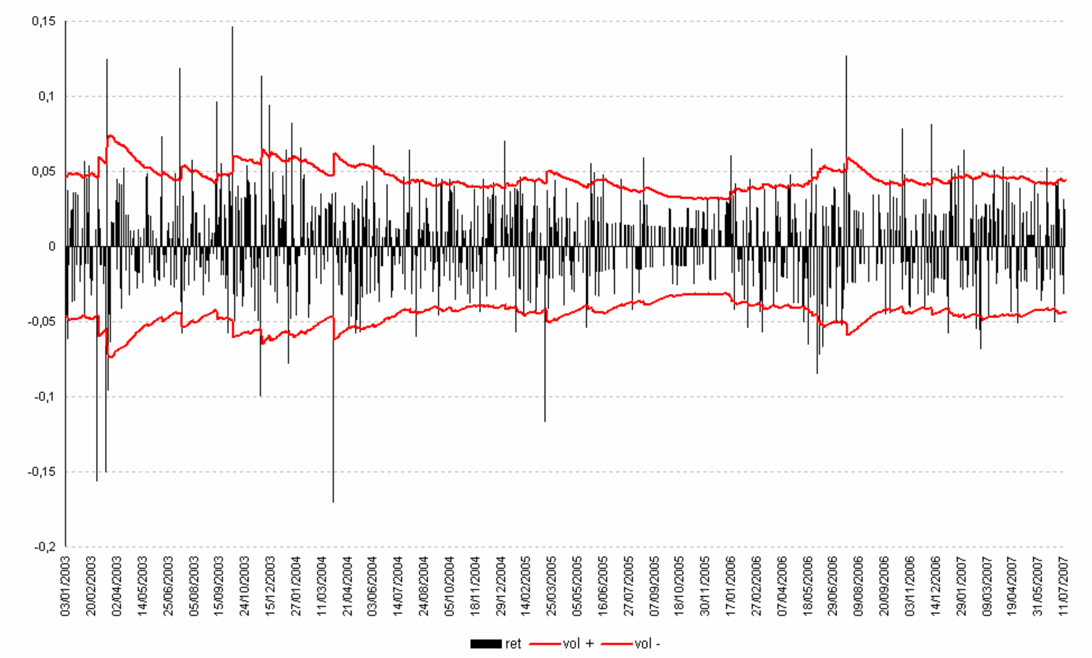


Figure 90 Return vs VaR on Garanti Bank with Norm Dist. - 95 c.i. for 3rd Period

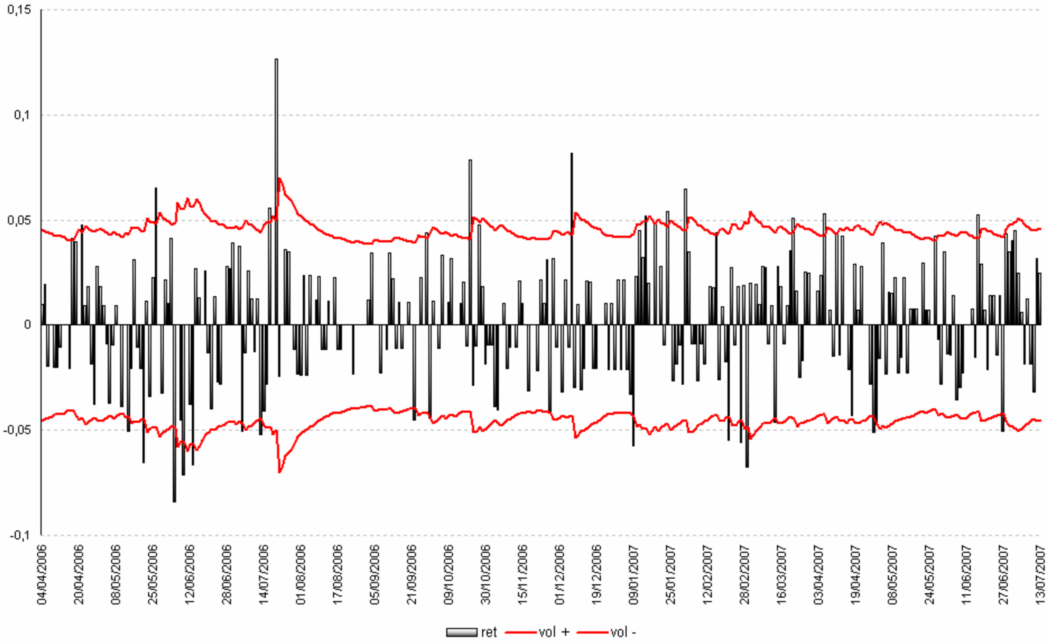


Figure 91 Return vs VaR on Garanti Bank with Norm Dist. - 95 c.i. for 4th Period