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YÜKSEK LİSANS TEZİ

MODELING VOLATILITY OF TURKISH STOCK INDEX FUTURES

Tolgahan YILMAZ

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YEMİN METNİ

Yüksek Lisans tezi olarak sunduğum **"Modeling Volatility of Turkish Stock Index Futures"** adlı çalışmanın, tarafımdan, bilimsel ahlak ve geleneklere aykırı düşecek bir yardıma başvurmaksızın yazıldığını ve yararlandığım eserlerin kaynakçada gösterilenlerden oluştuğunu, bunlara atıf yapılarak yararlanılmış olduğunu belirtir ve bunu onurumla doğrularım.

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ÖZET

Yüksek Lisans Tezi

Türkiye Hisse Senedi Endeksi Vadeli İşlem Sözleşmelerinin Oynaklık Modellemesi

Tolgahan YILMAZ

Dokuz Eylül Üniversitesi
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İngilizce Finansman Programı

Bu tezde, Vadeli İşlem ve Opsiyon Borsası (VOB)'nda işlem görmekte olan İMKB-30 Endeksi vadeli işlem sözleşmesinin oynaklığının hangi oynaklık modeliyle en iyi açıklandığı araştırılmıştır. 4 Şubat 2005-31 Mart 2009 dönemine ait günlük uzlaşma fiyatları kullanılarak GARCH ve EGARCH modelleri yardımıyla risk modellemesi yapılmıştır. İlgili dönem "Düşük ve Yüksek Oynaklık Dönemi" olmak üzere iki bölüme ayrılmıştır. Analizde her iki dönemi ve tüm veri setini ifade eden en iyi model olarak EGARCH (1,1) tespit edilmiştir. Çalışmanın devamında incelenen dönemlere ait koşullu standart sapma tahminlenmiş ve tahminlenen bu değerler kullanılarak her dönem için bir ve on günlük Riske Maruz Değer sonuçlarına ulaşılmıştır.

Anahtar Kelimeler: EGARCH, Koşullu Sapma, Riske Maruz Değer

ABSTRACT

Master Thesis

Modeling Volatility of Turkish Stock Index Futures

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The thesis investigates the best fitting volatility model for the ISE-30 Index Futures traded at the Turkish Derivatives Exchange (TURKDEX). The daily settlement prices of the contracts are used for the period of 4 February 2005-31 March 2009. The entire sample period is classified as "The Low Volatility Period" and "The High Volatility Period. The EGARCH (1, 1) appears to be the best fitted volatility model for the sub-periods and the entire sample period. Furthermore, the conditional Standard deviations for all periods are forecasted and then, one-day and ten-days Value at Risk values are calculated.

Keywords: EGARCH; Conditional Standard Deviation; Value at Risk

MODELING VOLATILITY OF TURKISH STOCK INDEX FUTURES

CHAPTER 2

TURKISH DERIVATIVES EXCHANGE

(TURKDEX)

CHAPTER 3

METHODOLOGY

CHAPTER 4

DATA AND EMPIRICAL RESULTS

LIST OF TABLES

LIST OF FIGURES

LIST OF GRAPHS

INTRODUCTION

Futures and options exchanges are one of the main entities of liberal economic systems. Although negative developments have shown its downside effects on the financial markets in recent years, trading volumes of futures exchanges have continued to increase. 2008 figures indicate that trading value of futures exchanges has exceeded USD 2,24 quadrillions; approximately 17 billions contracts have been traded. In the last two years, the trading volume has increased by 45%, while trading value have incresed by 24%.

In a free market economy, prices are determined by supply and demand. In Turkey, privatization has been gradually increasing and policies have been implemented to create sufficient conditions for a free market. In addition, free capital flows between countries are encouraged by removing most restrictions on the capital flows. These developments affected almost every company that they have becomemore sensitive to global economic fluctuations. Therefore, today, the firms operating in Turkey need for risk management tools than before. **The Turkish Derivatives Exchange (**TURKDEX hereafter) is offering an answer to those who need to manage their risks with significant opportunities and instruments.

This thesis investigates the behavior and characteristics of the ISE-30 Index futures of Turkish Derivatives Exchange. The analysis is based on the fitting of historical volatility models to the ISE-30 index return series for two different time periods to check whether the type of the best fitting model for the ISE-30 index future contracts has changed. Through the calculations on sub periods, we can see the impact of some shocks on the measures of VaR. The historical volatility models GARCH (1, 1) and EGARCH (1, 1) are examined. Firstly, we divide the sample period into two sub periods; the first is between February 4, 2005 and January 31, 2007, and the second is between February 1, 2007 and March 31, 2009. Secondly, we analyze the whole data set (between February 4, 2005 and March 31, 2009) and the two sub periods independently. While, Student-t distribution is used for the innovations in EGARCH, normal distribution is used in GARCH model.

Furthermore, Value at Risk (VaR hereafter) figures are obtained by the GARCH and EGARCH specifications, and also one-step a head VaR figures are forecasted.

The main reason that we use the time series models in the calculation of VaR is that the time varying variance has been proven to be the main characteristics of financial time series. These characteristics are:

a. While price series generally are non-stationary, return series are generally stationary and show no autocorrelation.
b. There is generally event of "Volatility Clustering".
c. There is serial dependency among the different lags of error terms.
d. The distribution of return series is generally leptokurtoic.
e. In financial markets (particularly in emerging financial markets), market participants show asymmetric behavior against to good news and bad news. When the bad news reaches to the investors, they start to sell their investments to take new positions. This creates more volatility than the buying behavior in the bullish market conditions as good news reach to the investors.

Autoregressive Conditional Heteroscedasticity (ARCH) model is developed by Engel (1982). ARCH model covers the main characteristics of the financial time series, especially the leptokurtosis by modeling conditional variances as squared error terms of the regression model. Bollerslev (1986) introduced the generalized ARCH (GARCH) models the time-varying conditional variance as a regression of moving averages of past squared residuals and the lagged values of variance.

The GARCH model was, then, extended to different type of time varying conditional variance models. One of the extensions of the GARCH model is the Exponential GARCH (EGARCH) model, developed by Nelson (1991). The details of these volatility models are discussed in Chapter 3.

Economies witnessed many financial crises in the last two decades. Volatility in stock indexes have became a good indicator for monitoring financial stability and understanding the mechanisms behind those crises. The concept of VaR has also become the major concern for the policy makers.

Since the GARCH model and it extensions contain the basic characteristics of the financial time series data, the conditional standard deviation forecasted by the GARCH models can be used as an input to the VaR calculation.

Therefore, we employ the GARCH and the EGARCH models to model the volatility of ISE-30 future return series in different time periods. Since the EGARCH model states that the conditional variance is always positive even if the parameter values are negative, there is no need to impose artificially the nonnegative constraint. In addition, the EGARCH model allows the conditional volatility to have asymmetric relation with past data.

The contribution of this thesis to the related literature is two-fold: First, this study pays particular attention to the listed ISE-30 futures contracts in Turkey. By dividing sample data into two periods, we are able to compare the results of historical volatility models between two periods. With this comparison, we can understand the effects of the news on the volatility changes. Second, in the analysis, the standard deviations are calculated using the GARCH and EGARCH model under the normal and the Student's t error distribution assumption, respectively. These forecasted values are, then, used in the VaR calculation.[1] The use of Student's t distribution is important in managing risk because compared to normal distribution it includes fat tail behavior.

The rest of the study is organized as follows. Chapter 1 presents the definition of the uncertainty, risk and volatility, and also literature review for the GARCH models family. Chapter 2 gives information about the Turkish Derivatives Exchange. The methodology including the Volatility Models and VaR are presented in Chapter 3. Data and Empirical results are presented in Chapter 4.

[1]Ruey Tsay, **Analysis of Financial Time Series-Financial Econometrics**, John Wiley & Sons, USA, 2002, s.265

CHAPTER 1
VOLATILIY AND GARCH MODELS FAMILY
IN THE FINANCE LITERATURE

1.1. UNCERTAINTY, RISK AND VOLATILITY

1.1.1. Uncertainty and Risk

As Frank H. Knight (1921) states that risk can be covered, but uncertainty cannot be calculated and forecasted. He states risk as the measurable part of uncertainty as he defines the uncertainty as immeasurable.

The common and well-known definitions of uncertainty, risk and volatility are stated in Say, *et al*. (1999). They define risk as the number of possible future events exceeding the number of actually occurring events, and some measure of probability can be attached to them.

Uncertainty is the cluster of the unknown possibilities. Uncertainty is a situation which may result in different outcomes, and the possibilities of these outcomes are not known before they occurred. If we examine the price of a financial instrument, the unknown possibilities of increasing and decreasing of price refer to the uncertainty.

However risk is the possibility of losing. If an investor loses his/her money when the price of the asset, in which he/she invests, decreases, the risk for the investor is the decreasing price. If an investor loses his/her money when the price of the asset, in which he/she invests increases, the risk for the investor is the increasing price. The concept of the risk depends on the losing. Risk is emerged by uncertainty and it is the one of the unknown possibilities of the uncertainty. Risk in finance has one direction, up or down.

1.1.1.1. The Types of Risk

The concept of the risk can be classified as two major types such as systematic and non-systematic risk.

1.1.1.1.1. Systematic Risk (Un-Diversifiable Risk)

It is the general definition of the risk that affects the all parts of the market and cannot be diversifiable.

- **Market Risk**

It means that the possibility of losing depends on the movements on market price. The correlation between individual asset or portfolio and market prices determines the degree of the market risk exposure.

- **Inflation Risk**

It means that the possibility of the decreasing in the value of purchasing power due to the increasing in the general price level.

- **Interest Rate Risk**

It means the possibility of the losing money because of the changes in the interest rates.

- **Political Risk**

Political depression and its financial and economic effects which are changes in tariffs, quotes, reflect the political risk.

- **War Risk**

War and its effects are the inseparable part of the economy and finance. It is highly correlated with the political risk and also un-diversifiable.

1.1.1.1.2. Unsystematic Risk (Diversifiable Risk)

It is the general definition of the risk that affects the only specific part of the entire market. Since the unsystematic risk relies on the conditions, which are created by a specific firm or a specific industry, it can be diversified.

- **Industry Risk**

While the profits and the value of the stocks of the firms in an industry can be affected by the reasons that are specific for that industry, firms in the other industries cannot be affected by these reasons that create specific risk which is called industry risk.

- **Management Risk**

It relates to the failures of the managers.

- **Default Risk**

It means that companies cannot be able to pay their debt obligations or go bankrupt. Default risk also can be stated for individuals who cannot pay their debt.

1.1.2. Volatility

Volatility is another concept, which may be hardly distinguished from risk and uncertainty. Volatility is a movement in a given period of time. Volatility in finance means the scale of the movement of the price or the return. Volatility can be measured by benefiting from the historical data. Volatility, which is called as implied volatility, can be measured by taking market or investors expectations into consideration.

Since volatility is not easily observable, it is hard to evaluate the forecasting performance of conditional heteroscedastic models. However, volatility has some common characteristics, which are;

i. Volatility clusters; volatility is being observed high or low in level but dense for certain time periods,

ii. Volatility has a continuous path over time, jumps are rarely seen,

iii. Volatility is not divergent; it has values within some fixed range. Hence, volatility often shows up as a stationary series.

iv. The reaction of volatility is dissimilar to a big increase or decrease in price.

These four characteristics of volatility have a significant role in the development of volatility models. Under these properties, we will examine the models.

After the basic descriptions of the concepts of uncertainty, risk and volatility, we can combine these concepts to understand the financial risk and its calculations. In finance, uncertainty creates the possibility of losing. We need to cover this possibility. In other words, we need to make risk measurable. To do this, we use volatility measures. Volatility measures provide investors, portfolio managers or investment specialists tools by which they can comment on the possible price movements in the future and they create investment decisions based on the volatility measures in order to cover their financial risks. Basic volatility measures are variance and standard deviations of the historical data in a given period of time. Risk or volatility measures which are forecasted by modeling the time varying variance are conditional variance and standard deviations.

There are two basic volatility types: Historical Volatility and Implied Volatility. Historical volatility measures rely on the historical prices that have already been observed in a time series rather than on future expectations which are reflected in the options' prices.

Implied volatility can be obtained from the given market price of the option. Basic assumption underlies the implied volatility calculation is all market players use the same theoretical option pricing model such as Black-Scholes-Merton, Cox-Ross-Rubinstein etc. Current price of the option, spot price of the underlying asset, exercise price, interest rate, maturity of the option are the parameters which are used to calculate the implied volatility. Since the implied volatility calculation depends on the current price of the option, implied volatility reflects the expectation of the market participants.

However, historical volatility method estimates volatility relying on historical data of the asset. It measures price movement in terms of past performance.

Historical volatility was most commonly measured by the standard deviation based on the historical data set of an economic variable. Standard deviation is still in common use. Especially financial analysts use standard deviation of the data in a given period as the measure of the volatility. But, in modern finance, volatility and time varying variance can be modelled by "GARCH Models Family", since the volatility or variance vary over time and the volatility tends to cluster. When the price trend of the underlying variable is predictable, near future volatility can be forecasted by using residuals and past variances of the historical data.

The idea that modeling the autoregressive conditional heteroscedasticity, was introduced by Robert F. Engle to the literature in 1982. The ARCH model capture the volatility clustering and serial correlation in time series data by calculating variance of the error terms by using the square of a previous period's error terms.

1.2. LITERATURE REVIEW

In this section we review the studies that used the GARCH model and its extensions to model the volatility of financial time series and calculate VaR.

So and Yu (2006) apply seven GARCH models, two of which are RiskMetrics and two long memory GARCH models, to Value at Risk (VaR) estimation. Considering both long and short positions of investment, models were applied to 12 market indices and four foreign exchange rates at various confidence levels to test which were more accurate in VaR calculation. The results indicate that both stationary and fractionally integrated GARCH models outperformed RiskMetrics. Asymmetric behaviour is 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 by using univariate GARCH models. The comparison between univariate GARCH model and several other common approaches in VaR estimation lead to predominance of GARCH estimates in terms of the accuracy and consistency of the probability level.

Goyal (2000) tests the accuracy of forecasted values, which were come from GARCH models, by using daily and monthly series of the CRSP value weighted returns. He concludes that the forecasting ability of simple ARIMA model is higher than that of the GARCH models.

Aiolfi and Timmermann (2004) also claim that GARCH models are not enough to catch volatility clustering and structural breaks. In addition to this claim, Hendry and Clements (2002) find that when volatility has a tendency to fall; VaR values have a tendency to return their previous values. Therefore, they conclude that the prediction ability of GARCH models in the short term is higher than the prediction ability of GARCH models in the long term.

Also, there are papers that show the accuracy of GARCH models especially in the period of financial crisis in the emerging markets.

Fabozzi, *et al.* (2004) apply GARCH models to Chinese stock markets, Shenzen and Shangai. They find that GARCH (1, 1) models the daily data on the Shenzhen while TAGARCH (1, 1) model fits the data on the Shanghai exchange and prove the presence of volatility clustering and strong serial correlation.

Nam *et al*. (2003) find the asymmetric behavior of investors against the positive and negative return shock. They claim that investors reduce the risk premium when the negative return shock occurs. This case is one of the major reasons that increased the stock prices because reduced risk premium converted the negative return to positive return faster.

One of the other major findings about asymmetric volatility was introduced by Jayasuriya, *et al*. (2005). They estimate the magnitude of asymmetric volatility for seven developed markets and fourteen emerging markets. In their work, both markets have large magnitude of asymmetric volatility. They claim that reasons for such asymmetric volatility are transaction costs (e.g. capital gains taxes) and certain trading strategies (e.g. short-selling).

Pan and Zhiang (2006) use seven models, namely; moving average model, historic mean model, random walk model, GARCH model, GJR model, EGARCH model and APARCH model to forecast the daily volatility of the two equity indices of the Chinese stock market. They find that for the Shenzhen stock market, the traditional method seems superior, and the moving average model is favored for the forecasting of daily volatility. For the Shanghai index the GARCH-t model, APARCH-N model and moving average models are found to be fitting models to the data. Other result is that in the Shenzhen stock market, the asymmetry model, i.e. the GJR and EGARCH, perform better than other GARCH-type models, but with little gain. The models with skewed student's t distribution ranks 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's t distribution is superior. Lastly, although they cannot find one model that performs best under all the criteria, it appears 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.

The other study about forecasting performance is prepared by Füss, Kaiser and Adams (2007). They examine the forecasting ability of different VaR approaches which were the normal, Cornish-Fisher (CF) and GARCH type VaR by focusing on the returns of the hedge fund strategies. They use GARCH and EGARCH models to forecast the conditional volatility which was used to measure VaR. The data set shows the kurtosis and skewness as it is expected. The presence of the leverage effect is also find out. Since the normal approach run under the assumption of normal distribution, it does not perform well. However, GARCH types VaR approaches outperform both CF and the normal approaches. They conclude that GARCH type VaR approaches can cover the downside risk in the hedge fund's portfolios.

Balaban, *et al*. (2004) employ eleven models which were 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 to evaluate accuracy of forecasting ability of these models in fourteen stock markets namely Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Netherlands, Philippines, Singapore, Thailand, the UK and the US. Data set was the daily returns on the stock market index of each country for the ten-year period 1988 to 1997. Daily and weekly volatility are forecasted. When they apply symmetric measure to evaluate the forecasting ability, they find that Exponential Smoothing approach provides more accurate forecasts of weekly volatility than others do. When they apply non-symmetric measure to evaluate the forecasting ability, they find that ARCH-type models are the best to forecast and the random walk is the worst.

McMillan and Ruiz (2009) test the presence of long memory. They utilized daily data of stock indices from ten countries (Canada, France, Germany, Hong Kong, Italy, Japan, Singapore, Spain, UK and US) over the period January 1990–December 2005. They find that time variation in the unconditional variance or structural breaks affect the degree of volatility persistence and there is no sign of long memory. They also conclude that GARCH model shows better volatility forecasting performance under the assumption of a constant unconditional variance.

One of the recent research about distribution and characteristics of volatility belongs to Lee (2009). He investigated the behavior of volatility by focusing on the Korea Composite Stock Price Index (KOSPI). He uses intraday data set, which had one minute interval, from 1992 to 2007. He finds that distribution of return series show non-Gaussian distribution with fat-tails. He also resembles the information about volatility with the energy in the fully developed turbulence.

Alagidede and Panagioditis (2009) compare the random walk model with the GARCH, GARCH-M and EGARCH-M by using the daily closing prices of seven indices of the Africa's largest markets. These markets are Egypt, Morocco, Kenya, South Africa, Tunisia, Zimbabwe and Nigeria. They find the presence of volatility clustering, leptokurtosis and leverage effect in the data set. Depending on this characteristic of the data, they show that GARCH, GARCH-M and EGARCH-M outperform the random walk model. The study also shows that investors in Tunisia, Kenya and Morocco take greater risks to get greater returns. The presence of the negative correlation is observed between the changes in the price level and volatility level.

In Turkey, GARCH models have been widely used in the fields extending from stock market volatility to inflation uncertainty.

Okay (1998) examins the Istanbul Stock Exchange from 1989 to the end of 1996. In the analysis Okay applied GARCH and EGARCH models. The dynamic volatility of the ISE has been explained by both models, but EGARCH could capture the asymmetric behavior of the stocks.

Mazıbaş (2004) applies GARCH, EGARCH, GJR-GARCH, Asymmetrical PARCH and Asymmetrical CGARCH models to forecast stock market volatility for daily, weekly and monthly volatility in composite, financial, services and industry indices of the Istanbul Stock Exchange (ISE). It is found that there is asymmetry and leverage effects in daily, weekly and monthly market data, and also weekly and monthly forecasts are more precise than daily forecasts. Mazıbaş claims that investor's negative attitude towards bad news, gained from severe financial crisis, is the reason for the leverage effect. ARCH-type models are found to be inadequate because of the high volatility in daily returns.

Duran and Şahin (2006) study whether there is a volatility spillover; if it exists between which of the IMKB services, financial, industrial and technology indexes has spillover effect. They used daily data from July 2000 to April 2004. In their study; first, they use EGARCH to obtain volatility series and second, they used Vector Autoregressive (VAR) model to these volatility series to test volatility spillover among the indexes. As a result, they find that there is a spillover among the indexes.

Turanlı, *et al*. (2007) use ARCH and GARCH models to compare their competency to the Istanbul Stock Exchange (ISE) 100 Index's daily closing values between the dates of 2002 and 2006. GARCH (1,1) show superior performance than ARCH (1).

Gökçe (2001) applies ARCH, ARCH-M, GARCH, GARCH-M, EGARCH and EGARCH-M models to daily data in the Istanbul Stock Exchange. The relationship between market returns and changes in volatility is found to be positive. GARCH (1,1) model is indicated as the best fitted one.

Akgül and Sayyan (2005) employ Asymmetric Autoregressive Conditional Heteroscedasticity models to investigate existence of the asymmetry effect and the long memory characteristic in the ISE30. They conclude that 13 of the stocks of the IMKB-30 present asymmetry effect, and 4 of these have long memory characteristic. The APARCH and FIAPARCH models provide accurate volatility forecasts.

Kasman A. and Kasman S. (2008) use EGARCH model to measure the volatility of ISE-30 futures and examined the impact of the index futures on the spot index values. They examine whether the stock index futures trading has negative impact on the volatility of spot market in Turkey. Their results show that there has been a decrease in volatility following the introduction of stock index futures.

CHAPTER 2
TURKISH DERIVATIVES EXCHANGE
(TURKDEX)

2.1. THE NEW FINANCIAL GUIDE OF TURKEY: TURKISH DERIVATIVES EXCHANGE

The TURKDEX started to operate after the company was registered in Registry of Commerce. This registration was officially announced through the Gazetta of Registry of Commerce, dated July 4, 2002. Trades in TURDEX started on February 4, 2005. It has eleven shareholders and its paid-in capital is 9 millions TRY as of December, 2005. The list of TURKDEX's shareholders is stated below:

Table 1: Shareholders of TURKDEX

Name of The Shareholders	Percentage
The Union of Chambers and Commodity Exchange of Turkey	%25
Istanbul Stock Exchange	%18
Izmir Mercantile Exchange	%17
Yapi Kredi Bank Inc.	%6
Akbank Inc.	%6
Vakif Investment Securities	%6
Garanti Bank Inc.	%6
Is Investment Securities	%6
The Association of Capital Market Intermediary Institutions of Turkey	%6
ISE Settlement and Custody Bank	%3
Industrial Development Bank of Turkey	%1

Source: Turkish Derivatives Exchange

The TURKDEX Inc. is the only entity authorized by the Capital Markets Board (CMB) to launch a derivatives exchange in Turkey and according to the CMB regulations, membership to the TURKDEX is restricted to financial intermediaries (brokerage firms and banks). It currently has 87 members (69 brokerage firms and 18 banks). All members are direct clearing members. Clearing is handled by the ISE Settlement and Custody Bank Inc. (Takasbank).

The TURKDEX is also fully electronic exchange with remote access. Its session starts at 9:15 am and ends at 5:15 pm, without a launch break. Daily settlement prices are determined at 5:25 pm.

From its start till now, the trades volumes and the number of open positions have been increasing substantially. In 2007, total volume (the number of contracts) was 24.9 million contracts. It is increased to 54.5 million contracts, nearly 2.2 fold of the 2007's total volume. The trading volume increased by 219% on average per year. In 2007, total notional value was 118 billions TRY. It is increased to 208 billions TRY, nearly 1.8 fold of the 2007's total notional value. The trading value increased by 376% on average per year.

In TURKDEX, only futures contracts are traded. Options have not been listed yet. The contracts which are listed in TURKDEX:

Index Futures:

- ISE-30 Index
- ISE-100 Index

Currency Futures:

- USD Dollar / TRY
- Euro / TRY Futures

Interest Rate Futures:

- T-Benchmark

Commodity Futures:

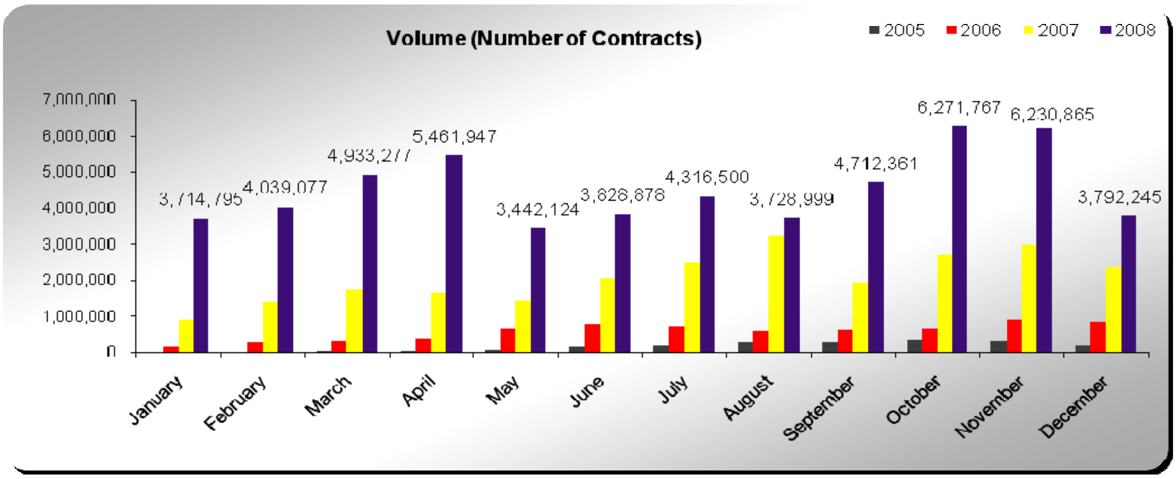
- Cotton
- Wheat

Precious Metal Futures:

- Gold

The trade value of TURKDEX mainly depends on the trade value of the index and currency futures. Other instruments almost have no effect on the total volume and total value of TURKDEX. In 2008, while 74% of the total volume (number of contracts) and 91% of the total value belongs to ISE-30 Index futures contrats, 24% of the total volume and 9% of the total value belongs to currency future. The annual statistics graphs are given below:

Graph 1: TURKDEX Monthly Volume (Number of Contracts)



Source: Turkish Derivatives Exchange

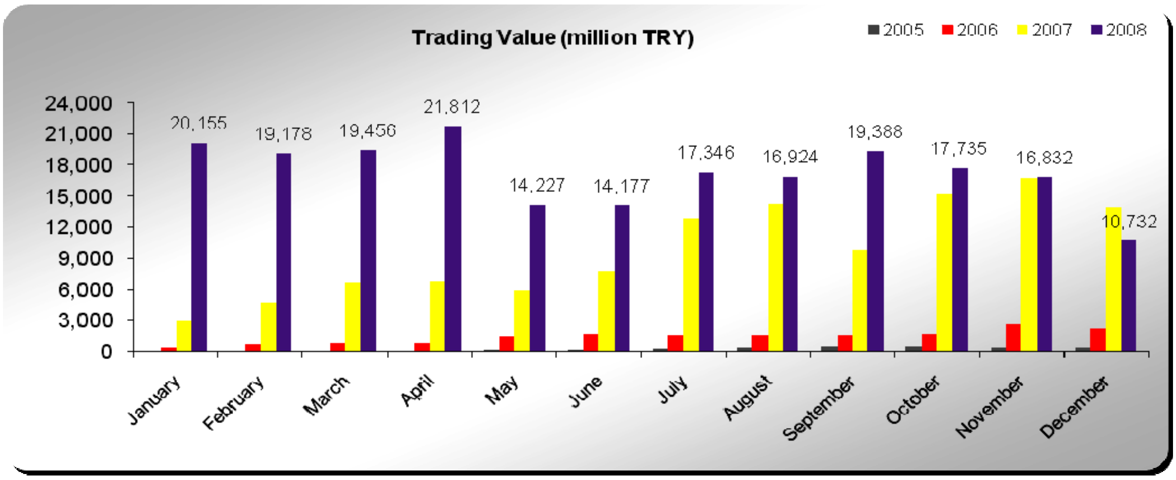
The annual number of traded contracts in 2008 is 54,472,835. The number of contracts traded in 2008 increased by 119% compared to that of 2007. This substantial performance placed TURKDEX to the 28th derivatives exchange in the world according to the Futures Industry Association (FIA). The Table 2 shows the ranking of the derivatives exchange.

Table 2: Ranking The Derivatives Exchange

RANK	EXCHANGE	Jan-Dec 2008	Jan-Dec 2007	% Change
1	CME Group (includes CBOT and Nymex)	3.277.645.351	3,158,383,678	3.8%
2	Eurex (includes ISE)	3,172,704,773	2,704,209,603	17.3%
3	Korea Exchange	2,865,482,319	2,777,416,098	3.2%
4	NYSE Euronext	1,675,791,242	1,525,247,465	9.9%
5	Chicago Board Options Exchange	1,194,516,467	945,608,754	26.3%
6	BM&F Bovespa	741,889,113	794,053,775	-6.6%
7	Nasdaq OMX Group	722,107,905	551,409,855	31.0%
8	National Stock Exchange of India	590,151,288	379,874,850	55.4%
9	JSE South Africa	513,584,004	329,642,403	55.8%
10	Dalian Commodity Exchange	313,217,957	185,614,913	68.7%
11	Russian Trading Systems Stock Ex.	238,220,708	143,978,211	65.5%
12	Intercontinental Exchange	234,414,538	194,667,719	20.4%
13	Zhengzhou Commodity Exchange	222,557,134	93,052,714	139.2%
14	Boston Option Exchange	178,650,541	129,797,339	37.6%
15	Osaka Securities Exchange	163,689,348	108,916,811	50.3%
16	Shanghai Futures Exchange	140,263,185	85,563,833	63.9%
17	Taiwan Futures Exchange	136,719,777	115,150,624	18.7%
18	Moscow Interbank Currency Ex.	131,905,458	85,386,473	54.5%
19	London Metal Exchange	113,215,299	92,914,728	21.8%
20	Hong Kong Exchange and Clearing	105,006,736	87,985,686	19.3%
21	Australian Securities Exchange	94,775,920	116,090,973	-18.4%
22	Multi Commodity Exchange of India	94,310,610	68,945,925	36.3%
23	Tel-Aviv Stock Exchange	92,574,042	104,371,763	-11.3%
24	Mercado Espanol	83,416,762	51,859,591	60.9%
25	Mexican Derivatives Exchange	70,143,690	228,972,029	-69.4%
26	Tokyo Financial Exchange	66,927,067	76,195,817	-12.2%
27	Singapore Exchange	61,841,268	44,206,826	39.9%
28	**Turkish Derivatives Exchange**	**54,472,835**	**24,867,033**	**119.1%**
29	Mercado a Termino de Rosario	42,216,661	25,423,950	66.1%
30	Tokyo Commodity Exchange	41,026,955	47,070,169	-12.8%
31	Italian Derivatives Exchange	38,928,785	37,124,922	4.9%
32	Bourse de Montreal	38,064,902	42,742,210	-10.9%
33	Tokyo Stock Exchange	32,500,438	33,093,785	-1.8%
34	National Commodity and Derivatives Ex.	24,639,710	34,947,872	-29.5%
35	Oslo Stock Exchange	16,048,430	13,967,847	14.9%
36	Budapest Stock Exchange	13,369,425	18,827,328	-29.0%
37	Warsaw Stock Exchange	12,560,518	9,341,958	34.5%
38	Tokyo Grain Exchange	8,433,346	19,674,883	-57.1%
39	Athens Derivatives Exchange	7,172,120	6,581,544	9.0%
40	Malaysia Derivatives Exchange	6,120,032	6,202,686	-1.3%

Source: Futures Industry Association (FIA)

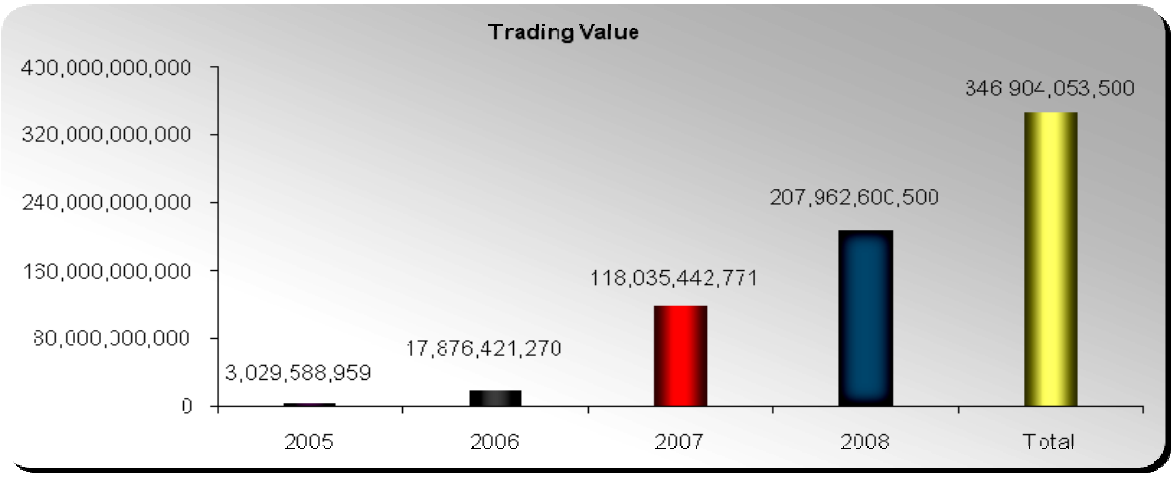
Graph 2: TURKDEX Monthly Trading Value (million TRY)



Source: Turkish Derivatives Exchange

The annual trading value increased by 76% in 2008 and reached 207.962.600.500 TRY.

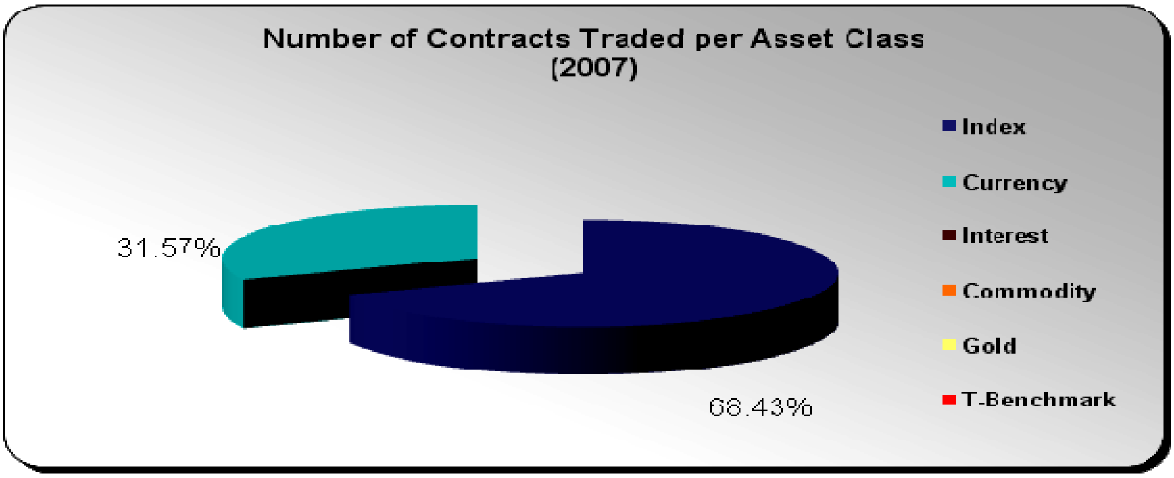
Graph 3: TURKDEX Total Trading Value (TRY)



Source: Turkish Derivatives Exchange

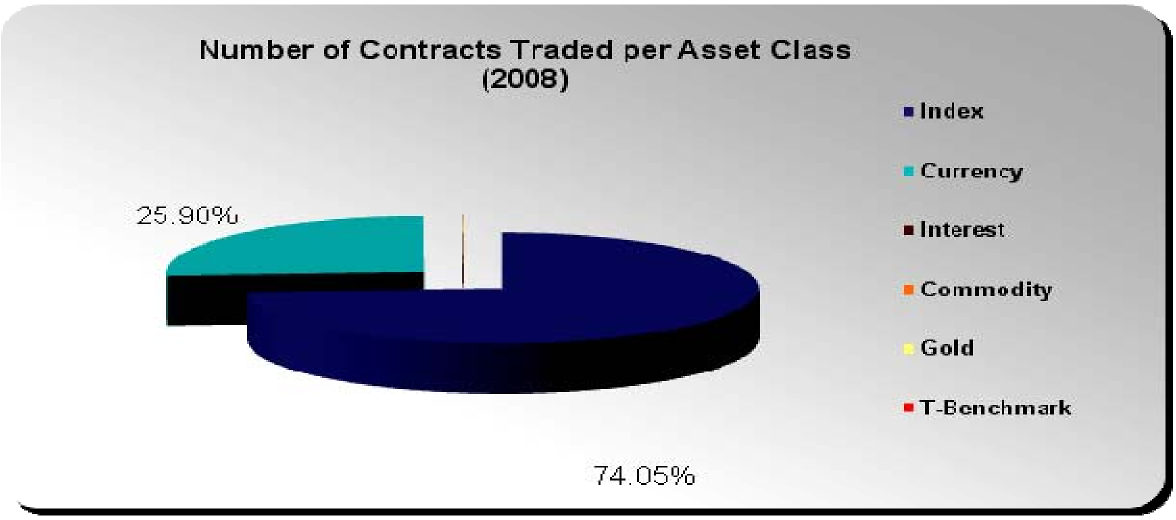
As seen in Graph 3, the annual trading value of TURKDEX increased substantially for each year. The sum of the annual trading value for each year is 346.904.053.500 TRY.

Graph 4: TURKDEX Trading Volume per Asset Class in 2007



Source: Turkish Derivatives Exchange

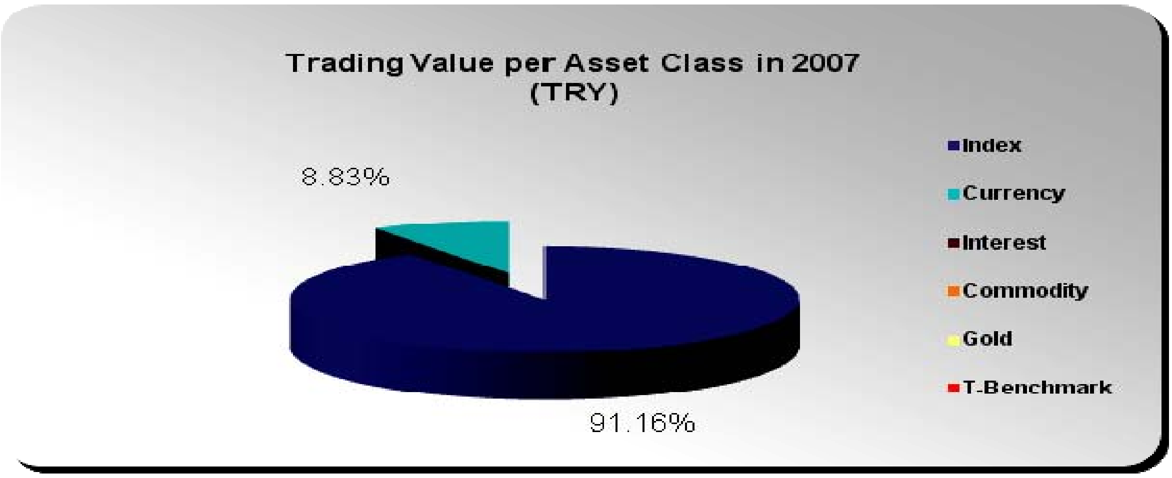
Graph 5: TURKDEX Trading Volume per Asset Class in 2008



Source: Turkish Derivatives Exchange

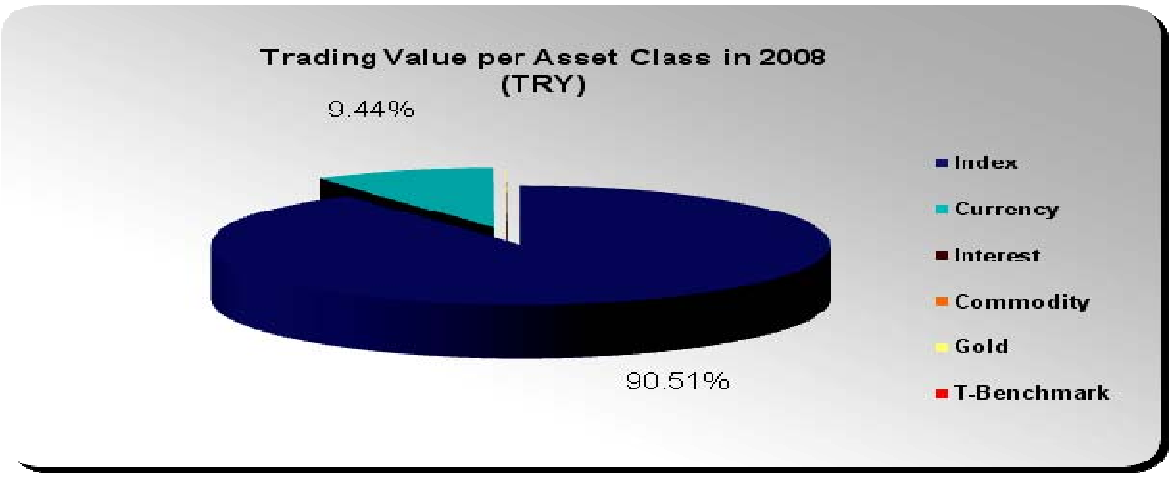
In 2007, while the yearly number of traded index contracts had a share of 68%, their share increased to 74% in 2008.

Graph 6: TURKDEX Trading Value per Asset Class in 2007



Source: Turkish Derivatives Exchange

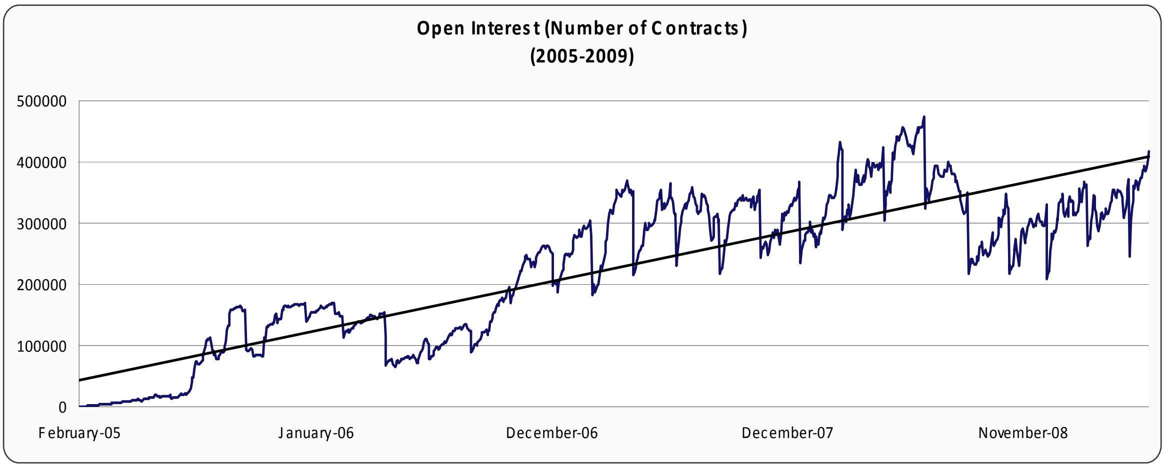
Graph 7: TURKDEX Trading Value per Asset Class in 2008



Source: Turkish Derivatives Exchange

The contract values of index future are higher than that of currency futures. This fact cause different share percentages of trading value and volume; index contracts' share of trading value is higher than their share of trading volume. In 2007, while the index contracts' annual trading value had a share of 91.16%, their share declined to 90.51% in 2008.

Graph 8: TURKDEX Open Interest (2005-2008)

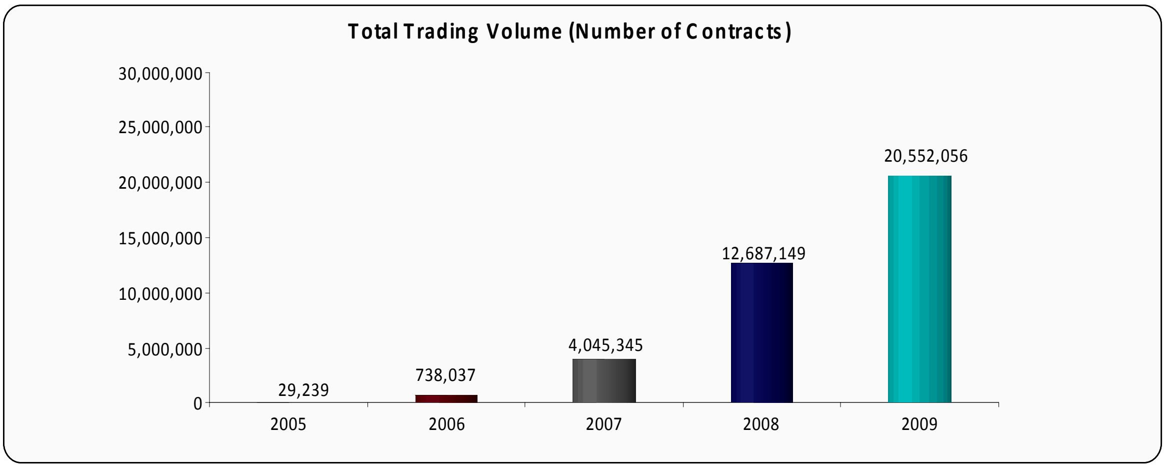


Source: Turkish Derivatives Exchange

As it can be seen from the graph, the number of open interest, which is the number of positions that investors hold, had an increasing trend from 2005 to the first quarter of 2009.

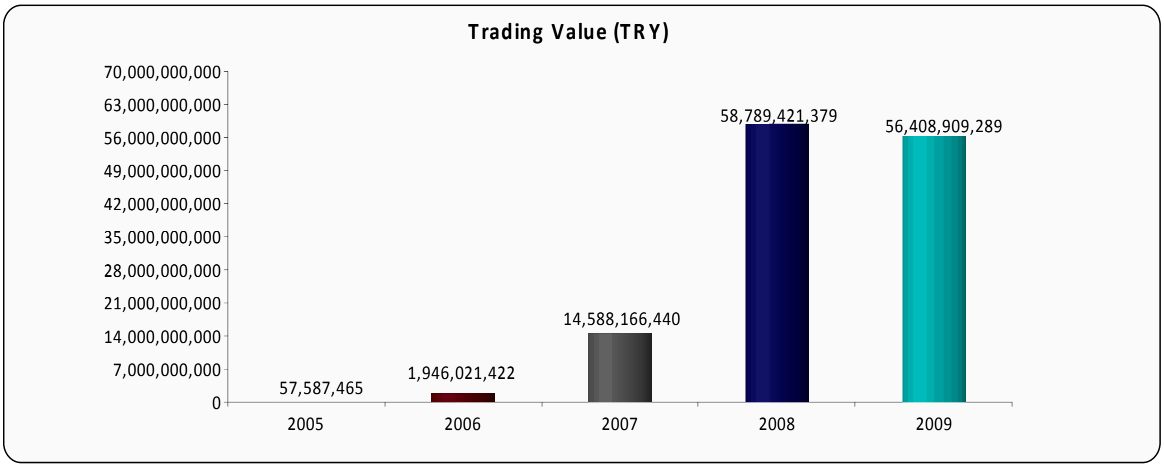
The effects of the global financial crisis on exchange rates disappeared on the trading volume and value of TURKDEX. In the first quarter of 2009, the currency futures' share in the total trading volume increased from 26% to 31% as the currency futures' share in the total trading value increased from 9% to 19%.

Graph 9: TURKDEX Total Volume at the 1st Quarter (Number of Contracts)



Source: Turkish Derivatives Exchange

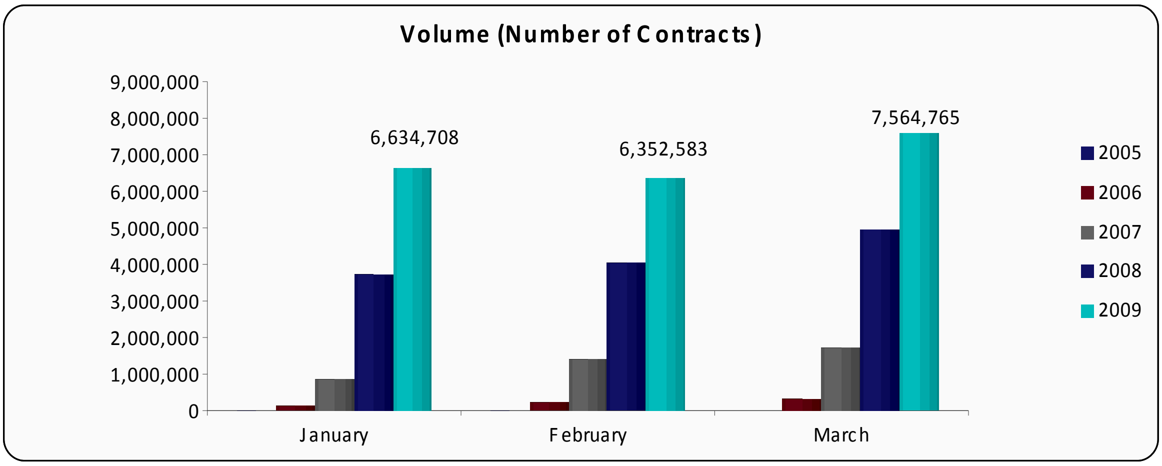
Graph 10: TURKDEX Total Trading Value at the 1st Quarter (TRY)



Source: Turkish Derivatives Exchange

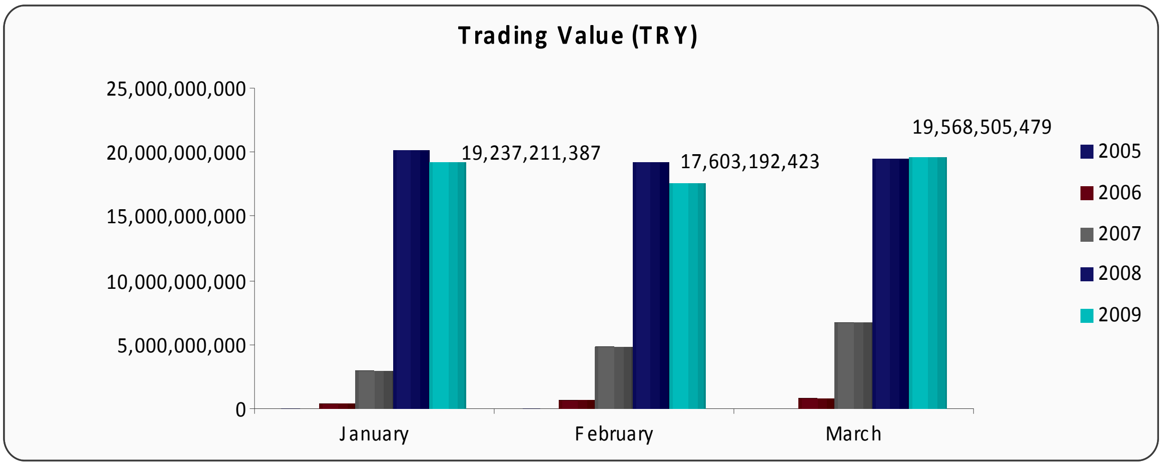
The effect of the increasing share of the currency futures can be traced by Graph 9; the total trading volume of 1st quarter of 2009 is increased by 61% compared to the 1st quarter of 2008.

Graph 11: TURKDEX Monthly Volume (Number of Contracts) at the 1st Quarter



Source: Turkish Derivatives Exchange

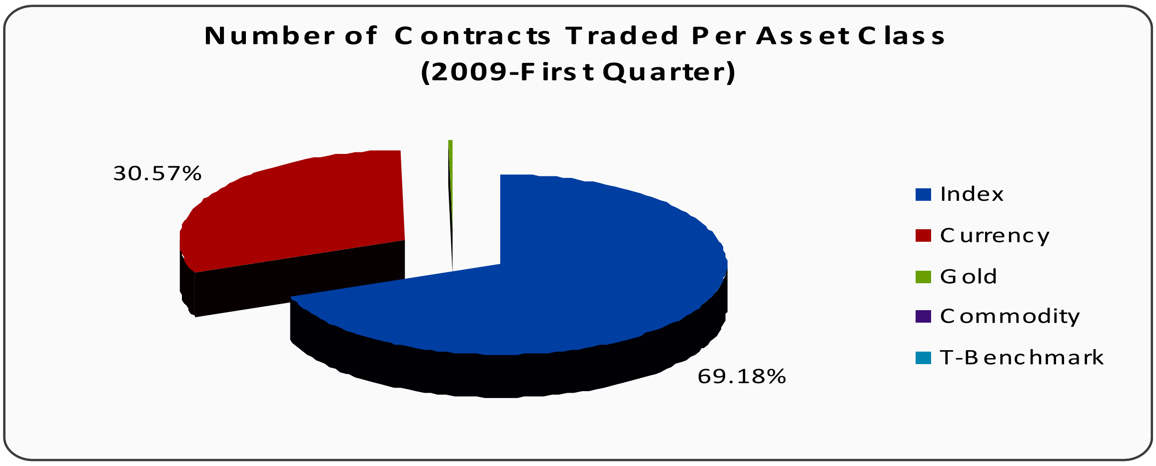
Graph 12: TURKDEX Monthly Trading Value (TRY) at the 1st Quarter



Source: Turkish Derivatives Exchange

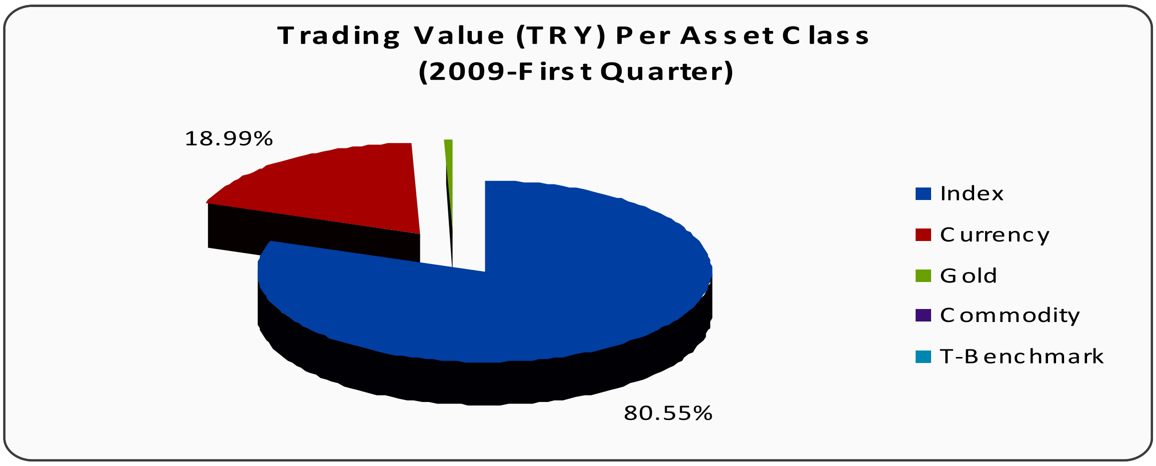
As seen in above graphs, the trading volume for each month in the first quarter of 2009 is higher than the trading volume for each month in the first quarter of 2008. On the contrary, it is not the case for the trading value at the first quarter of 2009. Except March 2009, trading value statistics of the first quarter of 2009 is lower than that of 2008. The reason is the increasing share of the currency futures in the trading volume and value. Since the contract value of the currency futures is lower than the index futures contracts at TURKDEX, investors should buy or sell more currency futures contracts to make profit which is almost equal to the profit from the index futures contracts. The increasing trading volume of currency futures raised the total trading volume in the first quarter of 2009 compared to 2008.

Graph 13: TURKDEX Trading Volume per Asset Class in the 1st Quarter of 2009



Source: Turkish Derivatives Exchange

Graph 14: TURKDEX Trading Value per Asset Class in the 1st Quarter of 2009



Source: Turkish Derivatives Exchange

In the first quarter of 2009, while the number of traded contracts of index futures had a share of 69.18%, their trading value had a share of 80.55%.

In January 2009, the volume of the USD/TRY futures at TURKDEX has reached to 1.748.350, becoming the world's third highest volume of the currency futures. When we examine the annual volume of the ISE-30 Index futures, it is the fourteenth highest volume in the world in the same period according to the Futures and Options Intelligence (FOI). Table 3 and 4 show that ranking statistics.

Table 3: Top Currency Futures and Options by Volume in January 2009

RANK	Contract	Exchange	Volume
1	US Dollar Future	BM&F	5.841.185
2	Euro FX Future	CME	3,574,541
3	TRYDollar Future	TURKDEX	1,748,350
4	Japanase Yen Future	CME	1,644,217
5	USD/RUR Future	RTS	1,638,971
6	US Dollar Option	BM&F	1,572,306
7	British Pounds Future	CME	1,446,314
8	USD/RUB Future	Micex	949,003
9	Total BSE Futures Future	BSE	723,464
10	US Dollar Option	Tase	703,295
11	US Dollar Future	KRX	690,165
12	Swiss Franc Future	CME	677,722
13	Canadian Dollar Future	CME	625,496
14	Australian Dollar Future	CME	602,927
15	Dollar/Rand Future	YieldX	200,497
16	Euro FX Option	CME	165,760
17	Mexican Peso Future	CME	164,000
18	World Currency Options JPY Opt.	PHLX	76,702
19	Total BSE Currency Options Opt.	BSE	55,930
20	World Currency Options EUR Opt.	PHLX	55,610
21	E-Mini Euro FX Future	CME	54,921
22	World Currency Options GBP Opt.	PHLX	52,857
23	British Pounds Option	CME	52,303
24	Japanase Yen Option	CME	51,980
25	TRYEuro Future	TURKDEX	44,597

Source: Futures and Options Intelligence (FOI)

Table 4: Top Equity Index Futures and Options by Volume in January 2009

RANK	Contract	Exchange	Volume
1	KOSPI 200 Option	KRX	167.735.176
2	E-Mini S&P 500 Future	CME	45,814,102
3	Dow Jones Euro STOXX 50 Option	Eurex	30,115,252
4	Dow Jones Euro STOXX 50 Future	Eurex	26,226,173
5	S&P CNX Nifty Option	NSE	21,215,671
6	S&P CNX Nifty Future	NSE	17,695,542
7	SPX S&P 500 Option	CBOE	11,719,415
8	DAX Option	Eurex	8,642,870
9	Nikkei 225 Mini Future	OSE	6,730,194
10	RTS Index Future	RTS	6,187,807
11	KOSPI 200 Future	KRX	5,894,342
12	E-Mini Nasdaq-100 Future	CME	5,713,178
13	TA 25 Index Option	Tase	4,858,364
14	ISE 30 Index Future	TURKDEX	4,836,732
15	mini-sized Dow Futures $5 multiplier Future	CBOT	3,707,910
16	CAC 40 Future	LIFFE	3,294,611
17	DAX Future	Eurex	3,283,863
18	OMXS30 Future	OMX	3,118,157
19	USD Index Future	Rofex	2,918,664
20	FTSE 100 Index Future	LIFFE	2,834,276
21	FTSE 100 Index (European-Style Exercise) Opt.	LIFFE	2,633,193
22	Russell 2000 Index - Mini Future	ICE Futures US	2,462,511
23	AEX Index Option	LIFFE	2,008,841
24	Nikkei 225 Option	OSE	1,984,539
25	Nikkei 225 Future	OSE	1,901,805

Source: Futures and Options Intelligence (FOI)

ISE-30 index futures and the USD dollar futures are the main contracts which lead the total volume and the total value of the trades in TURKDEX. From the end of 2005 till now, total value of the currency futures was higher than that of the index futures. Index futures, especially ISE-30, have been the flagship of the total value in TURKDEX.

CHAPTER 3
METHODOLOGY

3.1. LINEAR TIME SERIES ANALYSIS AND BASIC CONCEPTS

Time series is formed when one treats an asset returns as a series of random variables over time. One way to analyze this time series is to use Linear Time Series Analysis (LTSA, hereafter) which lets us to study dynamic structure of series.

The theories of LTSA are stationarity, dynamic dependence, autocorrelation function, modeling and forecasting.

Simple models estimate the linear relationship between a random variable at time t and a random variable prior to time t. Since these models deal with the relationship between random variable's correlations has a considerable role in understanding models. Thus LTSA focuses on the correlation between variable of interest and its past values. Saying that our variable of interest is $\mathbf{r_t}$ then for LTSA we will need correlation between $\mathbf{r_t}$ and $\mathbf{r_{t-i}}$. These correlations are referred to as serial correlations or autocorrelations.

3.1.1. Stationarity

Stationarity is the key assumption of LTSA. The time series that we use has to be stationary in order to have an accurate estimate with the use of LTSA.

A time series $\{r_t\}$ is said to be strictly stationary if the joint distribution of $(r_{t1},\ldots, r_{tk})$ is invariant under time shift; that is $(r_{t1+t},\ldots, r_{tk+k})$ identical joint distribution to $(r_{t1},\ldots, r_{tk})$ where k is an arbitrary positive integer.

The analysis at real time series data is not likely to fit this strong condition of stationarity. So, a weaker version at stationarity is assumed for analysing data.

A time series $\{r_t\}$ is said to be weakly stationarity if both the mean of r_t and the covariance between r_t and r_{t-j} are time invariant, where j is an arbitrary integer. That is to say;

$\{r_t\}$ is weakly stationary if

I) $E(r_t) = \mu,\ \mu$ is constant

II) $Cov(r_t, r_{t-j}) = \gamma_i$

In a graphical representation of data against time, the observed values would fluctuate with constant variation around constant level.

3.1.2. White Noise

If the time series $\{r_t\}$ is a sequence of independent and identically distributed (i.i.d, hereafter) random variables with finite mean and variance, then it is called white noise. All the autocorrelation functions (ACFs) of a white noise series are zero. With real time series data, if all sample ACFs are close to zero, then the series is a white noise.

3.1.3. Weakly Stationarity of LTSA

A time series $\{r_t\}$ is linear if it can be written as

$$r_t = \mu + \sum_{i=0}^{\infty} \psi_i a_{t-i}$$

where $E(r_t) = \mu,\ \psi_0 = 1$ and $\{a_t\}$ is a sequence of i.i.d random variables with mean zero and well-defined distribution (i.e a_t is white noise).

The dynamic structure of a linear time series is governed by weights of r_t. If $\{r_t\}$ is weakly stationary then its mean and variance is calculated as

$$E(r_t) = \mu \quad Var(r_t) = \sigma_a^2 \sum_{i=0}^{\infty} \psi_i^2$$

where $\sigma_a^2 = Var(a_t)$.

3.2. CONDITIONAL HETEROSCEDASTIC MODELS

Here, we will discuss volatility models since volatility is a significant factor in risk management. Value at risk of a financial position is calculated according to the volatility modeling. Volatility model of a time series can contribute to the parameter estimation and the interval forecast.

3.2.1. The ARCH Model

The first model is the ARCH model of Engle (1982), which constitute a base, furthermore, a framework for volatility modeling. ARCH models stands on the idea that;

(a) The mean corrected asset return a_t is serially uncorrelated, but dependent, and

(b) The dependence of a_t can be described by a simple quadratic function of its lagged values.

Specifically, an ARCH (m) model assumes that;

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2, \tag{1}$$

where $\{\varepsilon_t\}$ is a sequence of independent and identically distributed (iid) random variables with mean zero and variance 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$. The conditions on α_i is necessary in order to keep the unconditional variance of a_t finite. In practice, ε_t is often assumed to follow the standard normal or a standardized Student-t distribution.

The model can be read as that; the larger the past shocks $\{a_{t-i}^2\}_{i=1}^{m}$, the larger the conditional variance σ_t^2 for the mean-corrected return. Thus, a_t tends to a large value (absolute). According to this model there is a tendency that large shocks are to be followed by another large shock. It is only a tendency because the probability of a large volatility is greater than that of a smaller one. This characteristic of the model is called the ARCH effect.

- **Weaknesses of ARCH Models**

Despite their advantages, there are some considerable weaknesses of ARCH models:

1. Contrary to the practice, model assumes that positive and negative shocks have indifferent effects on volatility because it is explained with the squares of previous shocks.

2. The constraints on α_i 's becomes complicated when the order of the model increases.

3. The model explains only the behavior of the conditional variance without an indication of the cause of the occurrence of the behavior.

4. Since ARCH models do not respond quickly to large isolated shocks to the return series, they have the potential to over predict the volatility.

3.2.2. The GARCH Model

As we discussed, the volatility of returns of underlying stock can be described with ARCH model but the required parameters for modeling is so excessive that it is hard to deal with the constraints of these parameters. In order to overcome this problem, an alternative model, generalized ARCH (known as GARCH) model is developed by Bollerslev (1986). This model assumes that the current conditional variance depends on the first p past conditional variances as well as the q past squared innovations. For a log-return series r_t, letting $a_t = r_t - \mu_t$ be the mean-corrected log return, then a_t follows a GARCH (p, q) model

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

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad \textbf{(2)}$$

with the restrictions on the constants;

$$\alpha_0 > 0, \alpha_i \geq 0, \ \beta_j \geq 0 \text{ and } \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i) < 1$$

The last constraint indicates that the unconditional variance of a_t is finite and the unconditional variance σ^2 changes through time. It is often assumed that ε_t has a standard normal or standardized Student-*t* distribution. If $q = 0$, then the GARCH (p, 0) model is purely the ARCH (p) model. Predicting the current period's variance, the *GARCH* (p, q) model uses information of both the previous period's observed volatility, ARCH term, and the last period's forecasted variance, GARCH term. In other words, GARCH models use autoregressive and moving average components of time series data to forecast the heteroscedastic variance.

Inserting the past values of conditional variance, Bollerslev (1986) reduced the number of required parameters in the GARCH model. In general, the model can explain conditional variance by taking one lag for each variable. The GARCH (1, 1) model is specified as follows;

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \textbf{(3)}$$

In the GARCH (1, 1) model, the variance of the return of day t is forecasted with the independent variables as a weighted average of squared errors and forecast of day $t-1$ and a constant. On the condition that α_1 is small and $\alpha_1 + \beta_1$ is large, it is possible for the first-order autocorrelation coefficient to be considerably small and for the autocorrelations to die out quite slowly.

By examining GARCH (1, 1) model we can understand the properties of GARCH models. Firstly, if one of a_{t-1}^2 or σ_{t-1}^2 is large in value, then σ_t^2 would be large. Whenever a_{t-1}^2 is large, a_t^2 would tend to be large, generating volatility clustering. Secondly, the tail distribution of a GARCH *(*1, 1*)* process shows similarity to ARCH models that it is heavier than that of a normal distribution. Lastly, by GARCH models, volatility progress is forecasted with the use of a rather simple parametric function.

Although GARCH model has advantages, the model fails to operate on the condition that the asymmetric price shocks are involved, so that the magnitude of the volatility is underestimated. Thus, if there is an asymmetric effect between the negative and positive returns then GARCH model is not suited for the chosen time series. In addition, the GARCH model could not explain every time series because of the constraints on its coefficients. Because of these constraints the forecast of the model could be biased.

3.2.3. The Exponential GARCH (EGARCH) Model

Exponential GARCH model is proposed by Nelson (1991) in order to strengthen the weaknesses of GARCH model. It is noteworthy to know that in the EGARCH model the imposed nonnegativity constraints on the GARCH model are no longer exist. Also, the model includes asymmetric effects (leverage effect) between positive and negative returns of the underlying asset. To do the latter, Nelson (1991) considers the weighted innovation

$$g(\varepsilon_t) = \theta\varepsilon_t + \gamma[|\varepsilon_t| - E(|\varepsilon_t|)] \qquad \textbf{(4)}$$

where, θ and γ are real constants. The sequences $|\varepsilon_t|$ and $E(|\varepsilon_t|)$ are both iid with zero mean having continuous distributions. The EGARCH model is specified as follows;

$$\ln\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{p} \alpha_i g\left(\varepsilon_{t-i}\right) + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) \qquad \textbf{(5)}$$

In the model, the non-negativity of the unconditional variance σ_t^2 of the given data X_t at time t is warranted by using $\ln(\sigma_t^2)$ rather than forecasting σ_t^2 with the use of linear combinations of positive random variables imposing nonnegativity constraints.

3.3. VALUE AT RISK (VaR)

VaR is a method to calculate the value of a risk position of a firm or a portfolio. It focuses on the firm risk that is affected by the general market movements. Therefore, VaR is also related with the market risk.

The concept of VaR gained major attention due to the crash of 1987. The crash showed the deficiency of the standard statistical models and the necessity to reconsider the possibility of the recurring financial crisis.

The calculation of the VaR has some characteristics:

a) The confidence level is set at 99% or 95%

b) The time period chosen as one day or ten days (The time period can be determined by the regulatory bodies such as the Bank for International Settlements.)

c) The notional value of the portfolio or the financial position of an institution

d) The cumulative distribution function of the change in the value of the assets

e) The frequency of the data such as daily data

VaR can be defined as the worst loss with a level of probability, which is p, or as the least loss with the level of rest of the probability, which is 1-p, in a given period of time. The type of definition depends on the viewpoint of the institutions and regulatory bodies. For instance, if an institution has one day VaR of 50.000 TRY at the 99% confidence level, it means that this institution will not lose more than

50.000 TRY with 99% probability in a day or it can be said that this institution will lose at least 50.000 TRY with 1% probability in a day.

As it is stated before, risk is the probability of loss. Loss of a firm or portfolio depends on the direction of its position. The holder of a long position on an asset loses if the value of the asset decreases. If the value change in a given period of time t is defined as $\Delta V(t)$, the risk is needed to be calculated when $\Delta V(t) < 0$. So, the VaR value of a firm which has long position on an asset, with the probability p in given period of time t can be defined as follows;

$$p = \Pr[\Delta V(t) \le VaR] = 1 - \Pr[\Delta V(t) \ge VaR]$$

On the contrary, the holder of a short position on an asset loses if the value of the asset increases. The risk of the holder of the short position appears when $\Delta V(t) > 0$. Hence, the VaR value of a firm which has short position on an asset, with the probability p in given period of time t can be defined as

$$p = \Pr[\Delta V(t) \ge VaR] = 1 - \Pr[\Delta V(t) \le VaR]$$

If the cumulative distribution function of $\Delta V(t)$ is defined as $C_t(x)$, the left tail of the $C_t(x)$ is examined for the holder of the long position while the right tail of the $C_t(x)$ is examined for the holder of the short position.

RiskMetrics, the extensive VaR methodology, was introduced by the JP Morgan. It is the parametric calculation method for VaR. The use of VaR methodology was fostered by Basel II Accord. GARCH methodology is also used to calculate the VaR values as another parametric approach. Other VaR calculation methods can be classified as semi-parametric (extreme value theories) and non-parametric (historical simulation) methods.

3.3.1. Parametric Value at Risk

If a parametric model can be indexed by finite parameters and these parameters fit a single distribution, this model can be indicated as parametric model. Therefore, parametric VaR model assumes that returns have a single distribution and the VaR value of a portfolio can be measured by calculating the parameters, depending on that distribution.

•Mathematical proof for the VaR model at 99% confidence level

If P is the value of an asset, the return of the asset at the time t:

$$\Delta V(t) = \frac{P_2 - P_1}{P_1}$$

$$P_2 - P_1 = \Delta V(t) \times P_1$$

If we indicate the loss equation as follows:

$$Loss = -\Delta V(t) \times P_1$$

If the returns (R) show the standard normal distribution; $N(\mu, \sigma^2) = N(0,1)$ then,

$$Z = \frac{R - \mu}{\sigma} \approx N(0,1)$$

Now, we can compute the VaR at the 99% confidence level (or the minimum loss with the 1% probability).

$$\Pr[-\Delta V(t) \times P_1 \leq VaR] = 0.01$$

$$\Pr[\Delta V(t) \times P_1 \leq -VaR] = \Pr[\Delta V(t) \leq VaR / P_1] = 0.01$$

Let find the Z statistics for the probability of 0.01;

$$\Pr\left[\frac{R-\mu}{\sigma} \le \frac{\frac{-VaR}{P_1}-\mu}{\sigma}\right] = \Pr\left[Z \le \frac{\frac{-VaR}{P_1}-\mu}{\sigma}\right] = 0.01$$

Z table shows that $\Pr[Z \le -2.33] = 0{,}01$. Therefore,

$$\frac{\frac{-VaR}{P_1}-\mu}{\sigma} = -2.23$$

Then VaR at the 99% confidence level with standard normal distribution assumption can denoted as follows:

$$VaR = P_1 \times (2.33 \times \sigma - \mu)$$

with $\mu = 0$ under the standard normal distribution assumption. So, this equation turns out as follows:

$$VaR = P_1 \times 2.33 \times \sigma$$

For example, the value of a portfolio is 100.000 TRY and the unconditional or conditional standard deviation of the return series is 2% for one day then, the VaR value for that portfolio equals to

$$VaR = 100{,}000 \times 2.33 \times 0.02 = 4{,}660$$

It means that the value of the portfolio may diminish at least 4,660 TRY in one day with the 1% probability or the value of the portfolio may not diminish more than 4,660 TRY in one day with the 99% probability.

VaR can also be calculated for more than one day period by using below formula:

$$VaR = P_1 \times (2.33 \times \sigma) \times \sqrt{T} \qquad \textbf{(7)}$$

T denotes number of days for which VaR is calculated.

Then the VaR value for the same portfolio for ten days;

$$VaR = 100{,}000 \times 2.33 \times 0.02 \times \sqrt{10} = 14{,}736.21$$

It means that the value of the portfolio may diminish at least 14.736,21 TRY in ten days with the 1% probability or the value of the portfolio may not diminish more than 14.736,21 TRY in ten days with the 99% probability.

If the returns show no normality and one assumes that a_t has student's t distribution, the below formula is used to calculate VaR values:

$$Var = P_1 \times (3.3649 / \sqrt{5/3}) \times \sigma \times \sqrt{T} \qquad \textbf{(8)}$$

The standard deviation which is used in the VaR formulation is determined by the GARCH model family as an econometric approach to VaR calculation. So it can be called as conditional standard deviation. Therefore, if the best fitting model is the EGARCH, the VaR values can be calculated by the equation (8). Since the GARCH model run under the assumption of normal distribution of error terms, the VaR values for the data which is modeled by the GARCH, can be calculated by the equation (7).

Parametric VaR method needs the variance-covariance matrix of the asset returns. When new data enters to the time series, the variance-covariance matrix has to be updated. The use of this method is very easy. Since the parametric VaR method mostly depends on the normality assumption, it may underestimate the VaR values. However, this problem can easily be eliminated by using the econometric models which do not assume the normality distribution such as EGARCH. Moreover, parametric VaR methods can provide the complete determination of the distribution of the returns.

3.3.2. Semi-Parametric Value at Risk (Extreme Value Theory)

Extreme value theory is a model that measures extreme financial risks by modeling the tail of the distribution of data instead of focusing on the centre of the data. It depicts that the distribution of the extreme values are mostly free from the distribution of the asset returns.

The theory can be summarized as follows: Having the cumulative distribution function F of the return series, we need to divide the N-dimension return series (r_t) into sub-series, say n number of T units. Then, we form the Block Minima (Maxima) series of n dimension; that is $Z_n =$ min (minimum return of each sub-series) or $Z_n =$ max (maximum return of each sub-series). Assuming that the returns r_t are serially independent with a common cumulative distribution function $F(x) = P(r_t \leq x)$, where $r_t \in [l, u]$, we find the CDF of $r_{(1)}$ by considering its possible values below some number.

$$
\begin{aligned}
F_1(x) = P(r_{(1)} \le x) &= 1 - P(r_{(1)} > x) \\
&= 1 - P(r_1 > x, r_2 > x ... r_n > x) \\
&= 1 - P(r_1 > x).P(r_2 > x)...P(r_n > x) \qquad \text{(By serial independence of } r_t\text{)} \\
&= 1 - \prod_{i=1}^{n} P(r_i > x) \\
&= 1 - \prod_{i=1}^{n} [1 - P(r_i \le x)] \\
&= 1 - \prod_{i=1}^{n} [1 - F(x)] = 1 - [1 - F(x)]^n
\end{aligned}
$$

In most cases the CDF is not known, so is F_1. Although we do not know what the original distribution function is, we can observe that when n tends to infinity F_1 goes either to 0 or to 1 when $x \le l$ and $x > l$, respectively. Thus, this degenerated function has no mean in practice. In order to analyze the return series we need to normalize it by finding location series $\{\beta_n\}$ and scaling factors series $\{\alpha_n\}$ with $\alpha_n > 0$, such that $r_{(1*)} \equiv \dfrac{r_{(1)} - \beta_n}{\alpha_n}$ converges to a non-degenerated function as n goes to infinity. Limiting distributions of the normalized minimum (the generalized extreme value distribution for the minimum, Jenkinson) then turns out to be

$$
F_*(x) = \begin{cases} 1 - \exp[-(1+kx)^{1/k}] \\ 1 - \exp[-\exp(x)] \end{cases} , \quad \begin{matrix} k \ne 0 \\ k = 0 \end{matrix} \quad \text{for} \quad \begin{matrix} x < -1/k \\ x > -1/k \end{matrix} \quad \text{if} \quad \begin{matrix} k < 0 \\ k > 0 \end{matrix}
$$

The parameter k is the shape parameter (tail index) which gives information about the tail behavior of the distribution. The larger the shape parameter is, the thicker the tail. The generalized extreme value distribution for the minimum spans the Gnedenko's three types of limiting distributions for the interval that shape parameter involves;

1. k=0, the Gumbel family, with the CDF

$$F_*(x) = 1 - \exp[-\exp(x)] \quad , \quad -\infty < x < \infty$$

2. k<0, the Fréchet family, with the CDF

$$F_*(x) = \begin{cases} 1 - \exp[-(1+kx)]^{1/k} & \text{if} \quad x < -1/k \\ 1 & \quad\quad \textit{otherwise} \end{cases}$$

3. k>0, the Weibull family, with the CDF

$$F_*(x) = \begin{cases} 1 - \exp[-(1+kx)]^{1/k} & \text{if} \quad x > -1/k \\ 0 & \quad\quad \textit{otherwise} \end{cases}$$

In general, when modeling the fat-tailed financial data the Fréchet family distribution constitutes the best fit since this distribution corresponds to fat-tailed distributions. This three distribution family is of importance because regardless of the original distribution, which is mostly unknown, one of the three provides the best fit for the given data.

Extreme value theory has its advantages. First, the tail behavior of the original distribution function F determines the limiting distribution F_*. Second, the tail index is time invariant. This attribute of the theory makes it handy to use it when calculating VaR.

One problem with this theory is that one can only work with the univariate case because there isn't any definition in a vectorial space with dimensions greater than 1 (multivariate case) .

3.3.3. Non-Parametric VaR (Historical Simulation)

Historical Simulation measures the VaR by simulating the returns of the assets in a chosen period of time. The simulation process depends on the real asset returns. Since the historical simulation is a method which does not assume the distribution type of returns and captures the fat-tail behaviour, the model risk is low. So, it can be implemented to linear and non-linear financial instruments. On the other hand, historical simulation assumes that asset returns show independent and identical distribution, but the asset returns behaviour does not. Other deficiency for the historical simulation is that all returns are equally weighted. This case decreases the prediction power of the method.

Weighted Historical Simulation is another non-parametric VaR method. It gives more weight to the returns that are close to the present. So, Weighted Historical Simulation eliminates the problem of low predictability of the traditional historical simulation method. Also, i.i.d assumption is valid for the weighted historical simulation.

Another advantage of the traditional and weighted historical simulation method is that they have no parametric constraints. But historical simulation methods require intensive calculation, creating difficulty for the users. Since traditional and weighted historical simulation methods create scenarios relying on the path of the historical returns, these methods cannot make a true prediction at the transition periods when low volatility period ends and high volatility period begins or vice versa.

CHAPTER 4
DATA AND EMPRICAL RESULTS

4.1. DATA

The data consists of daily natural logarithmic returns derived from closing prices for ISE-30 Index futures, which is obtained from the database of TURKDEX. We divide the entire sample period into two sub periods to see the impact of some shocks over the sample period on the measures of VaR. The first period can be called as the low volatility period and the second period is called the high volatility period. Because the concerns about economic recession in the USA began spreading out in February 2007, we determine the February 2007 as the beginning of the second period (the high volatility period). At this time, crude oil prices started to increase and the former president of FED, Greenspan, declared that there is a high possibility of the beginning of the recession.

Table 5-6-7 show the descriptive statistics of the ISE-30 Index Futures returns in three different time periods. The descriptive statistics for daily ISE-30 Index futures return series cover mean, median, standard deviation, maximum, minimum, skewness, kurtosis and Jarque–Bera statistics for the three different time periods.

Table 5: Descriptive Statistics of ISE-30 Index futures' returns

The Low Volatility Period: (04/02/2005-31/01/2007)

Number of Observations	502
Mean	0,001
Standard Deviation	0,016
Maximum	0,067
Minimum	-0,082
Skewness	-0,263
Kurtosis	4,937
Jarque-Bera	84,265

The return distribution is non-symmetric and negatively skewed. Also, large value of kurtosis statistics indicates that underlying data are leptokurtic. Since the kurtosis value is higher than 3, it can be said that data series have non normal distribution. Also the large value of the Jarque-Bera statistics gives another reason to reject the normality at the 1% level.

Table 6: Descriptive Statistics of ISE-30 Index futures' returns

The High Volatility Period: (01/02/2007-31/03/2009)

Number of Observations	546
Mean	-0,001
Standard Deviation	0,026
Maximum	0,097
Minimum	-0,099
Skewness	0,001
Kurtosis	4,769
Jarque-Bera	71,265

The return distribution is non-symmetric and positively skewed. Also, large value of kurtosis statistics indicates that underlying data are leptokurtic. Because of the large value of The Jarque-Bera statistics, we reject the normality at the 1% level.

Table 7: Descriptive Statistics of ISE-30 Index futures' returns

The Entire Period: (04/02/2005-31/03/2009)

Number of Observations	1.048
Mean	-0,0001
Standard Deviation	0,022
Maximum	0,097
Minimum	-0,099
Skewness	-0,099
Kurtosis	5,603
Jarque-Bera	297,589

The return distribution is non-symmetric and negatively skewed. Also, large value of kurtosis statistics indicates that underlying data is leptokurtic. The large value of The Jarque-Bera statistics and excess kurtosis, It can be said that the data series show non-normality.

Table 5, Table 6 and Table 7 also show that the highest standard deviation is observed in the high volatility period which is between February 1, 2007-March 31, 2009. These results are expected because of the recent financial crisis effect. The high volatility period covers the whole shock period. However the standard deviation of the whole period is lower than the high volatility period since the low volatility period decreased the effect of the high volatility period. Variation is between 1.6% and 2.6%. In addition, the difference between the minimum and maximum values is 14.7% for the low volatility and 19.5% for the high volatility and the entire periods. The effect of the financial crisis, which is intensified by the collapse of the Lehman Brothers in October 2008, can easily be seen by analyzing these figures. Increasing volatility is reflected on the changes in the difference between minimum and maximum values.

The values of skewness for each period state that the distribution of the data is not symmetric. The structure of the skewness, named third moment, also can be traced by the below histograms.

Figure 1: The Distribution of Return Series for ISE-30 Index Futures

The Low Volatility Period

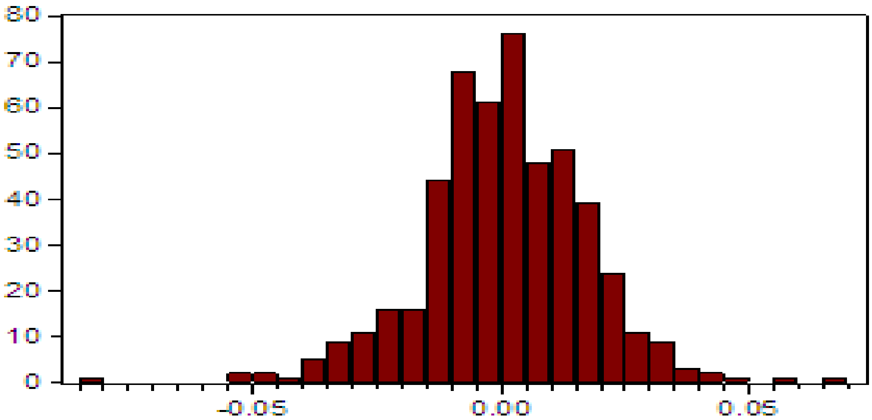


Figure 2: The Distribution of Return Series for ISE-30 Index Futures

The High Volatility Period

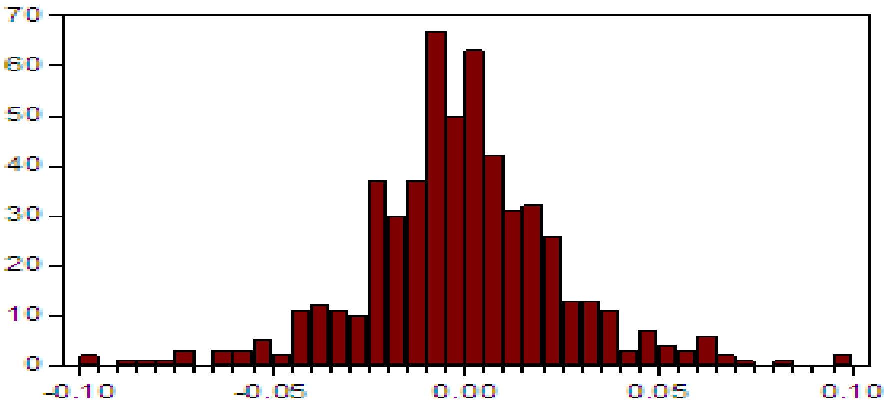
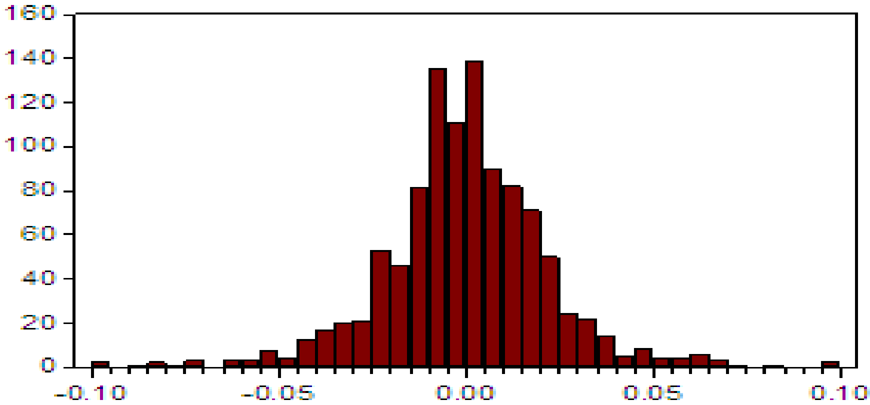


Figure 3: The Distribution of Return Series for ISE-30 Index Futures

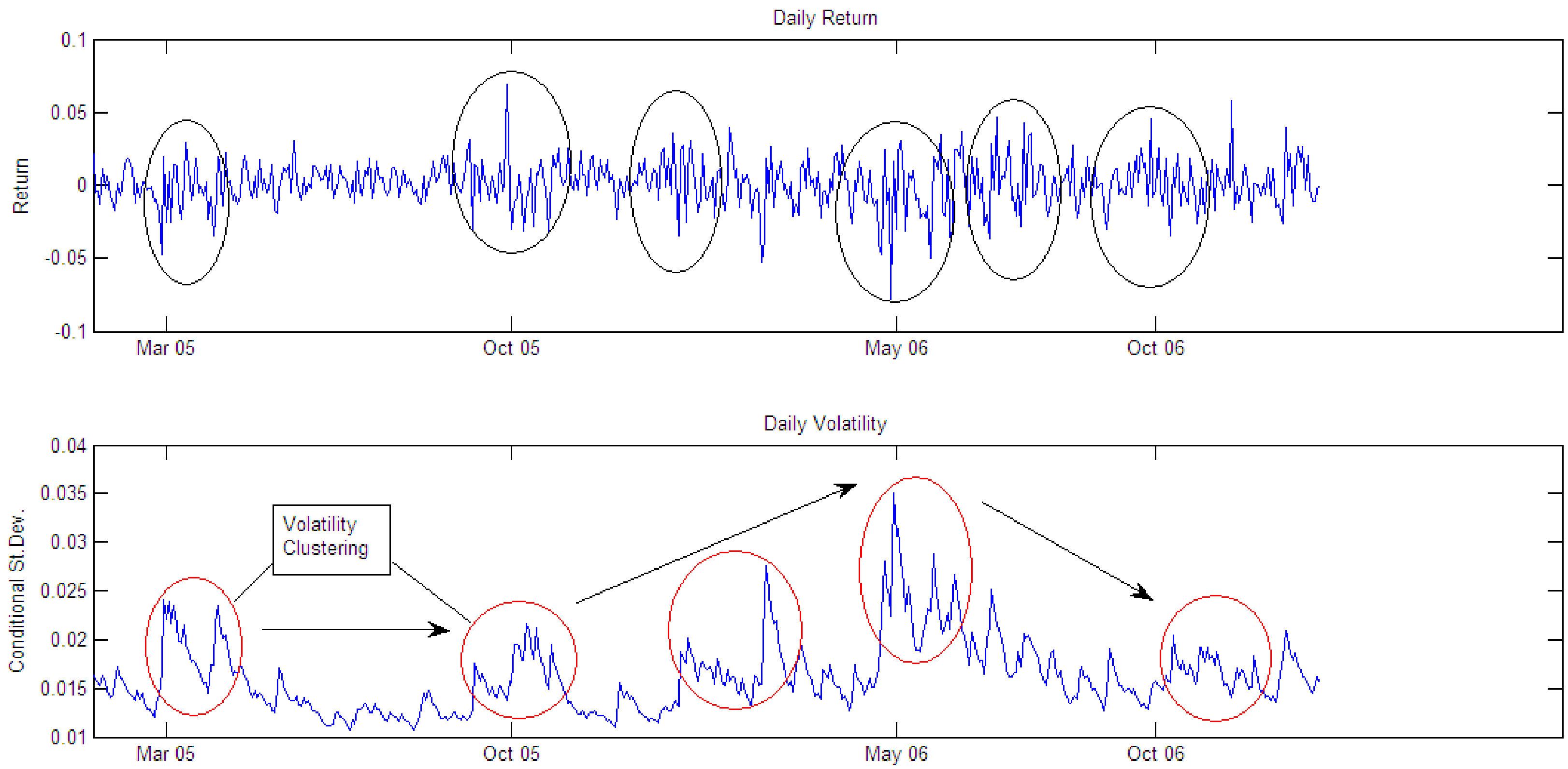
The Entire Period



The kurtosis is the measure of the fat tail behaviour; this behaviour can be seen from the above histograms. Fat tail behaviour (or leptokurtic behaviour) is the signal for the non-normality. Normal distribution states that there are less observations of extreme values and the tails of the distribution graph are close to the zero. As it can be seen from the above histograms data distribution of all the time periods show fat tail behaviour. At last, it can be said that all the data series have the same characteristics. They all show skewness and fat tail behaviour.

Figure 4: Return Series and Daily Volatility for ISE-30 Index Futures-Low Volatility Period

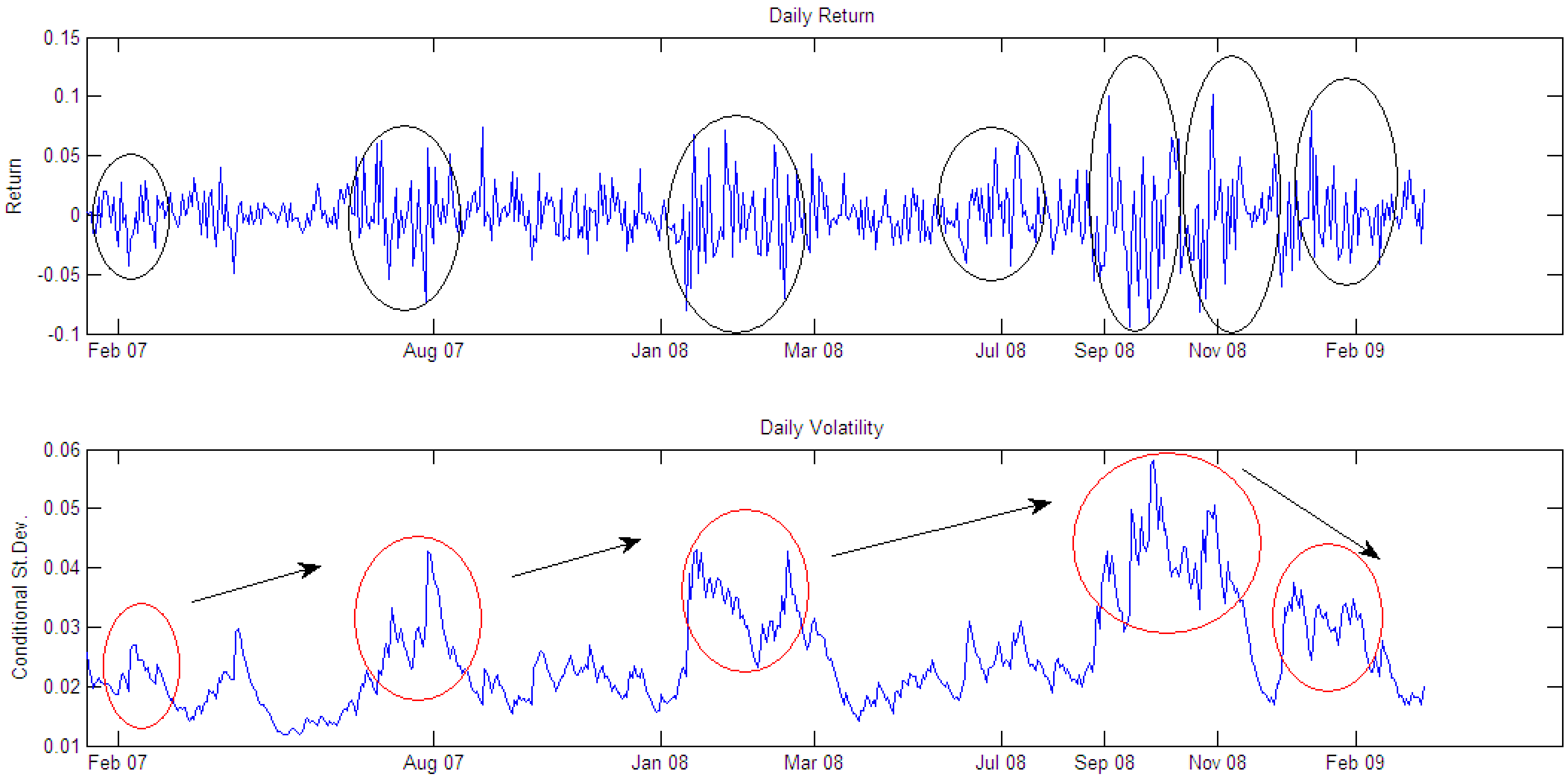
The Low Volatility Period



Since volatility creates positive or negative return; return and volatility clusters occur in the same time period. For the period of February 4, 2005-January 31, 2007, the daily volatility tended to increase from March 2006, when there was uncertainty on the selection of the president of the Central Bank of the Republic of Turkey, and reached to the peak point in May 2006, when the prices of gold and crude oil increased and the foreign financial market indexes decreased dramatically. Then daily volatility started to decrease due to expectations of a decrease in the inflation because of the recession in the USA. In addition, the FED decreased interest rates and this diminished the daily volatility. In October 2006, 20% of the Akbank's shares were sold to Citigroup. After that, volatility caused prices to increase.

Figure 5: Return Series and Daily Volatility for ISE-30 Index Futures-High Volatility Period

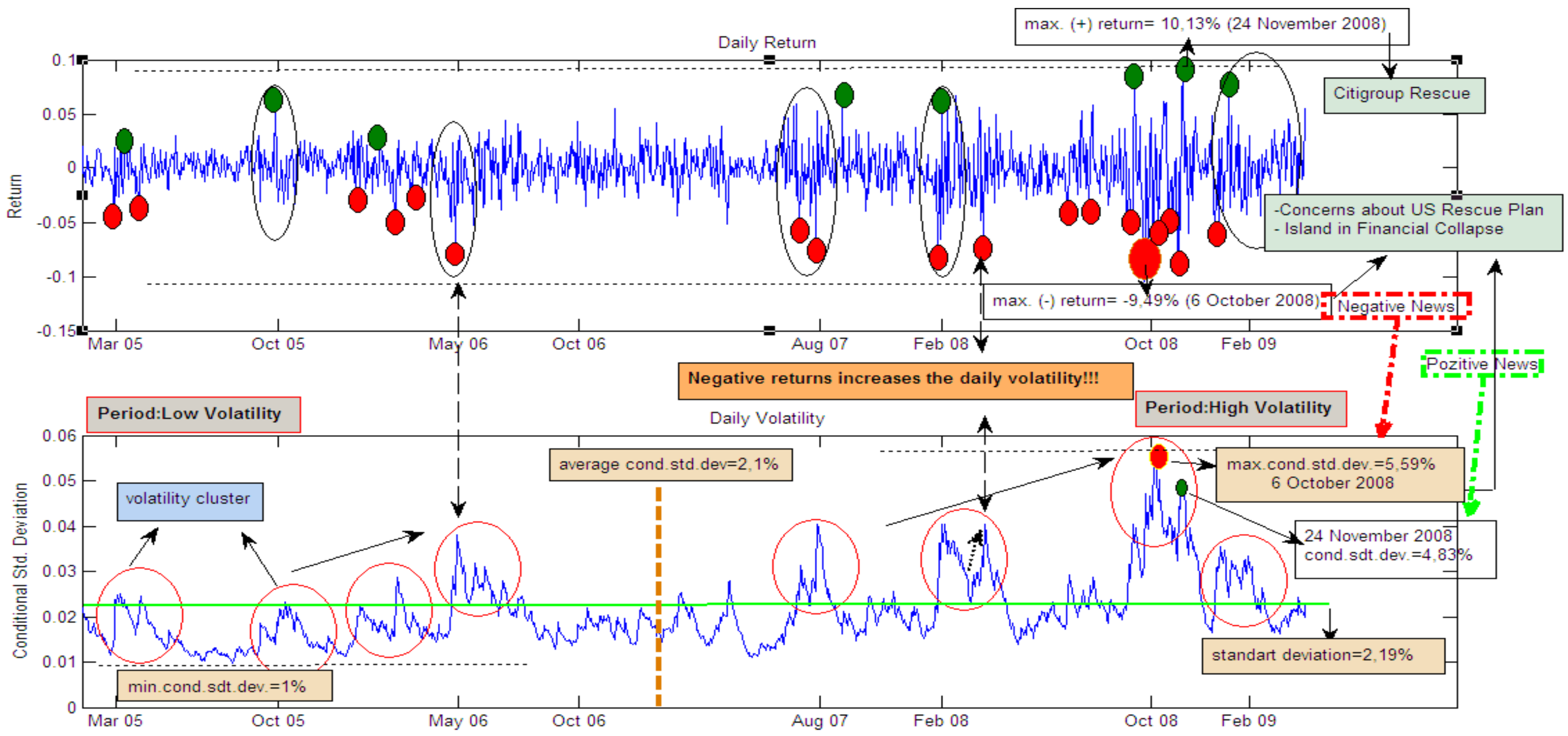
The High Volatility Period



The second period started with the increasing volatility because of the disagreement between the USA and Iran and the increasing crude oil prices. Also the adverse comments of the former president of the FED, Greenspan, about economic structure of the USA increased the negative volatility and this case continued to affect the ISE-30 Index futures market until the beginning of July 2007 when the Justice and Development Party won the election. The election result increased the expectations on the economic stability. Till the end of the July 2007, there was an increasing positive volatility. This increasing trend continued in negative direction because of economic disturbances about mortgage credit market and some hedge funds. Since the Fed diminished the interest rates, the daily volatility tended to decrease till the beginning of 2008. In January 2008, concerns about economic recession and decrease in the selling rate of real estates increased the volatility again in negative direction. Then Microsoft's buying proposal of Yahoo and another proposal from Warren Buffet for insurance companies in the USA created positive psychological conditions for investors. This case was supported by the declaration of the substantial profits by the major Turkish banks in February 2008 and so the daily volatility started to decrease. As it can be seen from the Figure 6, the daily volatility started to increase dramatically from September 2008 when the bankruptcy of Lehman Brothers occurred. This case was the first major result of the global financial crisis and it raised the expectation about global recession. The bankruptcy of the Lehman Brothers was followed by the declaration of the loss of the Goldman Sachs and Citigroup. Firstly, this negative news fostered the negative volatility in the US financial market and then the negative volatility spanned to global financial area. The risk on the developing markets increased due to the negative financial developments in Iceland and Hungary. The highest negative return of the ISE-30 Index futures occurred on October 6, 2008 when there was adverse expectation of market participants on the FED's rescue plan. However, at the end of the October 2008, the FED diminished the interest rates again and FED's new plan to restructure the debts of the borrowers created positive psychological environment. In addition, the victory of Barrack Obama in the US Presidency Elections supported these conditions and the volatility started to decrease at the end of November 2008. On November 24, 2008, the highest positive return occurred because of the rescue of the Citigroup. New Year started in a new volatility cluster that was in lower level than the level of the previous volatility cluster. At the beginning of the year, the negative news from the US' retailer sector created negative volatility, but then the positive expectations about agreement between Turkish government and IMF created local positive effect on the index futures market in Turkey. This case was accompanied with the increasing amount of the financial support, which was increased from $700 billions to $887, by the US Senate. These positive effects were counterbalanced the negative news from General Motors which was the declaration of the loss of $9.6 billions.

Figure 6: Return Series and Daily Volatility for ISE-30 Index Futures-The Entire Period

The Entire Period



Since the entire period covered the low and high volatility periods, the comments about Figure 5-6 is valid for this figure. The major result for the entire period is that the negative news affected the returns and volatility more than positive news. It is the indication of the leverage effect, which may be controlled by the EGARCH. Therefore, it can be expected that the EGARCH model fits best for the ISE-30 index futures.

During the entire period, the negative news created the maximum conditional standard deviation of 5.59% while the positive news caused the conditional standard deviation of 4.83%. Since the negative news caused more conditional standard deviation than positive news, it can be said that negative news was more effective on the volatility than positive news for the entire period.

4.2. EMPIRICAL RESULTS

As it can be seen from the Table 8, since the null hypothesis of the ADF test, which denotes time series has a unit root, is rejected at 1% level and the null hypothesis of the KPSS test, which denotes time series is stationary, is accepted at 1% level for the all periods; the logarithmic returns can be used to model conditional heteroscedastic variance and to forecast conditional standard deviation, accurately. However, it is expected that the closing prices of the ISE-30 Index futures show non-stationarity. The results of the ADF and KPSS tests are reported in Table 8.

Table 8: ADF and KPSS Unit Root Test Results

Periods	Trend/NoTrend	ADF		KPSS	
		Prices (Level)	**Log.Returns (Level)**	**Prices (Level)**	**Log.Returns (Level)**
1st	η_τ	-1,445(0)	-21,893(0)[a]	0,460[a]	0,117[b]
	η_μ	-1,159(0)	-21,915(0)[a]	1,691[a]	0,130[b]
2nd	η_τ	-2,186(0)	-22,330(0)[a]	0,527[a]	0,040[b]
	η_μ	-0,658(0)	-22,305(0)[a]	2,031[a]	0,196[b]
3rd	η_τ	-1,148(0)	-31,107(0)[a]	0,694[a]	0,050[b]
	η_μ	-1,398(0)	-31,051(0)[a]	0,855[a]	0,340[b]

[a] Indicates rejection of the null hypothesis at 1% level.

[b] Indicates acceptance of the null hypothesis at 1% level.

To determine which model fits best for the ISE-30 index futures data, we check whether the asymmetry coefficient is statistically significant for each time period. The variance equations of each period can be seen from Table 9-10-11.

Table 9: Variance Equation for the Low Volatility Period

$$\ln \sigma_t^2 = b_1 + b_2 \ln \sigma_{t-1}^2 + b_3 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_t^2 - 1}} + b_4 \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_t^2 - 1}}$$

	b1	b2	b3	b4
Estimate	-0,785[b]	0.906[b]	-0,011[b]	0,188[b]
z-statistics	-2,014	2,554	-2,349	2,509

[a] Indicates the significance level at 0,01

[b] Indicates the significance level at 0,05

Table 10: Variance Equation for the High Volatility Period

$$\ln \sigma_t^2 = b_1 + b_2 \ln \sigma_{t-1}^2 + b_3 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_t^2 - 1}} + b_4 \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_t^2 - 1}}$$

	b1	b2	b3	b4
Estimate	-0,375[b]	0.949[a]	-0,086[b]	0,263[a]
z-statistics	-2,185	4,746	-2,177	4,143

[a] Indicates the significance level at 0,01

[b] Indicates the significance level at 0,05

Table 11: Variance Equation for the Entire Period

$$\ln \sigma_t^2 = b_1 + b_2 \ln \sigma_{t-1}^2 + b_3 \frac{\varepsilon_{t-1}}{\sqrt{\sigma_t^2 - 1}} + b_4 \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_t^2 - 1}}$$

	b1	b2	b3	b4
Estimate	-0,336[a]	0,957[a]	-0,079[a]	0,232[a]
z-statistics	-3,062	6,027	-3,01	5,331

[a] Indicates the significance level at 0,01

[b] Indicates the significance level at 0,05

The variance equations for the three different time periods are presented in the table 9-10-11. As it can be seen from the tables, the coefficient b1 (the constant term) is statistically significant at 95% confidence levels for the low and high volatility periods and at 99% confidence levels for the entire period. Also, b2 and b4 are statistically significant at 95% confidence levels for the low volatility period and at 99% confidence levels for the high volatility and the entire period. Since the coefficient b3 refers to the coefficient that measures the asymmetric effects, the ISE-30 Index futures show statistically significant asymmetric effects at 95% confidence level for the low and high volatility periods and at 99% confidence level for the entire period. In addition, b3 is negative for all the periods. It means that the negative news which creates negative shocks has more effect on the ISE-30 futures market than positive news that creates positive shocks.

Since the significance of coefficients of the model is close to unity for each time period of returns, it can be said that volatility of returns show persistence. The effects of the price shocks, which create volatility, decay slowly. In other words, the volatility of returns has long memory. Because the conditional standard deviation changes over time, it can be said that volatility of the ISE-30 Index returns changes over time. In other words, the volatility of the ISE-30 Index returns is time dependent.

Then, to determine whether there is autocorrelation in the normalized residuals or not, the LB test and ARCH-LM test are employed. The results can be seen from Table 12-13-14-15.

Table 12: The Lung-Box Test for the normalized residuals

The Low Volatility Period

Lags	Autocorrelation	Partial correlation	Lung-Box Statistic
1	0,037	0,037	0,696
2	0,048	0,047	1,883
3	-0,018	-0,022	2,048
4	0,01	0,009	2,099
5	0,01	0,011	2,151
10	0,017	0,02	8,372
20	-0,036	-0,03	16,428

Figure 7: Autocorrelation of the Normalized Residuals

The Low Volatility Period

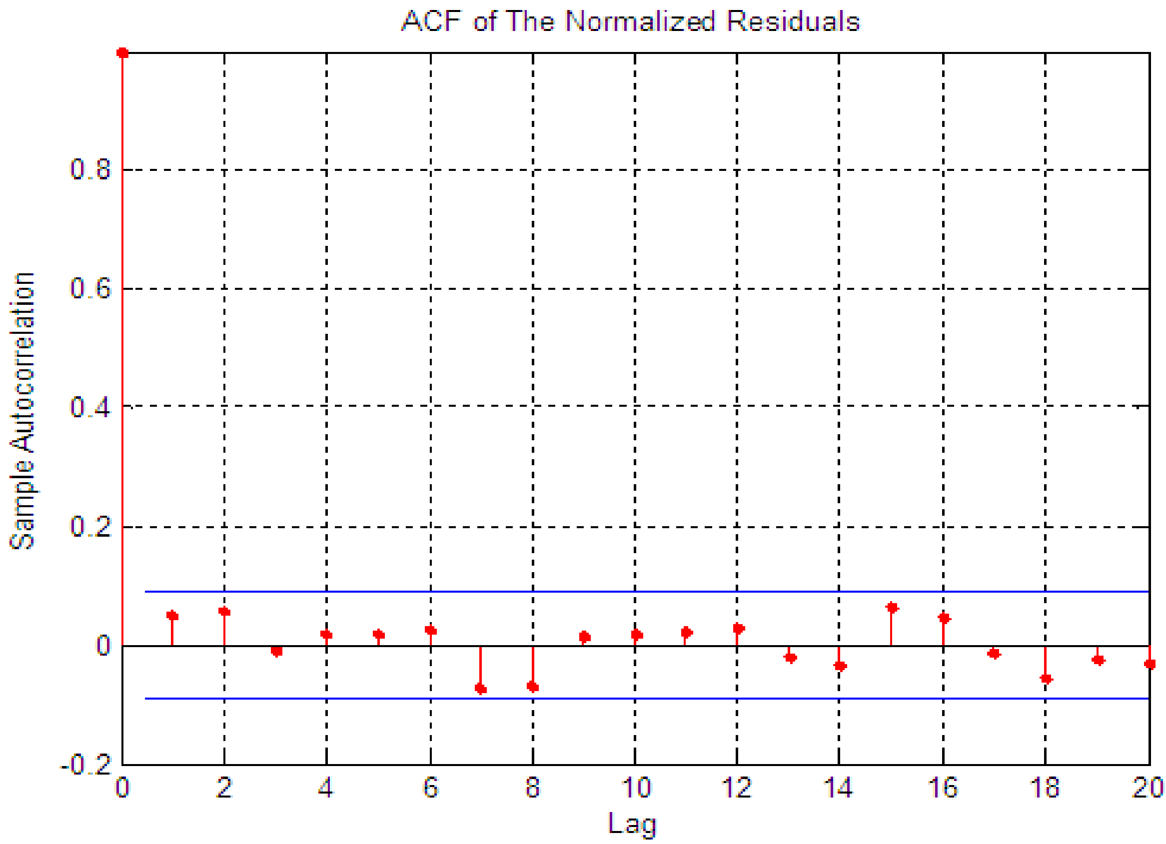


Table 13: The Lung-Box Test for the normalized residuals

The High Volatility Period

Lags	Autocorrelation	Partial correlation	Lung-Box Statistic
1	0,036	0,036	0,725
2	0,004	0,003	0,734
3	-0,015	-0,016	0,864
4	0,042	0,044	1,861
5	-0,08	-0,083	5,362
10	0,046	0,042	12,543
20	-0,064	-0,051	20,334

Figure 8: Autocorrelations and Partial Autocorrelations for Return Series

The High Volatility Period

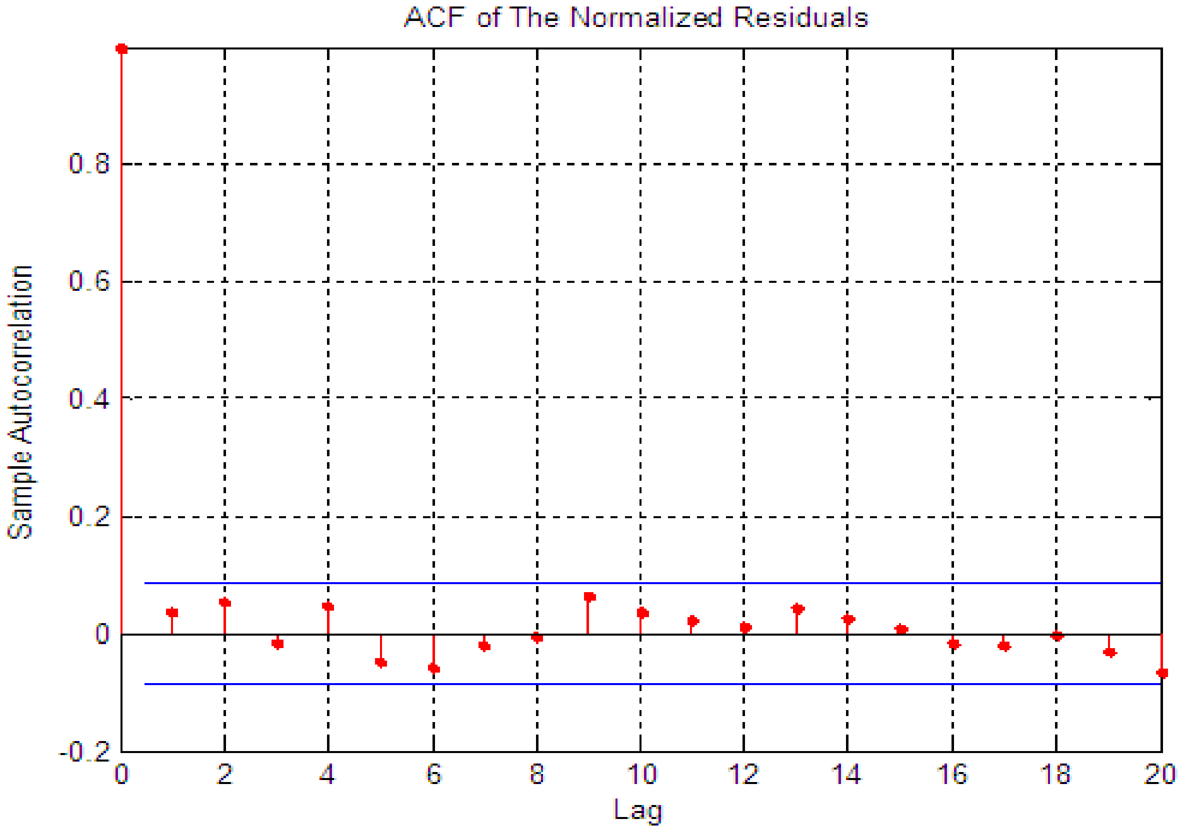


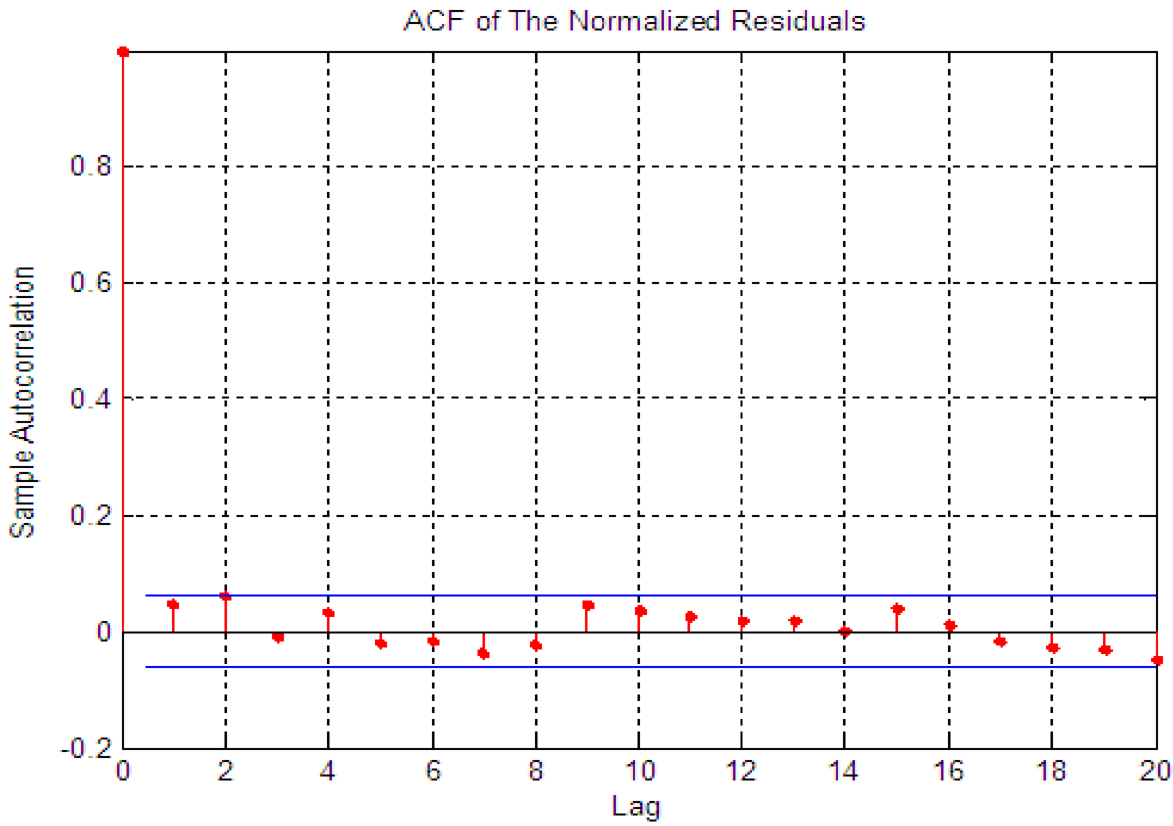
Table 14: The Lung-Box Test for the normalized residuals

The Entire Period

Lags	Autocorrelation	Partial correlation	Lung-Box Statistic
1	0,032	0,032	1,079
2	0,027	0,026	1,859
3	-0,026	-0,028	2,597
4	0,031	0,032	3,623
5	-0,057	-0,058	7,058
10	0,054	0,051	16,935
20	-0,066	-0,061	25,899

Figure 9: Autocorrelations and Partial Autocorrelations for Return Series

The Entire Period



As it is seen from the Table 12-13-14, Lung-Box statistics for each period of the data series show no autocorrelation in squared normalized residuals. The Figure 7-8 and 9 also show no autocorrelation in the normalized residuals. It means that the EGARCH model sufficiently explains the heteroscedasticity in the returns of the three different time periods in this thesis.

To test the serial dependence in the squared residuals, ARCH-LM Test is employed. Table 15 reports the ARCH-LM test results.

Table 15: ARCH-LM Test Results

ARCH-LM Test Results for The Low Volatility Period			
Constant	Squared Residuals	F-statistics	LM-statistics
1,011	-0,013	0,084	0,084
(0,000)	(0,772)	(0,772)	(0,771)
ARCH-LM Test Results for The High Volatility Period			
Constant	Squared Residuals	F-statistics	LM-statistics
1,061	0,007	0,026	0,026
(0,000)	(0,873)	(0,873)	(0,873)
ARCH-LM Test Results for The Entire Period			
Constant	Squared Residuals	F-statistics	LM-statistics
1,097	0,009	0,093	0,094
(0,000)	(0,759)	(0,759)	(0,759)

The ARCH-LM and also F-statistics state that there is no serial dependence in squared residuals. Since the Lung-Box Test and ARCH-LM Test indicate no autocorrelation and serial dependence in squared residuals, it can be said that conditional time varying variance model which are employed for the data series in this study, can get the ARCH effect.

Finally, we utilized the equation (4) and (5) to do one-step ahead forecasting for the conditional standard deviation for each time period. If we take the EGARCH (1, 0) model and assume that the model parameters are known and the error terms show standard normal distribution, the EGARCH model can be rewrite as follows;

$$\ln\left(\sigma_t^2\right) = \left(1-\beta_1\right)\alpha_0 + \beta_1 \ln\left(\sigma_{t-j}^2\right) + g\left(\varepsilon_{t-1}\right)$$

$$g(\varepsilon_t) = \theta\varepsilon_t + \gamma[|\varepsilon_t| - E(|\varepsilon_t|)]$$

We took the exponentials and the models was converted to

$$\sigma_t^2 = \alpha_{t-1}^{2\alpha_1} \exp\left[\left(1-\alpha_1\right)\alpha_0\right]\exp\left[g\left(\varepsilon_{t-1}\right)\right] \quad \textbf{(9)}$$

If k is the forecast origin, one-step ahead forecasting formula can be rewrite as follows;

$$\sigma_{t+h}^{2} = \alpha_{h}^{2\alpha_{1}} \exp[(1-\alpha_{1})\alpha_{0}]\exp[g(\varepsilon_{h})] \quad \textbf{(10)}$$

We obtained the one-step ahead forecasted values by benefiting from equation (10). Then these numbers are used to calculate VaR one-day and VaR ten-days with confidence level of 99% by using equation 8. Table 16 shows the forecasted conditional standard deviation and VaR values for each time period.

Table 16: Forecasted Cond. Std. Dev. and VaR Values

	Time Periods for The ISE-30 Index Futures Returns		
Model: EGARCH (1,1)	The Low Volatility Period	The High Volatility Period	The Entire Period
Conditional Std. Dev.	0.015	0.020	0.019
VaR One-Day (%)	3.792	5.277	4.908
VaR Ten-Days (%)	11.989	16.686	15.521

As it is seen from the Table 16, the highest conditional standard deviation and VaR values result in the high volatility period. The possibility of maximum loss with 99% is 5.277% in a day while the possibility of maximum loss with 99% is 16.686% in ten days. VaR calculation for the high volatility period is stated below:

$$Var = P_{1} \times (3.3649 / \sqrt{5/3}) \times \sigma \times \sqrt{T}$$

$$Var\ One - Day = 1 \times (3.3649 / \sqrt{5/3}) \times 0.020) \times \sqrt{1} = 5.277\%$$

$$Var\ Ten - Days = 1 \times (3.3649 / \sqrt{5/3}) \times 0.020) \times \sqrt{10} = 16.686\%$$

The entire period follows the high volatility period and the low volatility period is the period which is the least volatile period. Since the recent financial crisis which reaches to its peak point in the late 2008 and early 2009, the effects of that crisis can be seen on the VaR values. The entire period also covers the financial crisis period but also it includes the first period which has low volatility. Since the first period diminishes the effect of the period of crisis, the VaR values of the second period is higher than the third period.

For example, an investor takes 10 long positions on the ISE-30 Index futures. He pays the total amount of 5,000 TRY as the margin of the total position since the margin of a ISE-30 Index future contract is 500 TRY. Depending on the forecasted values of the entire period, the value of a portfolio may decrease 4.908% at maximum with 99% in one day. So, the one-day VaR value for that portfolio equals to

$$VaR\ One - day = 5{,}000 \times (3.3649 / \sqrt{5/3}) \times 0.019) \times \sqrt{1} = 776.05\ TRY$$

It means that the value of the portfolio may diminish at least 776.05 TRY in one day with the 1% probability or the value of the portfolio may not diminish more than 776.05 TRY in one day with the 99% probability.

VaR value for the same portfolio for ten days;

$$Var\ Ten - Days = 5{,}000 \times (3.3649 / \sqrt{5/3}) \times 0.019) \times \sqrt{10} = 2{,}454.09\ TRY$$

It means that the value of the portfolio may diminish at least 2,454.09 TRY in ten days with the 1% probability or the value of the portfolio may not diminish more than 2,454.09 TRY in ten days with the 99% probability.

CONCLUSION

We divided the entire sample period, which is between 4 February 2005 and 31 March 2009, to two sub periods as “Low Volatility Period” and “High Volatility Period”. The starting point of the “High Volatility Period” begins on February 1, 2007 and ends on March 31, 2009. The volatility tends to increase because of the concerns about recession in the USA. Also it can easily be traced from the Figure 6 which volatility clusters in the period of high volatility is higher than the volatility clusters in the period of low volatility. Then, we investigated the best fitting model for the ISE-30 Index future contracts data by examining whether the asymmetry coefficient is statistically significant. Results suggest that the asymmetry coefficient is statistically significant for each period and the EGARCH (1, 1) is the best fitting model for modeling the time varying variance for each period and capturing the ARCH effects. The coefficients of the variance equations for each term are statistically significant at 95% or 99% confidence level. In addition, the sum of the coefficients in each equation for each period tends to one. So, it can be concluded that the ISE-30 Index futures market shows the long memory behavior. It is also proven that the EGARCH model can capture the ARCH effect by employing the LB and ARCH-LM tests. These tests show that there are no autocorrelation and serial dependence in the squared residuals.

Since the best fitting model is EGARCH(1,1) for all periods, we can easily say that there are asymmetric price shocks at the ISE-30 Index futures market and also, the negative price shocks have greater impact on the market volatility than the positive price shocks have; because the coefficient that measures the asymmetric price shocks are negative for all periods. Negative news, which converts the market trend down, create the negative price shocks while the positive news, which convert the market trend upward, create the positive price shocks. Therefore, we can conclude that negative news affect volatility more than the positive news do.. These results are in line with the results about the emerging financial markets.

Afterwards, the conditional standard deviation for each period is forecasted and then VaR values are calculated. Since the conditional standard deviation is forecasted by EGARCH (1,1) and the EGARCH (1,1) is modeled on the assumption of student's t distribution, the parametric Value at Risk calculation is also depend on the student's t distribution. 99% is used for the VaR measures. These measures also confirm the analysis of the Figure 6. The highest VaR values belong to the "High Volatility Period", the entire period's values followed it and then the "Low Volatility Period". Since the "Low Volatility Period" decrease the volatility of the "High Volatility Period", the VaR values of the entire period is lower than those of the "High Volatility Period".

As a result, the results of this thesis show that there is time varying volatility with asymmetric price shocks at the TURKDEX ISE-30 Index futures market. This result is in line with the Wu (2001), Lee (2009) and Alagidede and Panagioditis (2009). Also, the time varying volatility of the market is modeled best by the EGARCH (1,1). Asymmetric price shocks at the market indicate that negative price shocks are caused by the negative news have more effect on the ISE-30 Index futures market volatility than positive price shocks, which are emerged from the positive news. This result also supports the findings of Mazıbaş (2004), which states the presence of the leverage effect and the effect of the negative news on volatility for the indices of the Istanbul Stock Exchange. Furthermore, the time varying volatility on the ISE-30 Index futures market shows long memory.

Since this thesis indicates the risk measures of the ISE-30 index futures market, risk managers, portfolio managers, financial intermediary institutions and investors in the market, which trade ISE-30 Index futures, can benefit from the results of the study. Market participants including the policy measures usually use the unconditional variance to calculate the VaR measures. However, this thesis shows that variance changes through time. The presence of the asymmetric price shocks is also proven by the thesis. It indicates that negative news affects the volatility and return of the ISE-30 index futures more than positive news. The presence of the asymmetry suggests the risk managers or investors to use the

EGARCH in order to model the time varying variance for the ISE-30 index futures. In addition, the VaR values for that future contracts are needed to be calculated under the assumption of student's t distribution of error terms because the EGARCH forecasts the conditional standard deviation relying on that distribution assumption to capture the fat tail behavior of the return series.

In conclusion, traders of the ISE-30 Index futures market in Turkey need to be aware of the presence of time varying variance and asymmetric price shocks. They could benefit from the accurate results of the EGARCH model that can model the time dependent variance by capturing the asymmetric behavior of the return series in order to create effective trading strategies.

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