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MASTER'S THESIS

THE IMPACT OF CHANGES IN INTEREST RATE POLICIES ON THE STOCK MARKET VOLATILITY: EVIDENCE FROM BORSA ISTANBUL

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ABSTRACT

Master's Thesis

The Impact of Changes in Interest Rate Policies on the Stock Market Volatility: Evidence from Borsa Istanbul

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In financial markets of 21st century, stock markets are no longer considered as places where people gamble their savings in a win-lose game but are rather considered as one of the main arteries of Turkish economy which represent financial stability and economical development. Especially after recent structural reformations, Borsa Istanbul's (BIST) predictability and stability is a much bigger concern for authorities and regulatory institutions in Turkey as well. Central Bank of Republic of Turkey's (CBRT) decision to retarget its objectives from just maintaining price stability to also maintaining financial stability may be an outcome of this new perspective. It is thought that when concluding interest rate decisions, CBRT considers volatility of stock market as an important factor.

In this study, the changes in policy rate announced by CBRT's effects on volatility of BIST 100 session closing prices are analyzed under structural breaks for period between 02.01.2002 - 15.11.2013. Results of analysis indicate that a decision of change in policy rate by CBRT has a negative impact on volatility of BIST 100 index session closing prices. Additionally, when structural breaks are added through Kappa 2, a modified algorithm of iterative cumulative sum of squares (ICSS) model, there is a significant reduction in persistence of volatility on closing price series.

Keywords: BIST 100, Volatility, Structural Breaks, Policy Rate

ÖZET

Yüksek Lisans Tezi

Faiz Politikasındaki Değişimlerin Hisse Senedi Piyasasının Oynaklığına Olan Etkileri: Borsa İstanbul Örneği

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İngilizce Muhasebe ve Finansman Programı

Türkiye'de 21. yüzyılın finansal piyasalarında, hisse senedi piyasaları tek tarafın kazançlı çıktığı bir kumar olarak görülmekten çıkmış, Türk ekonomisinin istikrarını ve gelişmişliğini temsil eden en önemli unsurlarından birisi olarak görülmeye başlanmıştır. Özellikle Borsa İstanbul'un geçirdiği yapısal reformlarla beraber BIST endeksinin istikrarı ve öngörülebilirliği, denetleyici ve düzenleyici kurumlar için çok daha önemli bir hale gelmiştir. Türkiye Cumhuriyet Merkez Bankasının (TCMB) görev tanımını sadece fiyat istikrarını sağlamanın yanında, ikincil olarak finansal istikrarı da sağlamak olarak yeniden tanımlaması, yeni bakış açısının bir sonucu olabilir. Faiz politikasına ilişkin kararları verirken TCMB'nin sermaye piyasası oynaklığını önemli bir faktör olarak değerlendirdiği düşünülmektedir.

Bu çalışmada, TCMB tarafından ilan edilen politika faiz oranının BIST 100 endeksinin seans kapanış fiyatlarının oynaklığı üzerindeki etkisi, 02.01.2002 - 15.11.2013 dönemi için yapısal kırılmalar göz önünde bulundurularak araştırılmıştır. Sonuçlar TCMB tarafından politika faizi üzerine yapılan bir etkinin BIST100 endeksi kapanış fiyatları oynaklığı üzerinde azaltıcı bir etkisi olduğunu ortaya koymuştur. ICSS algoritmasından uyarlanarak elde edilen Kappa 2, kullanılarak tespit edilen yapısal kırılmalar da modele dâhil edildiğinde, oynaklığın kalıcılığında belirgin bir azalış yaratmıştır.

Anahtar kelimeler: **BIST 100, Oynaklık, Yapısal kırılmalar, Politika Faizi**

THE IMPACT OF CHANGES IN INTEREST RATE POLICIES ON THE STOCK MARKET VOLATILITY: EVIDENCE FROM BORSA ISTANBUL

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criteria
APARCH	Asymmetric Power Auto Regressive Conditional Heteroskedasticity
AR	Auto Regressive Process
ARCH	Auto Regressive Conditional Heteroskedasticity
ARCH-M	Auto Regressive Conditional Heteroskedasticity in Mean
ARMA	Auto Regressive Moving Average
CBRT	Central Bank of Republic of Turkey
DJIA	Dow Jones Industrial Average
EGARCH	Exponential Generalized Auto Regressive Conditional Heteroskedasticity
EGARCH-M	Exponential Generalized Auto Regressive Conditional Heteroskedasticity in Mean
GARCH	Generalized Auto Regressive Conditional Heteroskedasticity
GARCH-M	Generalized Auto Regressive Conditional Heteroskedasticity in Mean
GJR-GARCH	Glosten Jagannathan Runkle Generalized Auto Regressive Conditional Heteroskedasticity
GMM	Generalized Method of Moments
ICSS	Iterative Cumulative Sum of Squares
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LM	Lagrange Multiplier
MA	Moving Average
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PP	Phillips Perron
SIC	Schwarz Information Criteria
TARCH	Threshold Auto Regressive Conditional Heteroskedasticity

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INTRODUCTION

Risk management has always been one of the main concerns of financial management under volatile market conditions. In this unforeseeable future, eliminating the risks with highest occurrence and impact and accepting the ones with a favorable Risk-to-Return ratio is essential. Volatility modeling is important for investors and policy makers in absorbing the negative effects of economical shocks.

Today we live in a world where a disturbance in Nikkei index due to elections in Japan cause fluctuations in New York stock exchange while a trivial keystroke fault(fat finger) caused by a trader in NYSE can cause a chain reaction that leads to the collapse of several developing country stock markets.

In a global market so interconnected, it is without doubt that countless financial and even non-financial factors affect stock markets. In this dynamic environment, regulatory institutions and governments have a rather limited set of tools to cope against various unforeseen events that cause volatility in financial markets.

Central banks have access to the widest selection of tools with highest amount of binding force on monetary policy. In regulation of financial markets, interest rate undoubtedly is the most widely known tool, due to its direct relationship with almost every indicator in the market ranging from required return on investments to risk premiums. Therefore we chose the CBRT’s policy interest rates as the most accurate indicator of the monetary policy and considered the dates in which these policies were changed as dummy variables representing the central bank's intervention points to the market.

The study consists of the four chapters. In Chapter 1 we define the most foundational elements of economic environment including financial markets, while briefly explaining the prevalent theories that shaped the literature to its current point. Conceptually explaining the relationship between interest rates and stock markets, and defining the terms "volatility" with a separate understanding from risk are the main points of this chapter.

Chapter 2 focuses on recent papers that worked in relevant fields with our study and compares our methods with those having parallel research objectives.

Chapter 3 continues with the methodology which briefly explains the empirical background and mathematical explanations of models that are used in empirical analysis of our study including the unit root tests, (G)ARCH, ICSS models and Kappa 2.

Finally, Chapter 4 consists of our data and the results of our empirical analysis. Unit root tests that are applied prove dataset to be stationary therefore analysis moves on to ARMA model selection part by using Akaike (AIC) and Schwarz (SIC) information criterion methods, upon determination of model ARCH LM Test confirms the existence of an ARCH effect which ensures usage of an ARCH based method to define volatility model of series. By trial and error method after trying GARCH, EGARCH, GARCHM and APARCH methods, most statistically significant results are found with APARCH model. Before creation of a final volatility model, for sake of further precision we apply ICSS algorithm and Kappa 2 to increase significance of results by adding structural breaks which turns out as expected for all return series applied. Our results show that an intervention made by the central bank has a reducing impact on volatility of stock markets.

CHAPTER ONE

THEORETICAL RELATIONSHIP BETWEEN THE INTEREST RATES AND STOCK MARKET

This chapter contains basic macroeconomic and financial information required to understand the dynamics underlying the mechanisms of the relationship between interest rates and stock prices. Understanding these basics is essential to notice the reason behind the volatility model used in this study.

1.1 FINANCIAL MARKETS AND PURPOSE OF STOCK MARKETS

Financial market can be defined as the system that regulates the cash flow by providing effective transfer of funds from entities with surplus funds to entities in need of funds in order for them to invest in the projects that yield higher returns. This cycle creates efficiency in economy by increasing investments, growth and several other indicators, as result of this; increased prosperity in overall economy is expected.

As a crucial part of the economic system, financial markets require stable and forecastable political and economic environment in order to function properly. Poor environmental factors might cause irrational human behaviors like panicking, distrust or misplaced trust in wrong instruments. This chain of undesired events often results in inefficient market situations.

In earlier times of financial market observations, researchers have had the idea of efficient or free market in which at any given time or point the nominal price of a financial security will be approximately the same of its intrinsic value (Fama, 1965: 33). Over time however it became clear that markets are neither fully efficient nor completely free. The question was that, what would make a security with same return better than the other?

Modern Portfolio theory in early 1950's was shedding light on this issue as a side concern of asset valuation. While its main objective was to develop a theory of maximized return under risky portfolio, the article also explained what risk is in detail and furthermore it also invented a way to virtually eliminate the risk in a systematic way. However article was too advanced for its time and it took financial researchers 30 years to comprehend its true value. The research was awarded with Nobel Prize in 1980 (Markowitz, 1950: 3).

Another topic to bear in mind is that general statistical approach of normal distribution is not necessarily valid in financial market observations, in studies of significant importance it was evident that certain financial assets demonstrate leptokurtic distribution characteristics (Mandelbrot, 1963: 7). While this may seem conflicting with literature's precedent studies it is actually a complementary finding demonstrating how far, a well-populated sample of assets can be from normal distribution due to volatility and several other elements. Mandelbrot also introduced a new concept to the literature by suggesting the existence of Volatility Clusters in certain periods. On following years of the literature, (Black, 1976: 12) stated that using leverage effect can be a reliable way to neutralize stock volatility in a portfolio by claiming that the two factors are negatively correlated.

Stock markets are a part of this financial system that allows buyers and sellers of equity to meet in an aggregate way, due to these, stock markets are also called Equity Markets.

Invention of stock market dates back to ancient Rome, recent studies indicate that development of financial market initially started with usage of debt instruments, and over time extended to stock market (Petram L., 2011: 13). As for Republic of Turkey, the first organized stock exchange was founded in 26 December 1985. Stock markets can be organized and over the counter (OTC) markets. Organized exchanges has a physical location, price listing announced and regulatory agencies, due to existence of these, there are transaction costs and higher level of administrative burden. OTC markets on the other hand have no transaction and much less administrative burden however they are riskier than their organized counterparts. Participation in either is a choice for the management of corporations; there are several Multi-National Corporations (MNC) that prefer to be traded on OTC markets while others don’t even consider participating in them.

Stock markets serve corporations as a source of funding other than debt instruments, but in return of company ownership. While there are several different types of stocks that have various advantages and disadvantages, owning a common stock widely means taking all risks a corporation inherits as a partner of the corporation. As in all free market transactions, prices in stock markets are completely dependent on supply and demand.

In practice the return of a stock consist of two components namely the capital gain (growth) and dividend yield. There are some widely known theories explaining the stock price movements. Among them, Gordon (Growth Growth) Model that is created by Gordon and Shapiro in 1956 stated that the price of a stock is equal to the present values of its future cash flows namely dividends and its face value. Another approach was stated by Modigliani, Franco, and Merton H. Miller in 1958, stated that the firm value is not relation with how it finances its activities in the long run under assumptions of efficient market, random walk price process and in existence of asymmetric information and no transaction costs. The theory is considered to be fundamental in the development of modern capital structure models. Capital Asset pricing model (CAPM) was developed by Treynor, Jack L extending the classical work of Portfolio Selection theory of Markowitz. CAPM model aims to determine required rate of return of an asset while taking into account the market (non-diversifiable) risk..

There are scientific approaches used to describe the behavior of stock markets, it must be kept in mind that its dynamic and resulting reactions are purely based on aggregate human behavior and as we know sometimes human behavior is irrational even at aggregate levels. Also several assumptions made in theories are usually incapable of fully representing the practical market conditions in several perspectives.

1.2 INTEREST RATE POLICIES OF CENTRAL BANKS

Central banks have been one of the main driving forces in a country's economy by regulating monetary policy which, in conjunction with government (fiscal policy) determines a nation’s or union's whole economical drivers. All around the world the primary objective of the central banks have similar definitions ranging from achieving and maintaining price stability to supporting growth or fighting unemployment as assistance to government policies. Central banks directly have control over a state's money supply, currency itself and interest rates. They also have regulatory power over financial institutions such as commercial banks or insurance companies. This combination of monopole strength and regulatory rights allows a central bank to use various intervention methods, some being direct while other being less direct through a mix of regulatory and direct intervention channels.

A good example to these complex intervention methods would be the Reserve Option Mechanism, recently implemented by CBRT. This unconventional monetary policy tool is assumed to help domestic financial stability through active usage of reserve requirements and adaptation of macro prudential policies. (Degerli and Fendoglu, 2013: 6) suggested that this mechanism acts as an automatic stabilizer of expectations about excessive movements in exchange rate, and that movement's sensitivity is decreased through use of this mechanism.

Forecasting the effects and results of complex intervention instruments can be hard to estimate. A policy shift in those instrument's rates at a particular time doesn't necessarily point out a change in central bank's policy. These instruments are more actively managed compared to direct instruments such as policy rate.

A shift in policy rate is thought to be a much more significant indicator of interest rate policy due to its effectiveness in both short and long run. According to (Bernanke and Reinhart, 2004: 3) pricing of most financial assets, especially the long lived ones such as equities and mortgages depends on the expected path of future short-term interest rates. Therefore through this mechanism it is possible for a central bank to influence the economic activity directly by influencing the expectations of market participants. This kind of manipulation can even allow central bank to affect asset prices indirectly. Due to this high level of representation capability, we have thought that it is safe to assume that changes in interest rate policies is a viable indicator to be a determinant in stock market volatility.

1.3 RELATIONSHIP BETWEEN THE INTEREST RATES AND STOCK MARKET

Interest rate influences the stock market through several channels in an efficient market economy. Since policy interest rate is a short term lending rate, it is actively managed to be able to absorb and recover from domestic or external shocks. As the rate that central bank lends funds to commercial banks through open market operations, the policy interest rate's effect on the stock market cannot be considered an immediate one.

The main channel that policy interest rate effects the stock markets is through deposit account being a substitution of stock returns. The higher the interest rate gets, the less attracting the stock returns will be for investors, assuming that companies do not instantly react to the changes by increasing dividends and even if they do react, this will only be a short term solution since their profitability will be reduced back due to reduction in retained earnings according to Modigliani & Miller theory.

Another channel which interest affects stock market is through banking system, the initial volatility caused within the banking system by a policy rate shift negatively affects banking system’s profitability and therefore it increases firm’s cost of debt as well as cost of financial transactions. (Hancock, D., 1985: 17) claims that bank’s profitability is directly related with the interest rate and therefore policy rate, both transaction charges and interest applied to flexible and fixed interests change accordingly.

Some corporations are directly affected by changes in interest rate due to debt structure based on flexible rate loans. Also according to the (Gordon and Shapiro, 1956: 4) the required rate of return from a stock will be increased due to the increases in the return on risk free instruments. An increase in policy interest rate both increases required risk premium by creating volatility in the market and in the same time by increasing the risk-free rate.

In addition to factors above, there are several minor factors that can contribute to this relationship such as expected reduction investments. However it should be kept in mind that all these factors affect the market at the same time and responses differentiate upon factors such as expectation gaps. Additionally, market’s reaction to positive and negative impulses is asymmetrical and therefore every event of same magnitude doesn’t create the same effect on volatility.

1.4 GORDON GROWTH MODEL

Known as the “Dividend Discount Model” or “Constant Growth Model”, is essential in understanding the relationship between the interest rates and stock prices. Published by Gordon and Shapiro in 1956, model states that a stock’s value is equal to sum of present value of all of its future dividends payments.

$$P = \frac{D_1}{r - g}$$

P represents price while D_1represents Dividend expected to be paid at next period R stands for required return and g stands for growth rate.

Since it is thought that when the risk free rate increases the required return also increases, it can be gathered from the equation that stock prices are negatively correlated with interest rates due to the fact that present value of future cash flows are getting lower.

Another point worth noting is the positive relationship between the growth and stock prices. When economy is soaring, growth rates of companies are expected to rise as well resulting in higher capital returns.

1.5 MONEY TRANSMISSION MECHANISMS

As we have covered, the interest rate (policy rate) is just one of the variables that central banks use to manage monetary policy. Before forming a model regarding to the effects of a change in policy rate on stock market, it would be best to first to focus on through which mechanisms does this change in interest rate affect the stock market. This way, it would be easier to see how a single regulation in just one market variable can be adjusted while it affects dozens of other macroeconomic variables in the meantime.

Most central banks around the world(CBRT included) while having different goals in different market structures, seems to generally embrace one main objective above all other objectives when determining their monetary policies, the price stability. This is probably due to that price stability is accepted as the outcome of every indicator in economy combined into one single variable. Therefore focusing on the price stability does not necessarily mean ignoring the other indicators but on the contrary it is focusing on them all in a balanced manner simultaneously.

Literature distinguishes transmission mechanisms in different number of channels in various names, however we can come up with 5 channels that are predominant in the literature. Those channels are; interest rates, credits, asset prices, exchange rates and expectations channels as stated by (Norman and Klaus, 2002: 1).

Interest rate channel is the most widely known one and is generally identified as the most direct and effective transmission channel as (Mishkin F., 1995: 16) describes. When CBRT announces a reduction in policy rate, due to reduced cost of capital investments increase, more investment will cause higher employment and cheaper credits for consumers as well resulting in increased consumer expenditures, this initial increase in aggregate demand is often met with an increase in prices. Focusing on financial indicators along with these macroeconomic variables is necessary. A reduction in interest rates will most likely cause an increased demand in stock market instruments which will likely result in cheaper cost of equity for firms. Debt market instruments will also evaluate against reduced risk-free rate.

Credits channel is actually affected through interest rates channel as well. Cheaper consumer and corporate credits stimulate the market in the short run however it has side effects in the long run. Credit channel is manipulated mainly by banking regulations banking specific variables announced by central banks such as interest rate corridor.

Asset Prices are explained by James Tobin (Tobin J., 1969: 2). According to him, an expansionary monetary policy increases the asset prices which in turn, combined with lower cost of capital, increases the investment in economy. Higher asset prices also increase the wealth which in turn may increase consumer spending.

Exchange rate channel works through relatively different mechanisms. It is mainly determined by the presence of foreign currency in an economy relative to domestic currency. While it is hard to relate this directly with a single variable, it is affected by both aggregate demand and output in an economy. It is also argued that it has a self regulating mechanism in the market through an increase in net export when domestic currency is undervalued and a reduction when its overvalued. Central banks directly control this through money supply but there are other ways of affecting this through monetary policy such as Reserve Option Mechanism implemented by CBRT.

Expectation is an ideological concept that encompasses all forecasts, feelings and thoughts of the whole market. It can be manipulated by authorities such as central banks but the effects cannot be very precisely estimated at all times. An attempt to manipulate expectations of the market may trigger no effect or even a completely unexpected effect in the market. Main elements that play role in success of manipulation of this instrument are thought to be the confidence reliability authorities. An announcement made by an untrustworthy institution may cause increased volatility in market however under normal conditions it is expected that volatility in the market will be decreased after an announcement by a regulatory institution.

1.6 EXPLANATION OF RELATIONSHIP WITH TOBIN'S Q

Tobin's Q ratio can be defined as the market value over replacement of tangible assets. The Model was developed by James Tobin in 1969 following another article written by the James Tobin and William Brainard together. Ratio is widely used both in financial market as an indicator of firm performance, and in academically as a variable of performance. Model's practical use however is limited, even though theory forms a theoretical basis for performance evaluation, there are still some shortcomings in its modeling under several certain circumstances.

According to the model of Tobin in 1969, the interest rate affects the firm's market performance by shifting expectation from future cash flows, since the model assumes that market price equals to present value of future expected cash flows. Simply put, a firm's market price will be negatively affected if the interest rates rise and positively affected if it falls.

It is for this reason that central banks change policy interest rates accordingly with the stock markets. Sum of whole market's price over sum of their replacement values give an approximate number for consideration of the regulatory institutions.

Other than direct effects through changes in net present value, there are other significant channels mentioned in the method that form a relationship between, one of them is investments. It is mentioned in several consequent papers that interest rates with stochastic behavior have significant influence over investment and with effects caused by reduction or increase in investments through change in policy rate directly affects Tobin's q ratio for the whole stock market.

1.7 CONCEPT OF RISK, VOLATILITY AND UNCERTAINTY

Risk and Uncertainty terms, while sounding similar are actually very different terms used to refer different situations. Risk, as can be understood from very beginning of literature, (Knight, 1921: 211) is a foreseeable term that has an independent variable presence in several theories while uncertainty is rather a term used to perceive general turmoil in a situation.

Volatility, in relevant literature is not perceived as a negative indicator, on the contrary it is the variable which is used to actually measure, forecast and eliminate the risk or even uncertainty.

As we discussed, the uncertainty is one of the main causes of inefficient markets, in an inefficient market it is much more challenging to achieve maximum profit in investments, this has rendered volatility a hot topic in recent years, several different scientific methods have been developed in order to gain a better understanding of the subject in the process.

A significant amount of modern researchers believe that volatility is one of the main drives that effect market efficiency, in a recent study of (Poon and Granger, 2003: 12) , volatility is perceived as directly related with investment, asset pricing, risk management and monetary policy.

Not surprisingly, one of the main goals of field of macroeconomics is to comprehend the short-run fluctuations in an economy, therefore we can derive that macroeconomics, as a discipline recognizes volatility (fluctuations) as one of the main drives in both long and short run decision making processes. This common base of volatility concept in both financial and macroeconomic fields helps literature and provides ease of access to various data that may prove useful.

Macroeconomic volatility in literature is widely perceived as a factor that holds back the growth by creating instability in market and therefore inefficiency. A relevant article on topic provides substantial results by using a sample of 79 countries between years 1960-2000.(Hnatkovska and Loayza, 2005: 6) It states that increasing average value in terms of its value in standard deviation by 1 point results in 1.3 point decrease in growth of GDP. The question remains however that whether increase in volatility is the reason or the result of decrease in growth of GDP. In a general look to the literature, the macroeconomic context takes the bigger picture in concept of volatility it observes the economy as a whole contrary to finance, in several financial papers diversification is presented as a cure to volatility in market which maybe a solution for an individual investor or fund manager however when taking the economy as a whole into account this solution remains futile in some explanations.

Especially obvious with the recent crisis, volatility is a vital concern for developing countries recent studies show that volatility is mainly affected by macro-economic factors such as external shocks, macroeconomic policies and power of the regulatory institutions. Literature also has a major consensus of greater effects of volatility on risk-averse people then on that of risk-takers. (Loayza et. al., 2007: 26) This supports the general idea on macroeconomic environment that volatility is an indicator of underdevelopment. Since developing countries are mainly financed by foreign capital (capital inflow), a sudden stop or decrease in the flow may have dire ramifications. Therefore shock absorption policies are likely to be implemented in such situations but depending on the exact mechanism that macroeconomic factors affect the financial system, effectiveness of these policies vary. Another one of the explanations on mechanism of volatility on macroeconomics was the theory of business cycles, examined Post-War U.S. economy (Prescott, 1982: 3). The model tries to explain cyclical variances in a set of time series economic data and co-variances in real output by using a modified version of equilibrium growth model.

1.8 EFFECTS OF CENTRAL BANK INTERVENTIONS IN SHORT AND LONG TERM

Central bank interventions into the markets play a crucial role in determining the future expectations of investors and corporations that are quoted in stock markets. Even though there are no more closed economies present in the world, even in an open market a central bank is widely accepted as the most important player. While an intervention is not necessarily always announced, sometimes the effects of announcement of an intervention exceeds that of intervention itself, therefore a central bank makes use of both psychological and substantial tools together.

There are several views in financial and macroeconomic literature about how central bank interventions affect the market. The nature of the effect is generally distinguished into long term and short term effects. In a study of Bonser-Neal, C., & Tanner, G. (1996), using similar GARCH model as ours, it is found that there is a little support for the hypothesis that central bank intervention decreases expected volatility in short term. Instead, central bank intervention is generally associated with a positive change in volatility. Other views such as (Campbell, J. Y., 1987: 7) claimed that central bank intervention affects the market through the same mechanism of that of terms structure of debt instruments by claiming that state of the term of interest rates predicts stocks' returns due to the inverse relationship between stock returns and nominal interest rates.

As for Turkey, in period after 2002 CBRT has changed its perception of monetary policy. Rather than just aiming for the price stability, it also started taking financial stability into consideration when determining policy rates. Since the invertors take decisions of central bank into consideration, any direct or indirect relation with the market has been responded with relevant movements. In the studies of (Aklan and Nargeleçekenler, 2012: 4) and (Kasapoğlu, 2007: 8), policy rate is considered as a variable that effects both short and long term decisions of investors and households together. In short term, an increase in interest rates is expected to have a negative correlation with stock returns by increasing the demand for debt instruments. However the majority of studies in the field fail to find a significant relationship between the policy rate and stock returns in the long term. The dominant conclusion in the literature remains as the central bank's intervention to policy rate, inversely affects the stock market returns in short term while increasing volatility, in the long run however stock market returns are normalized and independent of policy rate changes while structural volatility is still affected by the central bank policy.

CHAPTER TWO

LITERATURE REVIEW ON THE IMPACT OF INTEREST RATES ON STOCK MARKET VOLATILITY

This chapter contains the review of preceding studies on the impact of interest rate changes on stock market volatility. Studies are distinguished under 3 categories depending on their methodologies.

2.1 STUDIES USING THE ARCH-BASED VOLATILITY MODELS

Lobo, (2000: 2) studied the effects of federal fund rates on stock market using ASAR-EGARCH Method. He used 8-yearlong sample from 1990 to 1998 of daily federal fund rates and discount rates along with S&P2s 500 index variables. It is found out that announcements of a rate change affect the market and treated as incoming new information. He also pointed out that market is getting more risk averse on the period prior to an announcement of change in interest rate. He found a weak evidence supporting the overreaction of that the markets to a bad new while stating that interest rate volatility estimations send a more clear signal to market about intentions of the monetary policy.

Kashefi (2008: 11) analyzed the effect of change in federal fund rate on stock market prices, using a 12 year sample data from 1994 to 2006. Kashefi determined that Threshold GARCH model is the most suitable modification of ARCH models. He concluded that a reduction in federal fund rate increases that stock markets index values and boosts its growth. Accordingly, he stated that a one-day delayed federal fund rate change, created approximately the same effect as one that is created instantly. This situation conflicts with the efficient market theory that claims a stock price is an inclusive reflection of the future expectations from stock.

2.2 STUDIES USING VAR ANALYSIS BASED MODELS

Thorbecke (1997: 1) analyzed the reactions of stock returns to monetary policy shocks using VAR method for the period from 1967 to 1990. Federal fund rate is used as representative of monetary policy. Policy changes of FED reserve is analyzed with event study method. Results of study indicates that expansionary monetary policies have a positive effect on ex and post market returns. Also it has been noted that small size companies are affected more from these shocks than do large scale corporations.

Gregoriouet. al. (2009: 1), analyzed the expected and unexpected interest rate change's effects on stock returns under sectoral and total bases separately using panel data analysis for 1999 – 2009 period. Subsectors were distinguished on the same criteria as of FTSE index's. Monetary policy shocks are represented by 3 month LIBOR future contract rates. Their results indicate that a negative relationship between the changes in expected and unexpected interest rate and stock returns prior to a liquidity crisis, while this relationship becomes positive during the crisis.

Furlanetto (2011: 2), examined the relationship between the monetary policy and stock market returns using the VAR analysis. In the study the simultaneous interdependence was taken into account and thus the representative of interest rate was taken as 3-month Treasury bill rate instead of federal fund rate. He found that the asset prices react negatively to the changes in interest rates and therefore an increase in interest rate cause present value of expected future dividends to fall.

Akay and Nargeleçekenler (2009: 1), analyzed the influence of changes in monetary policy interest rate on stock market prices using SVAR method for Turkey. They have included inflation rate and production industry index variables in their model. Study mainly focuses on the relationship between the policy rate and stock prices in short term and long term. They found, a contradictionary monetary policy causes a reduction in stock prices by inducing an increase in both short term and long term interest rates.

Demiralp and Yılmaz (2010: 1), examined the effects of monetary policy expectations on Turkish capital market for the 2002 – 2009 period. . According to the efficient market hypothesis, after the announcements of central bank, market is only expected to react to unexpected events, since the expected events are reacted upon during their announcements already. With this assumption, researchers have measured the expectations of monetary policy with a survey. According to their results, benchmark interest rate changes as assumed in efficient market hypothesis while for stock markets efficient market hypothesis is only valid for certain periods of time.

2.3 VOLATILITY STUDIES USING OTHER MODELS

Angeloni and Ehrmann (2003: 3), for period between 1990 and 2002 have inspected the effects of monetary policy shocks on stock market indices of Euro zone by using forecast with data analysis method. As result, they have concluded that an increase in policy rates decrease the stock returns.

Rigobon and Sack (2004: 6), have examined the way that the changes in monetary policy affect asset prices. They have used a sample of 7 years data starting from 1994 November to 2001 January. Study derived data from Dow Jones Industrial Average (DJIA), S&P 500Nasdaq and Wilshire 5000. They used interest rate as representative of monetary policy tools and implemented event study method to determine the relationship. Along with event study method, they applied tool variable, and Generalized Method of Moments (GMM) approaches as well. They have decided that GMM method gives the most meaningful results. They have discovered a synonymy problem between short term interest rates and asset prices in other words, short term interest rates affect the asset prices while asset prices simultaneously reflect interest rates. Reaction to shocks that asset prices give against changes in monetary policy or significant political events such as FOMC meetings is defined based on increases in variances due to shocks. Results of study indicate that an increase in short term interest rate causes a reduction in stock prices and in the long run, it causes an upward movement in yield curve.

Ehrmann and Fratzscher (2004: 6) studied the execution of monetary policy through policy rate and credits for the US during the1994-2003period. They concluded that monetary shocks influenced the stocks returns more than expected.

In the study of Honda and Kuroki (2006: 5), effects of changes in long term and medium term interest rates on stock market price changes has been observed. Long term and medium term interest rates were considered as the representatives of shocks in monetary policy. Period observed was from 1989 to 2001 in Japanese market. Least squares method was used in estimation. As a result they concluded that unexpected reductions in interest rates have consistently increased the stock prices. They have also noted that their findings are parallel with those that are applied for the US market within the similar time periods.

In his study, Chen (2007: 3) analyzed the monetary policy's asymmetric effect on the stock market by using the Markov-switching models. He used federal fund rate and M2 money supply as variables on monetary policy while also using S&P’s 500 monthly stock return data as a base for fixed-transition-probability Markov-switching and time-varying-transition-probability Markov-switching models. He integrated his empirical studies with event studies as well. He found that especially in the markets where prices fall, the effects of monetary policy on stock market are high and, contradictionary monetary policy leads to a higher probability of switching to a bear-market regime.

Garg (2008: 2) studied the effects of federal fund rates as an indicator of monetary policy on stock market considering the sectoral segmentation. In this process, finance, energy, industry, basic materials, utilities, consumption goods, consumer services, information technologies, health and telecommunication sectors as listed in ICB Dow Jones have been analyzed using Ordinary Least Squares method. According to the results some sectors are more sensitive to changes in interest rate than others in terms of price and return. Utilities, finance, telecommunication and basic materials are affected most owing to high positive correlation between their prices and federal fund rate. In the meantime, for all sectors observed, a positive relationship between change in federal fund rate and stock prices was found. This relation’s effects are based on Keynesian economist’s theories defending that income effects influence cost effects.

Alam and Uddin (2009: 2),evaluated the effects of interest rate on stock markets for period from 1998 to 2003 on both the developed and developing country markets including Australia, Bangladesh, Canada, Chile, Colombia, Germany, Italy, Jamaica, Japan, Malaysia, Mexico, Phillippie, S. Africa, Spain, Venezuela. Study used the one-way and two-way constant and random effect panel data analysis. As a result they found a negative relationship between the interest rate and stock market prices. Additionally, they revealed that if interest rate is kept under control excessively, stock market prices start to bubble up due to increasing number of investors in the stock markets causing an above average profit.

Some studies in the field followed a different empirical path by inspecting effects of interest rates on stock markets via using GMM. GMM method is known for its resistance to synchronicity. Duran et al.(2010: 1)used this method in their analysis in addition to the event study technique.. They found that an increase in policy rates cause a reduction in stock prices while longer term rates cause a gradually decreasing increment.

Moya et al. (2013: 1), have studied the dynamic relationship between Spanish stock market and changes in interest rate policies. They used wavelet method to evaluate relationship at various time scales on different industries for a period of 19 years starting from 1993 until 2012. According to their results, Spanish stock market has been negatively affected by increases in interest rates. The results of the empirical analysis show that the Spanish stock market exhibits a remarkable degree of interest rate exposure, although sizeable differences can be observed across industries and depending on the time horizon under consideration. Unsurprisingly, regulated industries such as Utilities, heavily indebted industries such as Real Estate, Utilities or Food and Beverages, and the Banking industry emerge as the most interest rate sensitive. On the contrary, there is a broad range of industries such as chemicals and paper, financials, construction, health care and industrials hardly influenced by interest rate risk. Further, the link between movements in interest rates and industry equity returns is stronger at coarser scales (low frequencies), suggesting that the role of interest rates as a major determinant of stock prices may be held only in the long run for some specific industries. As expected, the interest rate exposure is predominantly negative, indicating that Spanish firms are, on average, adversely impacted by interest rate rises. In addition, a bidirectional relationship between changes in interest rates and industry stock returns is found at higher scales."

Aktaşet. al. (2008: 1) analyzed the effects of expected and unexpected monetary policy decisions on long term interest rates on BIST 100 index, exchange rates and risk premium in the financial markets using event study method for the period between 20/12/2004 - 17/08/2008. They found a negative relationship between interest rates and stock returns, however this relationship was not statistically significant.

The main purpose of our study is to examine the impact of interest rate policy changes on the volatility of the Turkish stock market. Different from the previous studies, we consider the structural breaks in our volatility models. We do not observe a study taking account for the structural breaks therefore this is the main contribution of this thesis to the literature. On the other and considering the structural breaks in the volatility analysis is important since our period covers the major latest financial turmoil. Additionally it provides more reliable results.

CHAPTER THREE

METHODOLOGY

In this chapter, we present all statistical techniques used in our analysis covering the unit root tests, volatility models and structural break models briefly.

3.1 UNIT ROOT TESTS

Evaluating the following model:

$$Y_t = \rho\, Y_{t-1} + e_t, \quad t = 1,2, \ldots$$

This model consists of an independent array of random variables where $Y_0 = 0$, ρ is a real number, $\{e_t\}$ has zero average and σ^2 is the variance (e_t NID $(0,\sigma^2)$) . If $|\rho| < 1$ then, Y_t time series converges to a stationary time series as $t \to \infty$. If $|\rho| = 1$, then time series is not stationary and variance of Y_t is $t\sigma^2$. Time series which $\rho = 1$ is named as random walk process series. If $|\rho| > 1$, then time series is not stationary and when time series' variance increases by t, it increases exponentially. (Dickey and Fuller, 1979: 427).

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + e_t$$

$$= (\rho - 1)Y_{t-1} + e_t$$

$$\Delta Y_t = \delta Y_{t-1} + e_t$$

In model, $\delta = (\rho - 1)$ and Δ is the first difference operator while, $e_t$is the white noise error term. Null Hypothesis state that H_0: $\delta = 0$. If $\delta = 0$ then, $\rho = 1$, in other words there is unity root in series and it's not stationary. Alternate Hypothesis is that $\delta < 0$, which states series is stationary. (Gujarati, 2004: 814).

Dickey ve Fuller, took 3 different regression equations into consideration when determining the existence of unit square root:

$$\Delta Y_t = \delta Y_{t-1} + e_t$$

$$\Delta Y_t = a_0 + \delta Y_{t-1} + e_t$$

$$\Delta Y_t = a_0 + \delta Y_{t-1} + a_2 t + e_t$$

Main difference between these three regression equations is the existence deterministic elements of a_0 and $a_2 t$. First equation is pure random walk model. In second model constant and twist is added to the model. Third model includes both twist and linear time trend. Main parameter focused in all equations is δ'. If $\delta = 0$,

$\{y_t\}$ array includes unit root. In order to find approximate values of δ and standard error, test estimates above equations using least squares method. In either situation estimated Y_{t-1} quotient is divided to its standard error to calculate tau τ statistic. Tau statistic is demonstrated on tables of Dickey-Fuller. Null hypothesis is rejected or cannot be rejected depending on the results of comparison between t statistic and values in Dickey-Fuller table. (Enders, 1995: 114), (Gujarati, 2004: 816).

3.1.1 Augmented Dickey Fuller (ADF) Test

It is assumed in Dickey Fuller test that, e_t error term is uncorrelated. However, in cases where e_t is correlated, Dickey and Fuller has developed a test known as, ADF test. This test, is the expansion of 3 equations acquired by summing of delayed variables of ΔY_t. ADF test includes following regression estimation:

$$\Delta Y_t = a_0 + \delta Y_{t-1} + a_2 t + \sum_{i=1}^{m} \alpha_i \, \Delta Y_{t-1} + e_t$$

In this model e_t represents pure white noise error term and $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$ and goes on. ADF tests if $\delta = 0$ and follows the same asymptotic distribution pattern as DF statistic, thus same critical values are used (Gujarati, 2004: 817).

3.1.2 Phillips Perron (PP) Test

An alternative approach to determining the existence of unit root in time series has been developed by Phillips (1987: 2). This approach uses a non-parametric statistical method and thus is valid for a wide range of time series models that contain unit root. This method provides significant advantages on situations where time series have moving average components. (Phillips and Perron, 1988: 336).

This test takes correlation of residuals into consideration. Phillps Perron test is composed based on the following regression's least squares estimation.

$$\Delta Y_t = \mu + \beta(t - T/2) + \rho Y_{t-1} + + e_t$$

Null hypothesis is $H_0: \rho = 1$, test statistcs are adapted to correct the correlation among residuals. Following statistic is used to test $Z(\hat{p})$, $H_0: \rho = 1$ null hypothesis:

$$Z(\hat{p}) = T(\hat{p} - 1) - (T^6/24D_x)(S_{Tl}^2 - S_u^2)$$

T is the number of observations here.

$$D_x = (T^2(T^2 - 1)/12 \sum Y_{t-1}^2 - T\left(\sum tY_{t-1}\right)^2 + T(T+1)\sum tY_{t-1}\sum Y_{t-1} - (T(T+1)(2T+1)/\,6)\left(\sum Y_{t-1}\right)^2$$

A consistent estimator of S_{Tl}^2, $\sigma^2 = lim_{T\to\infty} T^{-1}E(S_T^2)$ and here is as $S_T = \sum_{t=1}^{T} e_t$.

S_u^2, $\sigma_u^2 = lim_{T\to\infty} T^{-1}\sum_{t=1}^{T} E(e_T^2)$'s consistent estimator.

Phillps Perron test's asymptotic critical values are similar with that of Dickey Fuller test and critical values are as same as those at Dickey Fuller's table. (Ghosh, 1999: 323-324).

3.1.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

Kwiatkowski, Phillips, Schmidt and Shin (1992) has proposed a LM test with null hypothesis stating that series are either stationary trend or stationary level.This test, includes a limit distribution in its null hypothesis. On its alternate hypothesis difference stationary represents asymptotic power.(Phillips and Jin, 2002: 239).

If $Y_t, t = 1,2, \dots, T$, it is assumed that series are distinguished to the sum of Deterministic trend, random walk and stationary error:

$$Y_t = \xi t + r_t + e_t$$

Here r_t represents random walk process:

$$r_t = r_{t-1} + u_t$$

In this equation $u_t \sim iid\ (0, \sigma_u^2)$ first value takes role of r_0 constant. Stationary hypothesis checks if $\sigma_u^2 = 0$. Since e_t is considered stationary, under null hypothesis Y_t trend is stationary. (Kwiatkowski et. al.1992: 162).

3.2. VOLATILITY MODELS

3.2.1. Auto Regressive Moving Average (ARMA) Process

First order moving average can, MA(1), can be specified as below:

$$Y_t = \mu + e_t + \theta e_{t-1}$$

$\{e_t\}$ Represents the white noise in this equation while μ and θ are constants. “Moving Average” must be derived from weighted sums of term Y_t ‘s last two values which should be similar to mean.

Y_t’s expected value,

$$E(Y_t) = E(\mu + e_t + \theta e_{t-1}) = \mu + E(e_t) + \theta E(e_{t-1}) = \mu$$

Here μrepresents constant term. This constant term signifies the mean of the process.

Y_t’s variance,

$$E(Y_t - \mu)^2 = E(e_t - \theta e_{t-1})^2 = E(e_t^2 + 2\theta e_t e_{t-1} + \theta^2 e_{t-1}^2) = \sigma^2 + 0 + \theta^2\sigma^2$$
$$= (1 + \theta^2)\sigma^2$$

First Autocovariance,

$$E(Y_t - \mu)(Y_{t-1} - \mu) = E(e_t - \theta e_{t-1})(e_{t-1} - \theta e_{t-2})$$
$$= E(e_t e_{t-1} + \theta e_{t-1}^2 + \theta e_t e_{t-2} + \theta^2 e_{t-1} e_{t-2}$$
$$= 0 + \theta\sigma^2 + 0 + 0 = \theta\sigma^2$$

All higher Autocovariance levels equal to zero:

$$E(Y_t - \mu)(Y_{t-j} - \mu) = E(e_t - \theta e_{t-1})(e_{t-j} - \theta e_{t-j-1)} = 0 \qquad j > 1$$

In MA(1) process θ’s covariance is stationary regardless of its value.

J.th autocorrelation of Covariance stationary process (demonstrated with ρ_j) is calculated by dividing j.th Autocovariance to its variance.

$$\rho_j \equiv \gamma_j / \sqrt{\gamma_0}$$

Is the correlation between ρ_j, Y_t and Y_{t-j}

$$Corr(Y_t, Y_{t-j}) = \frac{Cov(Y_t, Y_{t-j})}{\sqrt{Var(Y_t)}\sqrt{Var(Y_{t-j})}} = \frac{\gamma_j}{\sqrt{\gamma_0}\sqrt{\gamma_0}} = \rho_j$$

For MA(1) process first autocorrelation is as following:

$$\rho_1 = \frac{\theta\sigma^2}{(1+\theta^2)\sigma^2} = \frac{\theta}{(1+\theta^2)}$$

All autocorrelations of higher level equal to zero.

MA(q) model is as following:

$$Y_t = \mu + e_t + \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

Average and Variance of MA(q) process is as following (Hamilton, 1994: 49):

$$E(Y_t) = \mu + E(e_t) + \theta_1 E(e_{t-1}) + \theta_2 E(e_{t-2}) + \cdots + \theta_q E\left(e_{t-q}\right) = \mu$$

$$E(Y_t - \mu)^2 = E\left(e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}\right)^2$$

For first order Autoregression process, AR(1), is as following:

$$Y_t = c + \emptyset Y_{t-1} + e_t$$

Since $|\emptyset| \geq 1$, stationary covariance process for Y_t is inexistent.

When $|\emptyset| < 1$however, stationary covariance process for Y_t is present.

Stationary AR(1)process average,

$$\mu = c/(1-\emptyset)$$

AR(1) process variance,

$$E(Y_t - \mu)^2 = E(e_t + \emptyset e_{t-1} + \emptyset^2 e_{t-2} + \emptyset^3 e_{t-3} + \cdots)^2$$
$$= (1 + \emptyset^2 + \emptyset^4 + \emptyset^6 + \cdots)\sigma^2 = \sigma^2/(1-\emptyset^2)$$

j.th Autocovariance,

$$E(Y_t - \mu)\left(Y_{t-j} - \mu\right)$$
$$= E\left[e_t + \emptyset e_{t-1} + \emptyset^2 e_{t-2} + \cdots + \emptyset^j e_{t-j} + \emptyset^{j+1} e_{t-j-1} + \emptyset^{j+2} e_{t-j-2} + \cdots\right] x$$
$$\left[e_{t-j} + \emptyset e_{t-j-1} + \emptyset^{j+2} e_{t-j-2} + \cdots\right] = [\emptyset^j + \emptyset^{j+2} + \emptyset^{j+4} + \cdots]\sigma^2$$
$$= \emptyset^j [1 + \emptyset^2 + \emptyset^4 + \cdots]\sigma^2 = [\emptyset^j/(1-\emptyset^2]\sigma^2$$

p.th level autoregressive process, AR(p) (Hamilton, 1994: 53-58),

$$Y_t = c + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + e_t$$

ARMA(p,d,q) model,

$$Y_t = \mu + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \cdots + \gamma_p Y_{t-p} + e_t + \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}$$

ARIMA (p,d,q) models have been discussed by, Box and Jenkins (1970: 27). “d” letter stands for the amount of levels of difference to convert data into a stationary state. In other words, d number equals to the number of unit roots in characteristics equation. Also, p stands for autoregressive (delayed dependant variable) while q stands for delayed moving average. It is observed that short models with smaller p and q values inherit a more accurate estimation potential (Said and Dickey, 1984: 599, Greene, 2002: 610).

3.2.2. ARCH-LM Test

We considera_t as the residual of mean equation. a_t^2then is used to control conditionaly Heteroskedasticity known as ARCH effect. There are two tests to determine the existence of ARCH effect. In first test we apply Ljung-Box $Q(m)$ statistic on $\{a_t^2\}$. This test has been developed by McLeod and Li (1983). Second test for Conditional Heteroskedasticity is named Lagrange multiplier test developed my Engle (1982). This test's result is indicated as F Statistic in linear regressions, $\alpha_i = 0\ (i = 1, \dots, m)$

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{m-1}^2 + e_t, \quad t = m + 1, \dots, T$$

Here, e_t is the error term and T represents sample size, m is a pre-specified positive integer. Null Hypothesis is $H_0: \alpha_1 = \cdots = \alpha_m = 0$

$$SSR_0 = \sum_{t=m+1}^{T} (a_t^2 - \overline{\omega})^2$$

$\overline{\omega} = (\frac{1}{T}) \sum_{t=1}^{T} a_t^2\ a_t^{2'}$s sample mean.

$$SSR_1 = \sum_{t=m+1}^{T} \hat{e}_t^2$$

and $\hat{e}_t$ represent here the Least squares residual of linear regression.

Thus,test statistics:

$$F = \frac{(SSR_0 - SSR_1)/m}{SSR_1/(T - 2m - 1)}$$

In this test, chi-square distribution in m degrees of freedom under asmytotic null hypothesis. If $F > \chi_m^2(\alpha)$ then null hypothesis is Rejected (Tsay, 2005: 102).

3.2.3 ARCH and GARCH Models

Most common methods prove to be inefficient in time series modeling on series where there is no constant mean or variance. New model have been developed over time to be able to better explain series with heteroskedasticity. One of these methods was the Auto regressive conditional heteroskedasticity (ARCH) model developed by Engle(1982). ARCH method has been widely used and discussed in the literature, several articles were written on the subject have also offered modified versions of ARCH method, deriving from the Engle’s method but taking additional factors into consideration or making different assumptions on the model. One of the derivations from this model which has been widely used and accepted is the generalized auto regressive conditional heteroskedasticity model (GARCH) developed by (Bollerslev, 1986). GARCH model makes symmetric conditional heteroskedasticity assumption. On the other hand, this perspective of the GARCH approach has been debated and countered in the literature with the claim that its assumptions are unrealistic due to the fact that volatility reacts asymmetrically to the shocks (Nelson, 1990; Christie, 1982; Schwert, 1989). Exponential GARCH model has been developed by Pagan and Schwert (1990) and Nelson (1991), advantage of EGARCH over GARCH was that all parameters in conditional variance were kept positive, thus allowing for determination of asymmetric effects in volatility (Duran, Şahin, 2006: 62 – 63).

3.2.3.1.ARCH Model

While there are only short periods of volatility for data like stock prices or exchange rates, there are large amount of occasions where data contains non-stationary periods in which there are consecutive days with high deviation levels. A significant increase in variance is observed after non-stationary periods when compared to variance prior to that period. Engle (1982: 19) has developed (ARCH) the first systematic framework that allows volatility modeling. Main idea behind ARCH models is that the shock in an asset’s return a_t is not serially linked but rather is dependent in such a way that its dependence can be defined by lagged values in basic quadratic formulation.(Milhoj, 1987: 100; Tsay, 2005: 102).

ARCH model was first used by Engle (1982) in estimation of inflation rate in United Kingdom. From that point on it was mainly used in volatility modeling of financial and economic time series. (Fan, Yao, 2003: 143).

If the random variable of$Y_t$is acquired fromf(Y_t/Y_{t-1}) conditional intensity function, under standard assumptions estimated current E(Y_t/Y_{t-1}) variance based on the historical information is V(Y_t/Y_{t-1}). Expected conditional variance is based on historical information and due to this, it can be considered as a random variable.

First order Autocorrelation,

$$Y_t = \gamma Y_{t-1} + e_t$$

Here$e_t$is white noiseand$V(e_t) = \sigma^2$. Conditional mean of$Y_t$is γY_{t-1}while, unconditional mean is Zero. Y_t's conditional variance isσ^2while, unconditional variance is$\sigma^2/1-\gamma^2$.

$$Y_t = e_t X_{t-1}$$

In this equation,$V(e_t) = \sigma^2$andY_t's variance is $\sigma^2 X_{t-1}^2$. Because of that estimation interval is dependent on the course of external variable.

The Model that allows for conditional variance has been defined by Granger and Anderson:

$$Y_t = e_t Y_{t-1}$$

Conditional variance is$\sigma^2 Y_{t-1}^2$. In this situation, unconditional variance is either infinite or zero.

Preferred Model,

$$Y_t = e_t h_t^{1/2}$$

$$h_t = \alpha_0 + \alpha_1 Y_{t-1}^2$$

$$V(e_t) = 1$$

This model is basically another demonstration of ARCH model. This model is not exactly bilinear. In addition to normality assumption, this situation can be directly explained in perspective of, ψ_t. $\psi_t$is the existing data set present at given time(t). By using conditional intensities:

$$Y_t/\psi_t \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 Y_{t-1}^2$$

Variance function is usually explained as following:

$$h_t = h(Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}, \alpha)$$

P Represents the degree of ARCH process and$\alpha$is the unknown parameter vector.

ARCH regression model is built by assuming the average of $Y_t$equals to $X_t\beta$. Also $X_t\beta$, is a linear combination of βunknown parameter vector,ψ_{t-1}external variables included in dataset anddelayed internal variables.(Engle, 1982: 986-989).

$$Y_t/\psi_{t-1} \sim N(X_t\beta, h_t)$$

$$h_t = h(e_{t-1}, e_{t-2}, \dots, e_{t-p}, \alpha)$$

$$e_t = Y_t - X_t\beta$$

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

$\alpha_0 > 0$ and $\alpha_i \geq 0, i = 1, \dots, p-1$and also$\alpha_p > 0$. Under these conditions, the conditional variance is always found positive (Kirchgassner and Wolters, 2007: 245-246).Another limitation is that each of or sum of all α_i‘s should be below 1. This limitation is a must to keep ARCH process stationary as well. Otherwise, the process will have an infinite variance (Özer, Türkyılmaz, 2004: 35).

Existence of a high positive or negative “e” value will cause big valued series for conditional variance. If the resulting shock is relatively small, it is assumed that smaller shocks will occur in near future. As p values get higher, volatility clusters get wider (Kirchgassner, Wolters, 2007: 246).

Some shortcomings of ARCH model are as following:

1. Model assumes that positive and negative shocks have same effect on volatility since model is based on square of previous shocks. In practice however, positive and negative shocks in price cause different reactions.
2. ARCH model has a limiting characteristic.
3. ARCH model is unlikely to create a new perspective for comprehending the source of volatile behavior in financial time series.. (Tsay, 2005: 103 – 109).

3.2.3.2. GARCH Model

GARCH model was created by Bollerslev (1986: 17). Key element in both ARCH and GARCH models is conditional variance. In classical GARCH models, conditional variance is a linear function of its squared vales in previous periods (Zakoian, Francq, 2010: 19).

In empirical application of ARCH model, a long delay in conditional variance equation is needed. In order to prevent negative variance parameter estimations, it is crucial to use a constant fixed lag structure. Expansion of the ARCH model allows for longer memory as well as to increased flexibility in delay structure. e_t Represents a constant in real varied discreet time stochastic process and ψ_t represents the dataset at time "t". GARCH(p,q) process can be expressed as below:

$$e_t/\psi_{t-1} \sim N(0, h_t)$$

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

$$= \alpha_0 + A(L)e_t^2 + B(L)h_t$$

Here,

$$p \geq 0, q > 0$$

$$\alpha_0 > 0, \alpha_i \geq 0, \qquad i = 1, \dots, q$$

$$\beta_i \geq 0, \qquad i = 1, \dots, p$$

For $p = 0$, process is down to an ARCH(q) process, and for$p = q = 0$,e_t is white noise. While in ARCH(q) model, conditional variance is expressed as a linear function of historical sample variances, on GARCH(p,q) process it includes delayed conditional variances as well (Bollerslev, 1986: 308-309).

$$V(\varepsilon_t) = E[\varepsilon_t^2] = \frac{\alpha_0}{1 - \alpha(1) - \beta(1)}$$

Thus for GARCH(p,q) process to have a variance

$$\alpha(1) + \beta(1) = \sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$$

condition must be met (Kirchgassner, Wolters, 2007: 252 – 254).

In GARCH model, conditional variance is an auto-correlated random variable and in determination of e_t^2 ARMA model is used. Error term's unconditional distribution is symmetrical and leptokurtic. Unconditional leptokurtic structure of GARCH model can be understood from the amount of changes in conditional variance which represents the presence of low volatility and high volatility clusters in tail and mid-section of unconditional variance. Conditional normal and unconditional moment of all levels can only occur when $\alpha(L) = \beta(L) = 0$. Conditional variance's persistence at high levels is dependent on the sum of αand β being close to 1(Özer, Türkyılmaz, 2004: 43 – 45).

3.2.3.3. EGARCH Model

Exponential Generalized Auto Regressive Conditional Heteroskedasticity (EGARCH) model is developed by Nelson (1991). If σ_t^2 is the conditional variance of information given at time "t", it has to be positive. GARCH model, allows this by definingσ^2 as a linear combination of positive random variables.Another method for making σ^2positive is linearizingln (σ_t^2) using delayed $z_t$as a function of time.

$$\ln(\sigma_t^2) = \alpha_t + \sum_{k=1}^{\infty} \beta_k\, g(z_{t-k}) \quad , \beta_1 \equiv 1$$

In this equation, z_t is the standardized residual. EGARCH model explains the asymmetric relationship between stock market returns and volatility shifts. In order for this process to be valid, the value of$g(z_t)$ must be a function ofz_t with same sign with it.$g(z_t)$, allows for conditional variance process to react asymmetrically to increases or decreases in $\{\sigma_t^2\}$stock market prices (Nelson, 1991: 350-351).

EGARCH model, not only reveals asymmetry but at the same time allows conditional variance to be always zero. EGARCH(1,1) model can be demonstrated as below:

$$ln(\sigma_t^2) = \alpha_0 + \alpha\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| + \delta\frac{e_{t-1}}{\sigma_{t-1}} + \beta ln(\sigma_{t-1}^2)$$

Standardized Errors e/$\sigma$are used in this equation. ARCH effect is demonstrated with absolute value of standardized errors instead of squared errors in above equation. In presence of a leverage effect, δ is expected to have a negative sign. (Kirchgassner, Wolters, 2007: 257 – 258)

EGARCH model is generally expressed as following:

$$ln\left(\sigma_{j,t}^2\right) = \omega_j + \beta_j \ln\left(\sigma_{j,t-1}^2\right) + \delta \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|e_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right]$$

α parameter represents symmetrical effect, and thus the GARCH effect. Regardless of any event that might occur in the marketβmeasures the continuity of conditional volatility. Since β is relatively higher span, it takes a considerable amount of time for volatility effect caused by crisis to “die out” from the market.δParameter measures asymmetry and leverage effect. If$\delta = 0$, then model is symmetrical. In cases where $\delta < 0$, positive shocks (Good New) create less volatility than negative shocks(Bad New). If$\delta > 0$then, positive variables are more destabilizing than negative variables (Su, 2010: 8-9).

3.2.3.4. TARCH Model

GARCH is left incapable of explaining asymmetry in error term variance. Due to this, TARCH (Threshold Auto Regressive Conditional Heteroskedasticity) model has been developed by Zakoian (1994) to be able to determine leverage effect in the model. TARCH model is created by adding leverage effect to the GARCH model. As main difference from GARCH, TARCH model explains asymmetry in error term variance (Arduç, 2006: 25).

TARCH model assumes separate GARCH models for positive and negative shocks. TARCH(1,1) model can be expressed as below: (Kirchgassner, Wolters, 2007: 257)

$$\sigma_t^2 = \alpha_0 + \alpha e_{t-1}^2 + \gamma e_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2$$

In this case,

$$d_t = \begin{cases} 1\,, & IF\ e_t < 0 \\ 0, & in\ all\ other\ cases \end{cases}$$

In this model, α parameter is an indicator of ARCH effect while parameter β represents GARCH effect and γ term represents leverage effect and through it the asymmetry.

In models where standard deviation is modeled instead of conditional variance, the equivalent of TARCH model is GJR – GARCH model. In both models, Threshold is a know variable. (Mikosh, Kreib, Davis, Anderson, 2009: 24)

TARCH (p) model is expressed as below:

$$\sigma_t = \omega + \alpha_1(|e_{t-1}| + \gamma_{1e_{t-1}}) + \alpha_2(|e_{t-2}| + \gamma_{1e_{t-2}}) + \cdots + \alpha_p\left(|e_{t-p}| + \gamma_{1e_{t-p}}\right)$$

In the model,ω, $\alpha_1, \ldots, \alpha_p$ is larger than zero. Reversion possibility of model implies that asymmetries can become inverted, when observed value of conditional variance is lower than expected at time t-1, positive errors cause higher amount of volatility than that of negative errors of same size.(FornariveMele, 1996: 198).

3.2.3.5. GJR – GARCH Model

GJR – GARCH model was developed by Glosten, Jagannathan and Runkle (1993). Model assumes that positive and negative unexpected returns have different effects on conditional variance. Also in the model it is indicated that there is a negative relation between conditional average market returns and their conditional variances (Glosten, Jagannathan, Runkle, 1993: 1799).

Despite advantages of EGARCH model empirical estimation of model is technically difficult because it includes several nonlinear algorithms. On the other hand, GJR – GARCH is much simpler. (Wang, 2007: 38)

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{k=1}^{r} \gamma_k\, e_{t-k}^2 d_{t-k} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

When the dummy variable present in above variance equation (d_t) takes$e_t < 0$ valuesthen$d_t = 1$, in other cases,$d_t = 0$.Due to this asymmetry parameter γ is meaningful when ,$d_t = 1$.In this model good news effect and bad news effect on the conditional variance have been taken into account. In the model, good news effect on conditional variance is demonstrated with α($\varepsilon_t > 0$) while bad news effect is demonstrated with (α+γ) ($\varepsilon_t < 0$). In cases where $\gamma > 0$it can be said that a leverage effect exists and bad news increasesvolatility on a higher basis. Where $\gamma \neq 0$news effect on volatility will not be symetrical. (Mazıbaş,2005: 8)

3.2.3.6. APARCH Model

APARCH model was developed by Ding, Granger and Engle(1993). Model's aim is to define heavy-tailed, excess kurtosis or leverage effect samples as precisely as possible.

$y_t = x_t\xi + \varepsilon_t t = 1,2, \dots, T$

$h_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \left(|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j}\right)^{\delta} + \sum_{i=1}^{p} \beta_i (h_{t-i})^{\delta}$

$\varepsilon_t = \sigma_t z_t \quad , z_t \sim N(0,1)$

$k(\varepsilon_{t-j}) = |\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j}$

Average equation ($y_t = x_t\xi + \varepsilon_t t = 1,2, \dots, T$) can be written as $y_t = E(y_t|\psi_{t-1}) + \varepsilon_t$as well. In the equation, □(□□|□□−1) , □□−1 are conditional average of y_t . While ψ_{t-1} is an information input in time t-1.

$$\psi_t = \{y_t, y_{t-1}, \dots, y_1, y_0, x_t, x_{t-1}, \dots, x_1, x_0\}$$

Parameters are ξ,ω, α_j,γ_j, β_i and δ. γ_j stands for leverage effect. A positive □□ indicates a stronger effect for negative information on price volatility. □ indicates strength of leverage effect.

APARCH equation must meet following conditions:

1. If $\omega > 0$, $\alpha_j \geq 0$, j=1,2,...,q, $\beta_i \geq 0, i = 1,2, \dots, p$, $\alpha_j = 0, j = 1,2, \dots, q, \beta_i = 0, i = 1,2, \dots, p$ then, $\sigma_t^2 = \omega$. For variance to be positive $\omega > 0$ is a must.
2. $0 \leq \sum_{j=1}^{q} \alpha_j + \sum_{i=1}^{p} \beta_i \leq 1$ (Ding, 2011: 5 – 6)

3.2.3.7. ARCH-M Model

This model has been developed by Engle, Lilienand Robins (1987). Model states that financial asset return’s conditional variance is included conditional average equation. In other words, a serial’s mean is dependent on its own conditional variance. This model is generally used in financial markets. Main idea lying behind model is that investors being risk averse and in order for them to hold a risk bearing instrument, they must be compensated. In model a financial asset’s risk is measured by variance of its returns. Risk premium is an incremental function of conditional variances in asset's return (Molva, 2008: 57).

ARCH-M model can be defined as below:

$$R_t = X_t\delta + \varphi\sigma_t^2 + e_t$$
$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta\sigma_{t-1}^2$$

In different variations of this model, conditional standard deviation and conditional heteroskedasticity's log is added to the average equation.

$$R_t = X_t\delta + \varphi\sigma_t + e_t$$
$$R_t = X_t\delta + \varphi log\ (\sigma_t^2) + e_t$$

On above equation,$\varphi$is estimated expected risk quotient and is an indicator of risk-return relationship (Songül, 2010: 16).

ARCH-M model is considered non linear due to conditional mean being dependent on conditional variance (Sorensen, 2005: 3).

3.2.3.8.GARCH-M Model

GARCH – M model was first discussed by Engle, Lilien and Robbins (1987). In these models conditional variance or conditional standard deviation serves as an explanatory variable in conditional mean model (Özer, Türkyılmaz, 2004: 46).

GARCH-M model can be expressed as following:

$$y_t/\psi_{t-1} \sim N(x_t\beta + \delta h_t, h_t^2)$$
$$y_t = x_t\beta + \delta h_t + e_t$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, e_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

δ is the risk premium parameter and its positive sign indicates its return's positive relation with its volatility.(Bollerslev, 1986: 44-48).

3.2.3.9. EGARCH-M Model

EGARCH model can be turned into EGARCH-M model in order to remove the restrictions regarding to signs of parameters and to determine whether the positive or negative shocks caused by news effect to volatility are persistent or not

$$\mu = E(e_t/h_t)$$
$$R_t = \beta R_{t-i} + \gamma h_t^2 + e_t$$
$$h_t^2 = V(\mathrm{e}_t/\Omega_{t-1}) = E(\mathrm{e}_t{}^2/\Omega_{t-1})$$
$$logh_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha\,(\mathrm{e}_{t-i}/\mathrm{h}_{t-i}) + \sum_{i=1}^{q} \alpha\,(|\mathrm{e}_{t-i}/\mathrm{h}_{t-i}| - \mu) + \sum_{i=1}^{p} \phi\, logh_{t-i}^2$$

R_t, represents the logarithmic stock price returns at period “t” (Kökcen, 2010: 46).

3.3. STRUCTURAL BREAK MODELS

3.3.1. ICSS Algorithm

ICSS algorithm has been proposed for the first time by Inclan and Tiao in year 1994 to reveal sudden breaks in variance. This method has been developed to find the sudden shocks that cause a shift in variance until another shock takes effect (Malik, 2003: 219). ICSS algorithm systematically uses cumulative sum of squares to find breaking points by searching for fractions within series (Bjerkseth, 2006: 5). ICSS algorithm is based on Inclan-Tiao test which proposes the existence of constant unconditional variance as the null hypothesis. Test statistics is calculated as following:

$$IT = max\left|\sqrt{T/2}\, D_K\right|$$
$$D_k = \frac{C_k}{C_T} - \frac{k}{T}\ , \quad k = 1, \dots, T$$

$C_k = \sum_{t=1}^{k} \varepsilon_t^2\ , t = 1, \dots, T$ is the sum of squares of ε_t. Also in the equation, $\varepsilon_t \sim iidN(0, \sigma^2)$. (Sanso et.al., 2004: 3).

ICSS test statistics only allows D_k function to detect a single point of break. When we want to detect multiple points of break, D_k function’s effect will be significantly reduced due to masking effect. To abolish this situation ICSS method is used. Under these circumstances the test statistics are as following. (Gürsakal, 2009: 327):

$$\max_{t_1 \leq k \leq T} \sqrt{(T - t_1 + 1)/2}\,|D_k(a[t_1 : T])|$$

An important weakness of ICSS algorithm is its inability to function properly when maximum number of points of break is unknown and also when the maximum number of observations between breaking points are inexact. Pooter and Dijk (2004), suggested that for daily data, there should be between 63 to 126 working days between points of break. (Pooter, Dijk, 2004: 8).

$$\text{If } e_t \sim iid(0, \sigma^2) \text{and } E(e_t^4) \equiv \eta_4 < \infty \text{ then,}$$

$$IT \to \sqrt{\frac{\eta_4 - \sigma^4}{2\sigma^4} sup_r |W^*(r)|}$$

3.3.2. Kappa 1

Due to this, distribution has nuisance parameters and when Brownian Bridge's maximization critical values are used, large distortions are expected. For Gaussian process $\eta_4 = 3\sigma^4$and $IT \to sup_r |W^*(r)|$. When $\eta_4 > 3\sigma^4$ then the distribution will be leptokurtic (heavily tailed) and it is expected that null hypothesis which states there is a constant variance is rejected (too many rejections of the null hypothesis of constant). As an antithesis, when $\eta_4 < 3\sigma^4$ then test will be too conservative. This is why Sanso et.al. (2004) suggests the correction to the previous test that will be free of nuisance parameters for identical and independent zero-mean random variables (Sanso et. al., 2004: 4):

$$\text{Kappa}_1 = sup_k \left| T^{-1/2} B_k \right|$$

$$B_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\widehat{\eta_4} - \widehat{\sigma^4}}}$$

$\widehat{\eta_4} = T^{-1} \sum_{t=1}^{T} e_t^4$ and $\widehat{\sigma^2} = T^{-1} C_T$.

Both IT and Kappa$_1$ are dependent on the independence of random variables. This is a strong assumption for financial data and this includes the evidence for conditional heteroscedasticity (Bera and Higgins (1993), Bollerslev et al.(1992,1994) and Taylor (1986)). To evaluate this, an estimation of the persistence may be used to correct the cumulative sum of squares. Along with that, some assumptions regarding to e_t is required:

1. $E(e_t) = 0$ and $E(e_t^2 = \sigma^2 < \infty \; for \; all \; t \geq 1$
2. $sup_t E(|e_t|^{\psi + e}) < \infty \;, \psi \geq 4 \; and \; e > 0$
3. $\omega_4 = \lim_{T \to \infty} E(T^{-1}(\sum_{t=1}^{T}(e_t^2 - \sigma^2))^2) < \infty$ exists
4. $\{e_t\}$ is a-mixing with coefficients α_j which satisfy $\sum_{j=1}^{\infty} \alpha_j^{(1-\frac{2}{\psi})} < \infty$

3.3.3. Kappa 2

This set of assumptions is similar to that of Herrndorf (1984) and Phillips and Perron (1988) but here we need to impose the existence of moments greater than four and a common unconditional variance for all the variables of the sequence. If e_t isindependent and identically distributed as student-t with three degrees of freedom, this sequence doesn't fulfill conditions 2 and 3. ω_4 can be interpreted as the long-run fourth moment of e_t or the long-run variance of the zero mean variable $\xi_t \equiv e_t^2 - \sigma^2$. Condition 4 controls of the "degree of independence" of the sequence and shows a trade-off between the serial dependence and the existence of high order moments (Sanso et. al., 2004: 5).

Kappa 2 test statistics are as following:

$$\text{Kappa}_2 = sup_k \left| T^{-1/2} G_k \right|$$

Here $G_k = \widehat{\omega}_4^{-1/2} \left(C_k - \frac{k}{T} C_T \right)$

and$\widehat{\omega}_4$ is a consistent estimator of ω_4. A non-parametric estimator of ω_4

$$\widehat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} (e_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T} \sum_{l=1}^{m} w(l, m) \sum_{t=l+1}^{T} (e_t^2 - \hat{\sigma}^2)(e_{t-1}^2 - \hat{\sigma}^2)$$

Here, $w(l,m)$ is a lag window, such as the Bartlett, defined as $(l,m) = 1 - \frac{l}{m+1}$, or the quadratic spectral. This estimator depends on the selection of the bandwith m, which can be chosen using an automatic procedure as proposed by Newey-West (1994) (Sanso et al., 2004: 5).

According to assumptions above, IT, kappa 1 and kappa 2 test statistics can be written as below:

$$IT \rightarrow \sqrt{\frac{\omega_4}{2\sigma^4}} sup_r |W^*(r)|$$

$$\text{Kappa}_1 \rightarrow \sqrt{\frac{\omega_4}{\eta_4 - \sigma^4}} sup_r |W^*(r)|$$

$$\text{Kappa}_2 \rightarrow sup_r |W^*(r)|$$

CHAPTER 4
DATA AND EMPIRICAL RESULTS

This Section explains the results of numerical methods and models used in analysis. The way results are interpreted is explained in detail in corresponding sections.

4.1. DATASET USED IN ANALYSIS

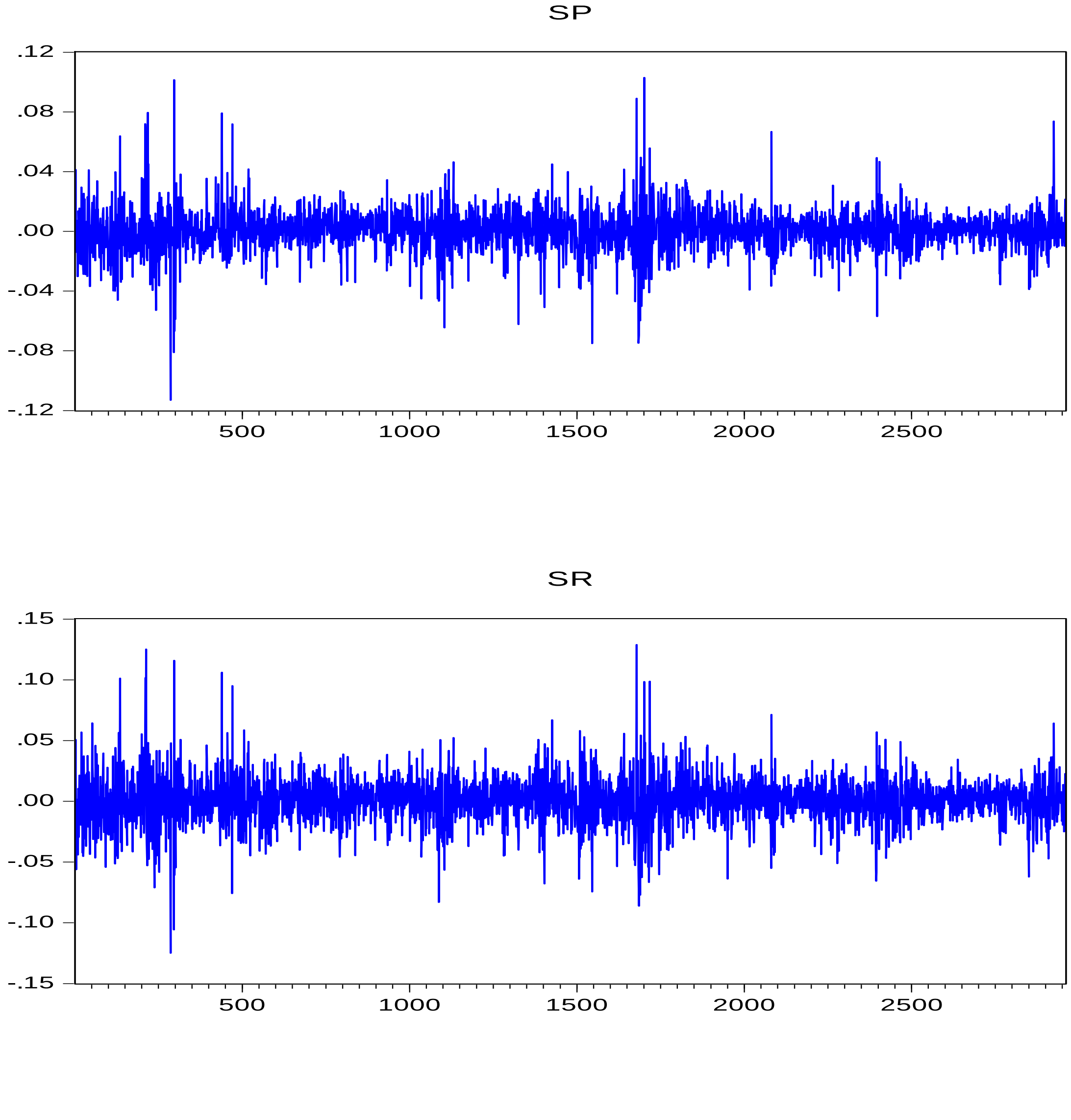
Purpose of this study is to analyze the impact of the CBRT's policy rate, over-night rate and over-night liquidity corridor decision's on the volatility of BIS 100 index on a sessional basis. The data is provided from the webpage of Borsa İstanbul database, consisting of approximately 12 years of closing prices of BIS 100 index from 02.01.2002 to 15.11.2013 period. The variables denoted by SP, SR and ST represent respectively the first session, second session and daily percentage changes of BIS 100 index. Additionally, we use dummy variables representing CBRT's policy changes, abbreviated as "dg". Variables were separated into sessional basis in order to determine whether if the shocks created by policy changes have a statistically more significant effect on a specific session over others. Variables used in analysis are shown in detail on Table 4.1.

Table 1: Explanations regarding to variables used in analysis.

Variable Used	Explanation
SP	BIS 100 index 1st Session closing price percentage change
SR	BIS 100 index 2nd Session closing price percentage change
ST	BIS 100 index daily closing price percentage change
Dg	Dummy variable that represents CBRT'S policy changes.

Figure 4.1 demonstrates timeline graphs of the variables SP, SR and ST. It can be observed from Figure 4.1 that series largely remain close to the mean which indicates a stationary characteristic for all three of them. Additionally, return series are seen to be clustered at certain gaps. These clusters in return series also cause volatility to fluctuate and cluster at certain periods. Also known as volatility clustering in the literature, large scale effects follow large scale events while small scale effects follow small scale events.

Figure 1: Timeline Graphs of variables SP, SR and ST



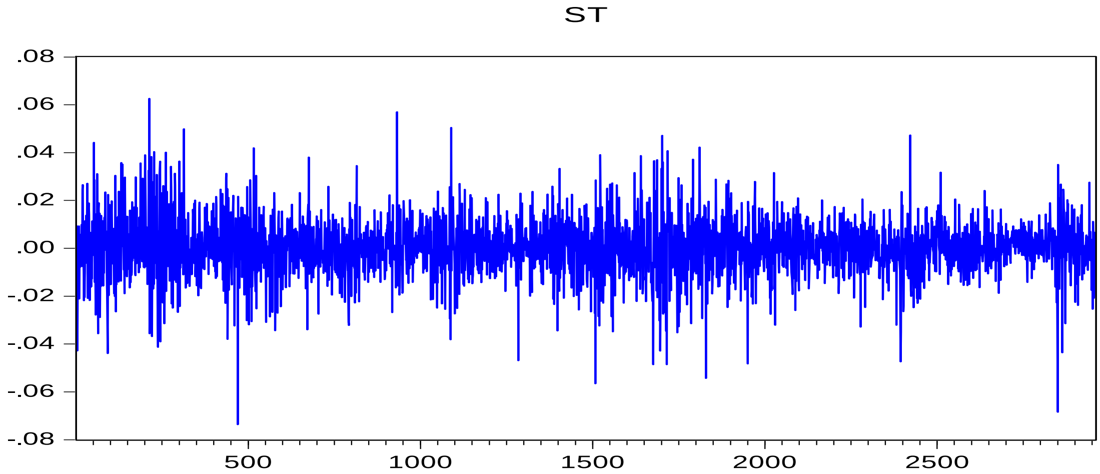


Table 4.2 demonstrates the descriptive statistics for return series SP, SR and ST. The highest mean is observed on series SR while lowest mean return is observed on series ST. Taking standard deviations into consideration, most volatile return values belong to SR (0.019763). Additionally for all series, kurtosis values are excessively higher than the critical value of "3" and shows characteristics of heavy tail. Skewness values on the other hand are positive for series SP and SR while negative for series ST. Jarque-Bera test statistics are considerably above the critical value of "5.99", therefore null hypothesis that claim error terms are normally distributed is rejected at 0.05 significance level. It can also be derived from this fact that returns are not normally distributed but rather show leptokurtic distribution characteristics.

Table 2: Descriptive Statistics of the variables SP, SR and ST

	SP	SR	ST
Mean	0.000442	0.000755	0.000301
Median	0.000773	0.00098	0.000367
Maximum	0.103072	0.1289321	0.062583
Minimum	-0.113130	-0.124892	-0.073679
Std. Dev	0.014549	0.019763	0.012186
Skewness	0.001897	0.109276	-0.156672
Kurtosis	9.510694	7.102262	5.642659
Jarque-Bera	5227.996***	2081.413***	873.4261***

*Note: *** Indicates 0.01 level of significance.*

4.2 UNIT ROOT TEST RESULTS

In order to determine whether the variables SP, SR and ST are stationary or not, we implemented the Augmented- Dickey Fuller (ADF), Philips-Perron and KPSS unit root tests. According to the results presented in Table 4.3, for all three variables it can be concluded that the Null Hypothesis which signifies the presence of a Unit root within the series is rejected due to the results of ADF and Phillips-Perron Unit Root test statistics being absolutely higher than critical levels at significance level of 0.01. On the other hand according to the results of KPSS test, at 1% level of significance the null hypothesis claiming that series are stationary cannot be rejected. Thus, it can be concluded that series SP, SR and ST are stationary.

Table 3: ADF and Philips-Perron Unit Root Test Results of Variables

	SP		**SR**		**ST**	
ADF	Test Statistic	Mac-Kinnon Critical Value	Test Statistic	Mac-Kinnon Critical Value	Test Statistic	Mac-Kinnon Critical Value
	-53.42781	-3.432370*** -2.862318** -2.567228*	-53.33420	-3.432370*** -2.862318** -2.567228*	-57.71141	-3.432370*** -2.862318** -2.567228*
Philips-Perron	Test Statistic	Critical Values	Test Statistic	Critical Values	Test Statistic	Critical Values
	-53.55161	-3.432370*** -2.862318** -2.567228*	-53.34308	-3.432370*** -2.862318** -2.567228*	-58.12869	-3.432370*** -2.862318** -2.567228*

KPSS	Test Statistic	Critical Values	Test Statistic	Critical Values	Test Statistic	Critical Values
	0.150726	0.739000*** 0.463000** 0.347000*	0.077877	0.739000*** 0.463000** 0.347000*	0.221001	0.739000*** 0.463000** 0.347000*

*Note: Appropriate lag values has been determined by Schwartz data criteria for ADF Unit Root Test and by determined by Newey –West bandwidth for Unit Root Tests of Phillips- Perron and KPSS. *, ** and *** respectively represents, 0.10, 0.05 and 0.01 critical values.*

4.3 DETERMINING APPROPRIATE ARMA MODEL

Various ARMA (p,q) models for series SP, SR and ST have been created by evaluating Autocorrelation and Partial Autocorrelation together. The most appropriate model among the ones created was determined using Akaike (AIC) and Schwarz (SIC) information criterion methods. Estimated ARMA(p,q) model results for return series SP, SR and ST are respectively demonstrated at Table 4.4, Table 4.5 and Table 4.6.

Table 4: Estimated ARMA (p,q) Models for series SP

	ARMA(1,1)	ARMA(2,2)
Constant Term	0.000672* (0.000403)	0.000428 (0.000268)
AR(1)	0.992868*** (0.005498)	0.097909*** (0.002685)
AR(2)	-	-0.988577*** (0.002642)
MA(1)	-0.989884*** (0.006903)	-0.092527*** (0.001320)
MA(2)	-	0.997164*** (0.001202)
F Statistic	4.877438***	6.850830***
Log Probability	8323.454	8332.904
AIC	-5.623829	-5.630767
SIC	-5.617753	-5.620638

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Table 5: Estimated ARMA(p,q) Models for series SR

	ARMA(2,2)
Constant Term	0.000739** (0.000366)
AR(1)	0.148252*** (0.033978)
AR(2)	-0.914961*** (0.033752)
MA(1)	-0.118097*** (0.035854)
MA(2)	0.904882*** (0.035801)
F Statistic	5.765142***
Log Probability	7424.206
AIC	-5.016367
SIC	-5.006238

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Table 6: Estimated ARMA(p,q) Models for series ST

	ARMA(1,1)	ARMA(2,3)
Constant Term	0.000299 (0.000217)	0.000296 (0.000209)
AR(1)	-0.728123*** (0.130563)	0.357242** (0.183575)
AR(2)	-	-0.699388*** (0.150903)
MA(1)	0.679787*** (0.139699)	-0.415786** (0.184009)
MA(2)	-	0.736987*** (0.149994)
MA(3)		-0.064694*** (0.019248)
F Statistic	7.299593***	4.368657***
Log Probability	8850.559	8850.947
AIC	-5.980101	-5.980356
SIC	-5.974025	-5.978202

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Taking statistical significance values, Akaike and Schwarz data criteria minimum values and log probability values into consideration for series SP, SR and ST, several ARMA(p,q) models have been created and most appropriate ones have been determined by choosing ones with highest significance, lowest Akaike and Schwartz data criteria values and highest log-probability values. Respectively, ARMA (2,2), ARMA(2,2) and ARMA(2,3) models have been found most appropriate. Estimated models for each are presented in respectively equation 4.1, 4.2 and 4.3:

$$\widehat{SP}_t = \underset{(0.1105)}{0.000428} + \underset{(0.0000)}{0.097909} SP_{t-1} - \underset{(0.0000)}{0.988577}\, SP_{t-2} - \underset{(0.0000)}{0.092527} e_{t-1} + \underset{(0.000)}{0.997164} e_{t-2} + e_t \tag{4.1}$$

$$\widehat{SR}_t = \underset{(0.0436)}{0.000739} + \underset{(0.0000)}{0.148252} SR_{t-1} - \underset{(0.0000)}{0.914961} SR_{t-2} - \underset{(0.0010)}{0.118097} e_{t-1} + \underset{(0.000)}{0.904882} e_{t-2} + e_t \tag{4.2}$$

$$\widehat{ST}_t = \underset{(0.1573)}{0.000296} + \underset{(0.0517)}{0.357242} ST_{t-1} - \underset{(0.0000)}{0.69938} ST_{t-2} - \underset{(0.0239)}{0.415786} e_{t-1} + \underset{(0.000)}{0.736987} e_{t-2} - \underset{(0.0008)}{0.064694} e_{t-3} + e_t \tag{4.3}$$

4.4 DETERMINING APPROPRIATE VOLATILITY MODEL

Existence of ARCH effect has been tested using ARCH-LM test. Results are shown in Table 4.7. Accordingly, ARCH-LM test result values for variables SP, SR and ST are as following respectively; 122.7212, 94.95163 and 38.72524. At 0.01 level of significance, the null hypothesis that rejects the presence of an ARCH effect is rejected and thus it is concluded that there is ARCH effect in the model proposed.

Table 7: ARCH-LM Test Results

	SP	SR	ST
Test Statistics	122.7212***	94.95163***	38.72524***

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance.*

Presence of ARCH effect in series enables us the use of ARCH models in order to determine their volatility.

We start the procedure by applying series SP the ARMA(2,2) GARCH(1,1) models. Results are demonstrated in Table 4.8. GARCH model takes historical volatility into the model by addition of lagged error terms. In GARCH model variance can be said to be stationary if the sum of lagged error terms and historical volatility quotient is smaller than 1. Additionally, in order to obtain a well-defined GARCH process, all parameters must have a non-negative value. When we evaluate ARMA(2,2)-GARCH(1,1) model results, we can see that α parameters which represent ARCH effect and β_1 parameters which represent GARCH effect are statistically significant at significance level of 0.05. Another definitive fact is that the sum of α and β parameters is smaller than 1. This situation indicates that, conditional variance has the necessary attributes to be treated as stationary. Distance of these parameter's sum to 1 signifies its resistance in volatility structure. We can confirm that the requirement for variance to be a non-negative number is met since all variance model parameters are positive. Thus it can be said that GARCH(1,1) model is statistically significant.

In next step of analysis we try ARMA(2,2)-GARCH-M(1,1) model. In GARCH-M model, conditional standard deviation is added to the averaging equation as an explanatory variable. Results show that risk parameter is statistically insignificant at significance level of 0, 05.

It is assumed in ARCH and GARCH models that the new market information causes simultaneous reaction. Along with these, methods that assume new positive or negative market information can be reacted to separately and therefore can cause varying volatility increases, such as EGARCH and PARCH are used in analysis as well. In model, the sign of the parameter named as “Asymmetric Leverage” is considered to be an indicator of the direction of leverage effect. Specifically, EGARCH model demonstrates a correlation between conditional variance and lagged error terms. In order to avoid limitations that may occur to prevent the result from being zero, model states them logarithmically.

According to ARMA(2,2)-EGARCH(1,1) model results; α_0 parameter which shows ARCH effects and β parameter which shows GARCH effects are statistically significant at 0.05 level of significance. Therefore significance of ARCH – GARCH is evident. It is observed that the impulse term δ_1 parameter is statistically significant. However along with these, AR(1) and MA(1) parameters in averaging model become statistically insignificant. Similarly, it is being observed in the ARMA(2,2)-APARCH(1,1) parameters that the averaging model is becoming statistically even more insignificant.

4.5 EMPIRICAL RESULTS OF THE VOLATILITY MODELS WITHOUT STRUCTURAL BREAKS

As a result, it is concluded that ARMA(2,2)-GARCH(1,1) model is the most viable model to explain SP series. When ARMA(2,2) - GARCH(1,1) model's variance equation is analyzed, we realize that $\alpha < \beta$ thus it can be said that resistance to volatility is greater than initial affects created by instant changes in the market. A decision of reduction in policy rate is, as expected in the theory reduces the volatility of SP return series. This situation can be explained by a chain of relationships. A change in policy rate affects the discount rate which corporations use to capitalize their cash flows while also effecting their cash flow expectations and therefore cost of capital. An increase in policy rate causes stock prices to fall by increasing expected returns from them. Additionally, an increase in interest rate increases the return of alternate instruments that yield interest and triggers a substitution of stocks with interest yielding instruments. Increase in real interest rates creates an increased demand for bonds and reduces demand of stocks. Thus existence of a negative relationship between interest rates and stock market demand is found (Öztürk, 2008: 13).

Table 8: ARMA(2,2)-GARCH(1,1), ARMA(2,2)-EGARCH(1,1), ARMA(2,2)-GARCH-M(1,1) and ARMA(2,2)-PARCH(1,1) Estimation Results for Series SP

	GARCH(1,1)	EGARCH(1,1)	GARCH-M(1,1)	APARCH(1,1)
		Average Model		
Constant	0.001418*** (0.000539)	0.000994*** (0.000371)	0.001438* (0.072472)	0.000924** (0.000381)
σ			-0.051656 (0.072472)	
dg	-0.002281 (0.001467)	-0.001687 (0.001407)	-0.002231 (0.001449)	-0.001817 (0.001458)
AR(1)	1.309773*** (0.148512)	0.151653 (0.145263)	-0.384610*** (0.016371)	0.350936 (0.374043)
AR(2)	-0.313597** (0.147726)	0.827034*** (0.143062)	0.591331*** (0.040558)	0.630646* (1.709139)
MA(1)	- 1.300558*** (0.148212)	-0.128663 (0.138448)	0.401473*** (0.000580)	-0.326854 (0.369933)
MA(2)	0.307933** (0.146928)	-0.835879*** (0.134805)	-0.575801*** (0.037167)	-0.642628* (0.361522)
		Variance Model		
Constant	5.57E-06*** (8.38E-07)	-0.444090*** (0.040290)	8.33E-06*** (1.04E-06)	3.73E-05** (1.54E-05)
α_1	0.116410*** (0.007770)	0.967015*** (0.004230)	0.128422*** (0.008612)	0.116538*** (0.007380)
β_1	0.862660*** (0.009118)	0.209186*** (0.011268)	0.831973*** (0.010805)	0.870931*** (0.008504)
δ_1	-	-0.067286*** (0.007601)	-	0.231990*** (0.031027)
γ	-	-	-	1.570043*** (0.089880)
Log-likelihood	8655.752	8665.145	8643.091	8667.301
AIC	-5.846350	-5.852025	-5.837113	-5.852807
SIC	-5.828118	-5.83176	-5.816855	-5.830523

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

GARCH, GARCH-M, EGARCH and PARCH models created for series are presented in Table 4.9. In ARMA(2,2)-GARCH(1,1) model created for SR series, quotients of averaging equation are statistically significant at significance level of 0,05. Both α_1 Parameter which represents shocks to SR series returns and β_1 parameter which represents the effect of previous terms volatility on current term volatility are statistically significant at significance level of 0.05. Also the sum of α and β parameters is smaller than 1 and signs of all variance model parameters are positive. Thus ARMA(2,2)-GARCH(1,1) model is statistically significant. In ARMA(2,2)-GARCH-M(1,1) averaging model, σ risk parameter which represents conditional standard deviation is found statistically insignificant.

In ARMA(2,2)-EGARCH(1,1) model which takes into account asymmetry in volatility structure, δ_1 parameter which represents the asymmetric effect has a negative sign and statistically significant. According to this result, negative shocks tend to increase volatility of SR series more than positive shocks do. As another model that explains asymmetry in volatility, ARMA(2,2)-PARCH(1,1) model also proves the existence of asymmetry in volatility due to the statistical significance of δ_1 parameter at 0.05 level of significance.

Among all models applied for SR return series, the model that has lowest AIC and SIC data criteria values and highest log probability values has been preferred. ARMA(2,2)-APARCH(1,1) model stood out as the most suitable model and therefore chosen. APARCH model is considered to be one of the best models that identify heavy-tailed and excess kurtosis samples under leverage effects. Positive γ_j , indicates that negative information has a stronger effect on volatility compared to positive information. Variance equation of APARCH (1,1) model for series SR results with $\gamma_j > 0$ therefore, for series SR it can be said that negative information has a stronger effect on volatility. In the mean time it can be observed that a policy rate reduction decision by CBRT has a negative effect on volatility.

Table 9: ARMA(2,2)-GARCH(1,1), ARMA(2,2)-EGARCH(1,1), ARMA(2,2)-GARCH-M(1,1) and ARMA(2,2)-APARCH(1,1) Estimation Results for Series SR

	GARCH(1,1)	EGARCH(1,1)	GARCH-M(1,1)	APARCH(1,1)
		Average Model		
Constant	0.001482*** (0.000314)	0.001218*** (0.000301)	0.002070* (0.001132)	0.001226*** (0.000310)
Σ	-	-	-0.036565 (0.067212)	-
Dg	-0.005878*** (0.001791)	-0.005474*** (0.001701)	-0.005867*** (0.001792)	-0.005512*** (0.001724)
AR(1)	0.184822*** (0.037805)	0.234924*** (0.056065)	0.182359*** (0.037591)	1.777295*** (0.002433)
AR(2)	-0.901376*** (0.037162)	-0.869487*** (0.052777)	-0.902602*** (0.036930)	-0.995560*** (0.002354)
MA(1)	-0.166306*** (0.038633)	-0.224438*** (0.058390)	-0.163619*** (0.038328)	-1.775612*** (0.003651)
MA(2)	0.893962*** (0.038590)	0.858661*** (0.054921)	0.895605*** (0.038276)	0.990996*** (0.003488)
		Variance Model		
Constant	6.93E-06*** (1.26E-06)	-0.371771*** (0.036531)	6.87E-06*** (1.25E-06)	9.30E-06 (6.58E-06)
α_1	0.091672*** (0.007160)	0.972415*** (0.004194)	0.091649*** (0.007254)	0.091855*** (0.008449)
β_1	0.893102*** (0.007514)	0.194908*** (0.011692)	0.893342*** (0.007576)	0.886546*** (0.008058)
δ_1	-	-0.051126*** (0.006878)	-	0.188195*** (0.030075)
γ	-	-	-	1.965878*** (0.177473)
Log-likelihood	7697.034	7702.589	7697.184	7714.384
AIC	-5.198130	-5.201210	-5.197555	-5.208509
SIC	-5.179898	-5.180952	-5.177297	-5.186225

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Table 10: ARMA(2,3)-GARCH(1,1), ARMA(2,3)-EGARCH(1,1), ARMA(2,3)-GARCH-M(1,1) and ARMA(2,3)-APARCH(1,1) Estimation results for series ST.

	GARCH(1,1)	**EGARCH(1,1)**	**GARCH-M(1,1)**	**APARCH(1,1)**
		Average Model		
Constant	0.000575*** (0.000174)	0.000382** (0.000187)	0.001533* (0.000852)	0.000450** (0.000194)
Σ	-	-	-0.087141 (0.078197)	-
Dg	-0.003008** (0.001322)	-0.002421* (0.001257)	-0.002968** (0.001332)	-0.002913** (0.001320)
AR(1)	1.475098*** (0.219971)	0.296786*** (0.002639)	1.067015** (0.448882)	0.335488*** (0.044738)
AR(2)	- 0.638381*** (0.208221)	-0.991788*** (0.002524)	-0.202313 (0.396682)	-0.926130*** (0.046071)
MA(1)	- 1.516386*** (0.221434)	-0.330340*** (0.019781)	-1.107633** (0.448380)	-0.367829*** (0.048291)
MA(2)	0.707494*** (0.216826)	1.006426*** (0.006085)	0.256460 (0.413553)	0.946460*** (0.044031)
MA(3)	-0.049389** (0.020249)	-0.028078 (0.019801)	-0.032432 (0.021604)	-0.030942 (0.020121)
		Variance Model		
Constant	2.40E-06*** (3.75E-07)	-0.391849*** (0.039245)	2.36E-06*** (3.66E-07)	2.64E-06 (2.66E-06)
α_1	0.059691*** (0.004902)	0.158528*** (0.011338)	0.059484*** (0.004865)	0.064394*** (0.007538)
β_1	0.925160*** (0.005293)	0.969532*** (0.004139)	0.925476*** (0.005210)	0.915270*** (0.006363)
δ_1	-	-0.046823*** (0.007956)	-	0.184960*** (0.044321)
γ	-	-	-	2.012003*** (0.221668)
Log-likelihood	9029.309	9026.187	9026.753	9032.833
AIC	-6.098248	-6.095461	-6.095844	-6.099278
SIC	-6.077991	-6.073177	-6.073560	-6.074969

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Table 4.10 contains models created for series ST. In ARMA(2,3) GARCH(1,1) model, quotients in average model are statistically significant at 0.05 level of significance. Quotient of variable dg is as expected negative and statistically significant at level of 0.05. On variance model, α parameter that represents ARCH effect and β_1 parameter that represents GARCH effect are both statistically significant at level of 0.05 and as expected has positive signs. Thus, ARMA(2,3)-GARCH(1,1) model is statistically significant.

On ARMA(2,3)-EGARCH(1,1) model there is a reduction in level of significance. MA(3) becomes statistically insignificant. In ARMA(2,3)-GARCH-M(1,1) model quotient of σ which represents conditional standard deviation is not statistically significant at significance level of 0.05. Lastly, in ARMA(2,3)-APARCH(1,1) model, MA(3)'s quotient in average model loses its statistical significance. Taking all these into consideration, for return series ST ARMA(2,3)-GARCH(1,1) model is chosen as most appropriate.

Most fitting autoregressive conditional heteroscedasticity models for series SP, SR and ST are respectively, ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) models. These estimated models are shown in equations 4.4, 4.5 and 4.6 respectively.

ARMA (2,2)-GARCH (1,1) model for variable SP,

$$\widehat{SP}_t=\underset{(0.0085)}{0.001418}-\underset{(0.1201)}{0.002281}dg+\underset{(0.0000)}{1.309773}SP_{t-1}-\underset{(0.0338)}{0.313597}SP_{t-2}\underset{(0.000)}{1.300558}e_{t-1}+\underset{(0.0361)}{0.307933}e_{t-2}+e_t \tag{4.4}$$

$$h_t=\underset{(0.0001)}{5.57E\text{-}06}+\underset{(0.0000)}{0.116410}e^2_{t-1}+\underset{(0.0000)}{0.862660}h_{t-1}$$

ARMA(2,2)-APARCH (1,1) model for variable SR,

$$\widehat{SR}_t=0.001226-0.005512dg+1.777295SR_{t-1}-0.995560SR_{t-2}-1.775612e_{t-1}+0.990996e_{t-2}e_t$$
$$\quad(0.0001)\quad(0.0014)\quad(0.0000)\quad(0.0000)\quad(0.0000)\quad(0.0000)$$

(4.5)

$$h_t^2=9.30E\text{-}06+0.091855\left(|\varepsilon_{t-1}|-0.188195\varepsilon_{t-1}\right)^{1.965878}+0.886546\left(h_{t-1}\right)^{1.965878}$$
$$(0.1579)\quad(0.0000)\quad(0.0000)\quad(0.0000)$$

ARMA(2,3)-GARCH (1,1) model for variable ST,

$$\widehat{ST}_t=0.000575-0.003008dg+1.475098ST_{t-1}-0.638381\ ST_{t-2}$$
$$(0.0010)\quad(0.0229)\quad(0.0000)\quad(0.0022)$$

$$-1.516386e_{t-1}+0.707494e_{t-2}0.049389e_{t-3}+e_t$$
$$(0.0000)\quad(0.0011)\quad(0.0147)$$

(4.6)

$$h_t = 2.40\mathrm{E}-06+0.059691e_{t-1}^2+0.925160h_{t-1}$$
$$(0.0001)\quad(0.0000)\quad(0.0000)$$

ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) model's standardized residuals for series SP, SR and ST are given at appendix section in that order. Re-applied ARCH-LM results of standardized residuals are shown in Table 4.11 to confirm the presence of ARCH effect. From Table 4.11 it can be seen that ARCH effect is inexistent. Additionally, models including ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) created for series SP, SR and ST's standardized residual's autocorrelation and partial autocorrelation functions are given at appendix section on the tables A.1 – A.6.

Table 11: ARCH-LM Test Results

	SP	SR	ST
Test Statistics	1.198475	0.146534	1.078009

ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) model's conditional standard deviations that are most fit for series SP, SR and ST's graphical demonstrations are shown in Figure 4.2, Figure 4.3 and Figure 4.4. From these figures we can see that for the period from 2002 to 2004 and from 2008 to 2009 there is an increase in volatility of series SP, SR and ST. In other words it can be understood that conditional standard deviations increase the volatility in economically unstable periods.

Figure 2: Conditional Standard Deviation Graph for models ARMA(2,2)-GARCH(1,1) of SP Return Series

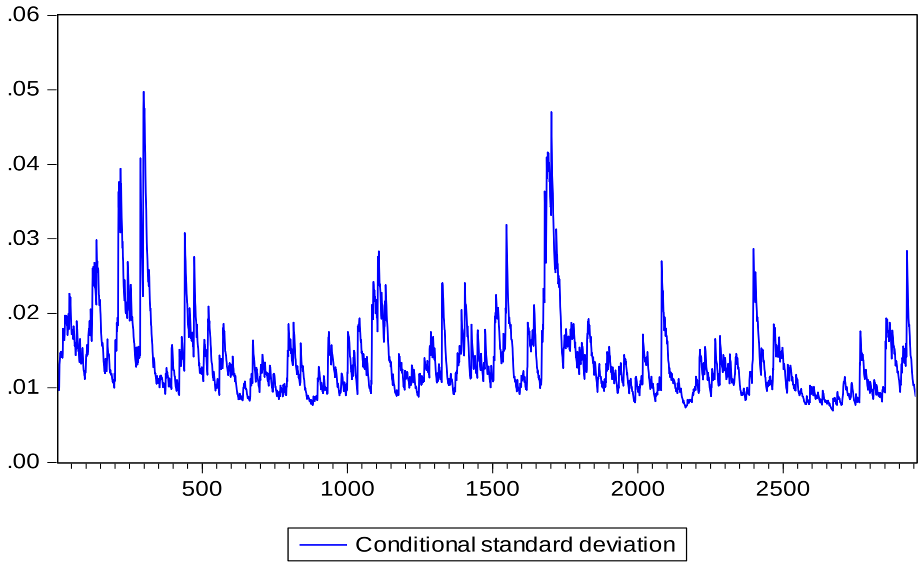


Figure 3: Conditional Standard Deviation Graph for models ARMA(2,2)-APARCH(1,1) of SR Return Series

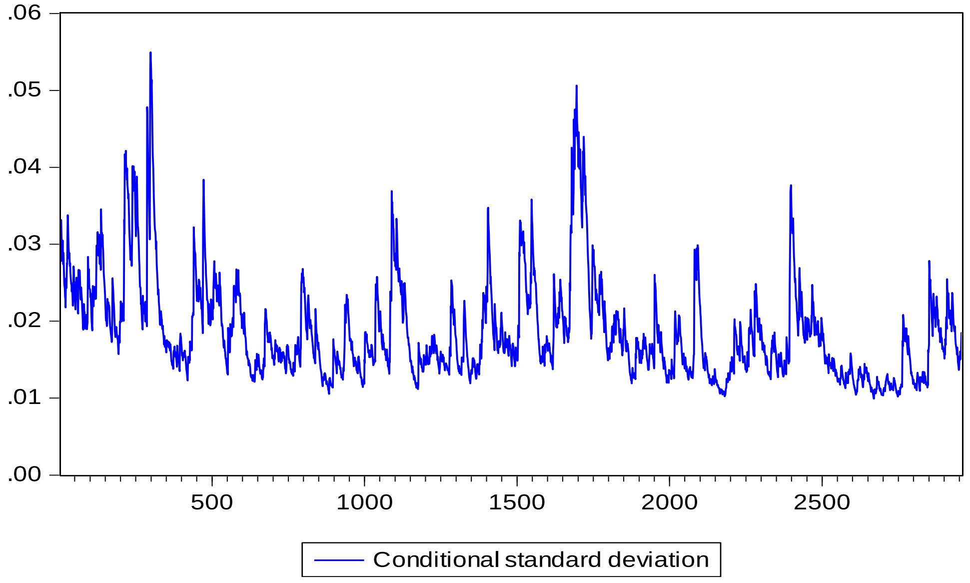
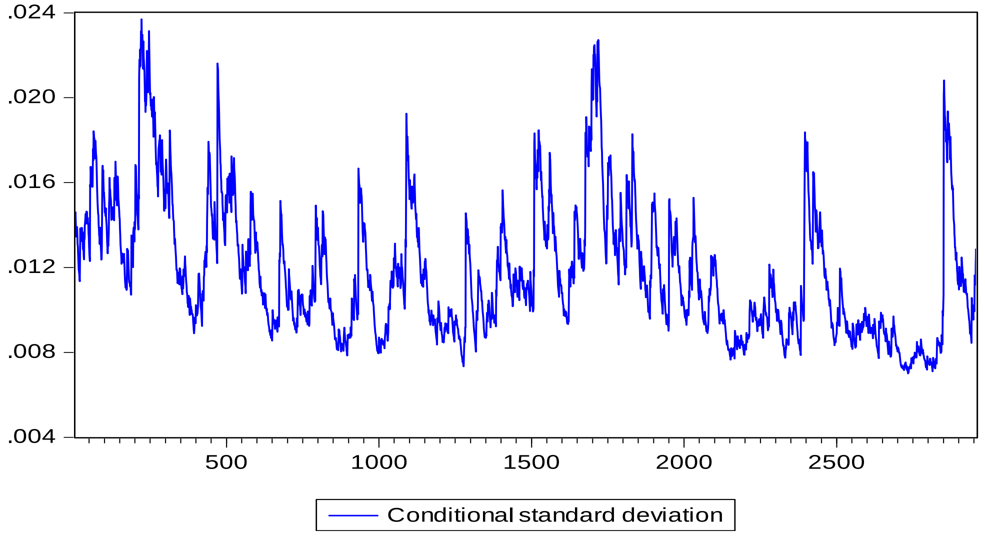


Figure 4: Conditional Standard Deviation Graph for models ARMA(2,3)-GARCH(1,1) of ST Return Series



4.6 EMPIRICAL RESULTS OF THE VOLATILITY MODELS WITH STRUCTURAL BREAKS

ICSS algorithm method which was first developed by Inclan and Tiao, is used to determine sudden breaks in variances of return series SP, SR and ST. Break points in variance and their corresponding dates found by using ICSS method for series SP, SR and ST are shown in Table 4.12:

Table 12: Break Points and Dates of Volatility for Series SP, SR and ST

SP		**SR**		**ST**	
Break Points	***Break Dates***	***Break Points***	***Break Dates***	***Break Points***	***Break Dates***
45	12.03.2002	209	1.11.2002	210	2.11.2002
106	06.06.2002	221	19.11.2002	245	26.12.2002
285	28.02.2003	253	8.1.02003	319	17.04.2003
303	25.03.2003	285	28.02.2003	2649	10.08.2012
317	15.04.2003	298	19.03.2003	2846	27.05.2013
420	09.09.2003	316	14.04.2003	2872	2.07.2013
471	01.12.2003	419	8.09.2003	2960	4.11.2013
521	16.02.2004	469	18.11.2003		
2392	03.08.2011	2960	4.11.2013		
2404	19.08.2011				
2544	14.03.2012				
2761	24.01.2013				
2765	30.01.2013				
2850	31.05.2013				
2924	17.09.2013				
2960	4.11.2013				

An important shortcoming of ICSS algorithm is its inability to determine maximum break points and maximum number of observations between variance break points. Sanso et. al. have developed Kappa 2 test to mend these shortcomings in ICSS model in year 2004. Table 4.13 contains rearranged break points and corresponding dates for return series SP, SR and ST using Kappa 2 model. In a closer look at Table 4.13, it can be seen that break points and corresponding dates are intersecting with periods of crisis.

Table 13: Break Points and Dates of Volatility for Series SP, SR and ST (Rearranged for Kappa 2)

SP		SR		ST	
Break Points	***Break Dates***	***Break Points***	***Break Dates***	***Break Points***	***Break Dates***
316	14.04.2003	209	01.11.2002	524	19.02.2004
1502	15.01.2008	1837	20.05.2009	1505	18.01.2008
1837	20.5.2009			1974	08.12.2009

The breakpoint on 01.11.2002 might be the result of a sharp decline in IMKB (BIST100) index prior to general elections in 3 November 2002.

The breakpoint on 14.04.2003might be the result of a decline in Japanese Nikkei index so large that withdrew the index below its 1983 value.

The breakpoint on 19.02.2004 might be the result of Palestinian-Israel conflict.

Breaks on 15.01.2008 and 18.01.2008 may be related with the Mortgage crisis in the USA, started with problems in credit market and followed by a major structural collapse in worldwide financial market with corruption in derivative instruments and fast paced shift in real estate market prices.

Breaks on 20.05.2009 and 08.12.2009 might be related with the European Union Debt Crisis. Process started with revelation of Greece's actual public debt. Crisis quickly spread to Portugal, Ireland, Spain and several other European countries.

Table 4.14 shows, SP, SR and ST return series' estimated break points rearranged by Kappa 2 method for ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) models. To better demonstrate the difference between volatility model that takes break points into account and the one that does not take them into account, Table 4.15 is drawn. A significant difference between two is a reduction in persistence of SR variables volatility.

Table 14: Estimated Results of Volatility Models with Variance Breaks for Return Series SP, SR and ST

	GARCH(1,1) for SP	APARCH(1,1) for SR	GARCH(1,1) for ST
		Average Model	
constant	0.001020***	0.001182***	0.000574*
	(0.000216)	(0.000317)	(0.000193)
Σ	-	-	
Dg	-0.002146	-0.005459***	-0.003006***
	(0.001480)	(0.001738)	(0.001343)
AR(1)	-1.549359***	0.231416***	0.352534***
	(0.212661)	(0.051433)	(0.041005)
AR(2)	-0.793054***	-0.865976***	-0.935341***
	(0.173724)	(0.050583)	(0.036980)
MA(1)	1.553722***	-0.215854***	-0.388114***
	(0.217940)	(0.053115)	(0.045531)
MA(2)	0.785931***	0.857141***	0.958376***
	(0.183167)	(0.051967)	(0.034808)
MA(3)			-0.035093*
			(0.020172)
		Variance Model	
Constant	5.17E-06***	1.10E-05	2.46E-06***
	(7.95E-07)	(7.21E-06)	(3.87E-07)
α_1	0.111260***	0.093436***	0.061165***
	(0.007626)	(0.008233)	(0.005257)
β_1	0.869356***	0.193204***	0.923157***
	(0.008896)	(0.029934)	(0.005697)
δ_1	-	0.885392***	-
		(0.007957)	
γ	-	1.934721***	-
		(0.165253)	
Log-likelihood	8650.042	7710.898	9027.776
AIC	-5.841137	-5.205475	-6.095860
SIC	-5.833116	-5.181166	-6.071550

*Note: *, ** and *** respectively represent 0.10, 0.05 and 0.01 level of significance. Values in parenthesis represent standard errors.*

Table 15: Volatility Parameters of Series with and without Dummy Variables.

	Model without Dummy			Model with Dummy		
	α	β	$\alpha + \beta$	α	β	$\alpha + \beta$
SP	0.116410	0.862660	0.97907	0.111260	0.869356	0.980616
SR	0.091855	0.886546	0.978401	0.093436	0.193204	0.28664
ST	0.059691	0.925160	0.984856	0.061165	0.923157	0.984322

CONCLUSION

In this study, we examine the effects of the monetary policy changes including the changes in policy rate, overnight rates and over-night liquidity corridor announced by CBRT's on volatility of BIST 100 index with and without considering the structural breaks on the closing prices series of each session for the period between 02.01.2002 - 15.11.2013 by using ARCH models. We define SP, SR and ST return series as independent variables and CBRT's policy rate intervention dates representing interest rate policy changes as dummy variables.

Several deviations of ARCH model have been applied for each of return series SP, SR and ST with both GARCH and GARCH-M models which define effect of conditional variance as symmetrical and with models that define conditional variance's asymmetrical effect such as EGARCH and APARCH. Lastly a deviation from ICSS algorithm Kappa 2 break points have been determined and applied to model.

Results of analysis indicate that fittest models for series SP,SR and ST are ARMA(2,2)-GARCH(1,1), ARMA(2,2)-APARCH(1,1) and ARMA(2,3)-GARCH(1,1) models respectively. In order to determine the effects of CBRT's policy rate changes on return series SP, SR and ST's volatility, dummy variables are added. As a result of this analysis, it is found that changes in interest rate policy reduce the volatility of BIST 100 closing price series. After the addition of break points determined by ICSS algorithm, Kappa 2 technique, we observe a reduction in persistence of volatility for the series of SR. Our results are consistent with the findings of major part of the existing literature and support the theory of APARCH (Ding, Granger and Engle (1993)) by indicating that negative shocks cause a greater volatility in magnitude. Additionally our findings support the theories of James Tobin and Gordon model by confirming the negative relationship between interest rates and stock prices. Different from the previous studies this is the first one examining the impact of policy interest changes (covering the changes in policy rate, overnight rates and over-night liquidity corridor) on volatility of BIST 100 index by considering the structural breaks. Additionally it is the first study that examines its impact on index volatility for the first and the second sessions separately. Results indicate a significant relationship for daily and second session series. The reason why relationship with first session is insignificant may be due to CBRT's announcement hours. As a result, we can say that monetary policy tools including policy rate, over-night rates and over-night liquidity corridor are all used by the CBRT to reduce the fluctuations in the stock market in the long term.

The main purpose of our study is to examine the impact of interest rate policy changes on the volatility of the Turkish stock market. Different from the previous studies, we consider the structural breaks in our volatility models. We do not observe a study taking account for the structural breaks therefore this is the main contribution of this thesis to the literature. On the other and considering the structural breaks in the volatility analysis is important since our period covers the major latest financial turmoil. Additionally it provides more reliable results.

We believe that this study provides beneficial information to the investors and portfolio managers to forecast the impact of changes in policy interest rates on the volatility of their stock market investments and to the policy makers on how and when they can use these policies to reduce stock market volatility in order to eliminate the negative effects of financial shocks.

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APPENDICES

APPENDIX 1: Autocorrelation and Partial Autocorrelation Function for SP Series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.018	0.018	0.9160	0.339
		2	-0.004	-0.004	0.9554	0.620
		3	0.002	0.002	0.9635	0.810
		4	-0.012	-0.012	1.3595	0.851
		5	0.065	0.066	14.034	0.015
		6	-0.009	-0.011	14.269	0.027
		7	-0.015	-0.014	14.952	0.037
		8	0.033	0.033	18.147	0.020
		9	0.023	0.023	19.715	0.020
		10	0.087	0.083	42.324	0.000
		11	-0.014	-0.016	42.905	0.000
		12	0.017	0.021	43.741	0.000
		13	0.069	0.065	58.024	0.000
		14	0.005	0.003	58.108	0.000
		15	0.009	-0.000	58.338	0.000
		16	-0.011	-0.007	58.689	0.000
		17	-0.021	-0.021	60.046	0.000
		18	0.022	0.008	61.435	0.000
		19	-0.011	-0.014	61.792	0.000
		20	-0.006	-0.012	61.909	0.000
		21	-0.026	-0.028	63.867	0.000
		22	-0.020	-0.023	65.003	0.000
		23	-0.035	-0.050	68.670	0.000
		24	-0.011	-0.008	69.044	0.000
		25	0.040	0.039	73.790	0.000
		26	0.020	0.018	74.982	0.000
		27	-0.011	-0.008	75.360	0.000
		28	0.010	0.012	75.642	0.000
		29	-0.001	0.007	75.645	0.000
		30	-0.022	-0.022	77.122	0.000
		31	-0.008	-0.003	77.307	0.000
		32	-0.031	-0.021	80.144	0.000
		33	-0.029	-0.023	82.698	0.000
		34	0.004	0.006	82.754	0.000
		35	0.016	0.016	83.493	0.000
		36	-0.003	-0.001	83.519	0.000

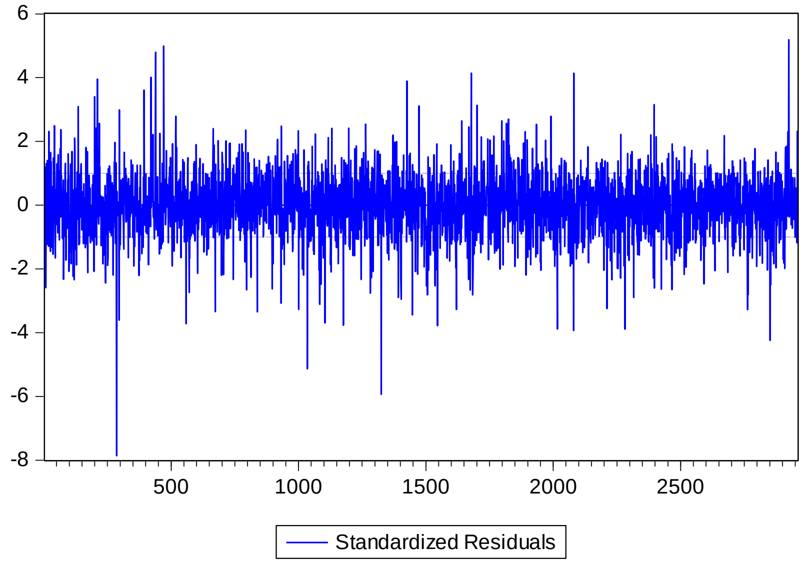
APPENDIX 2: Autocorrelation and Partial Autocorrelation Function for SR Series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.019	0.019	1.1214	0.290
		2	-0.006	-0.006	1.2297	0.541
		3	-0.009	-0.008	1.4556	0.693
		4	-0.016	-0.016	2.2432	0.691
		5	0.015	0.016	2.9407	0.709
		6	-0.046	-0.047	9.1634	0.165
		7	-0.036	-0.034	12.919	0.074
		8	0.000	0.001	12.920	0.115
		9	0.040	0.039	17.563	0.041
		10	0.074	0.071	33.822	0.000
		11	-0.028	-0.030	36.189	0.000
		12	0.011	0.013	36.548	0.000
		13	0.066	0.065	49.513	0.000
		14	0.001	-0.002	49.514	0.000
		15	-0.006	-0.005	49.610	0.000
		16	0.004	0.015	49.650	0.000
		17	0.018	0.022	50.563	0.000
		18	0.010	0.005	50.845	0.000
		19	-0.008	-0.007	51.019	0.000
		20	-0.024	-0.021	52.688	0.000
		21	-0.015	-0.011	53.382	0.000
		22	0.004	-0.003	53.435	0.000
		23	-0.004	-0.012	53.483	0.000
		24	-0.023	-0.018	55.079	0.000
		25	0.008	0.008	55.287	0.000
		26	0.032	0.023	58.379	0.000
		27	-0.049	-0.057	65.684	0.000
		28	-0.026	-0.025	67.778	0.000
		29	0.007	0.010	67.915	0.000
		30	-0.026	-0.028	69.887	0.000
		31	-0.011	-0.015	70.273	0.000
		32	-0.028	-0.023	72.594	0.000
		33	-0.039	-0.036	77.254	0.000
		34	-0.018	-0.021	78.201	0.000
		35	-0.009	-0.015	78.439	0.000
		36	0.009	0.008	78.670	0.000

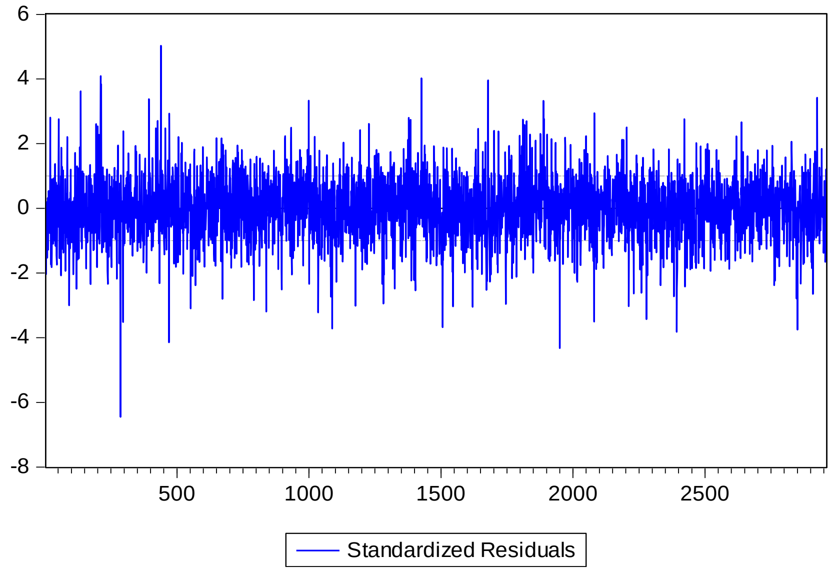
APPENDIX 3: Autocorrelation and Partial Autocorrelation Function for ST Series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.059	-0.059	10.436	0.001
		2	0.022	0.019	11.936	0.003
		3	-0.040	-0.037	16.605	0.001
		4	-0.006	-0.011	16.722	0.002
		5	-0.039	-0.039	21.318	0.001
		6	-0.001	-0.006	21.319	0.002
		7	-0.036	-0.036	25.121	0.001
		8	-0.033	-0.040	28.316	0.000
		9	-0.017	-0.022	29.218	0.001
		10	0.031	0.025	32.015	0.000
		11	-0.008	-0.009	32.229	0.001
		12	0.009	0.001	32.446	0.001
		13	0.010	0.010	32.752	0.002
		14	-0.014	-0.017	33.361	0.003
		15	0.003	0.000	33.388	0.004
		16	0.006	0.005	33.514	0.006
		17	0.027	0.028	35.683	0.005
		18	0.006	0.011	35.792	0.008
		19	0.027	0.027	37.917	0.006
		20	0.020	0.026	39.095	0.006
		21	0.017	0.021	39.911	0.008
		22	0.009	0.014	40.129	0.010
		23	-0.013	-0.010	40.664	0.013
		24	0.010	0.016	40.963	0.017
		25	0.013	0.021	41.467	0.020
		26	0.006	0.013	41.588	0.027
		27	-0.024	-0.019	43.300	0.024
		28	-0.042	-0.041	48.514	0.009
		29	-0.002	-0.003	48.521	0.013
		30	0.002	0.002	48.532	0.018
		31	0.025	0.023	50.446	0.015
		32	0.003	0.003	50.467	0.020
		33	-0.025	-0.026	52.298	0.018
		34	-0.001	-0.005	52.300	0.023
		35	0.011	0.006	52.653	0.028
		36	0.008	0.003	52.857	0.035

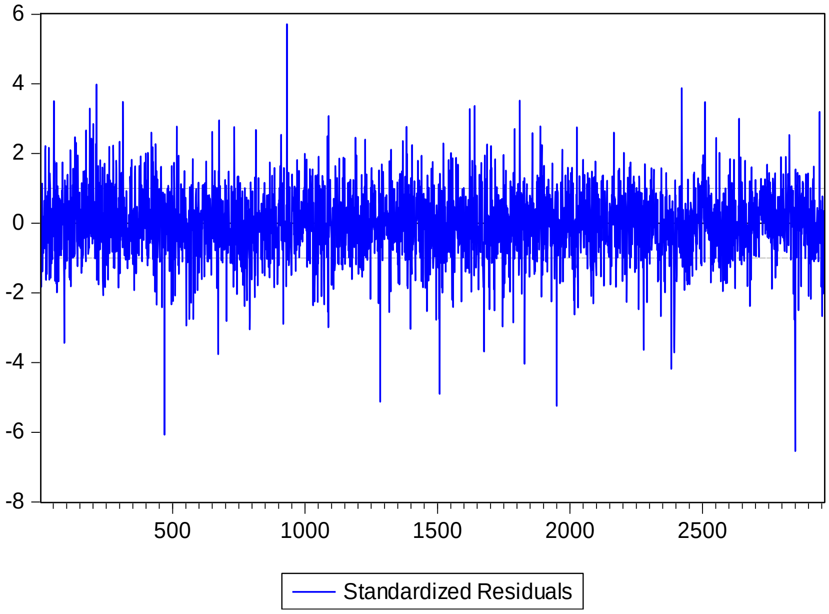
APPENDIX 4: Figure A.1: Standardized Residual Series of model ARMA(2,2)-GARCH(1,1) of Series SP



APPENDIX 5: Standardized Residuals of Model ARMA(2,2)-APARCH(1,1) of Series SR



APPENDIX 6: Standardized Residuals of Model ARMA(2,3)-GARCH(1,1) of Series ST



APPENDIX 6: Autocorrelation and Partial Autocorrelation Functions of Standardized Residual Series of model ARMA(2,2)-GARCH(1,1) of Series SP

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.006	0.006	0.1120	
		2	-0.010	-0.010	0.3998	
		3	0.020	0.020	1.5853	
		4	-0.008	-0.008	1.7814	
		5	0.023	0.024	3.3860	0.066
		6	-0.024	-0.025	5.1177	0.077
		7	-0.002	-0.001	5.1346	0.162
		8	0.011	0.009	5.4687	0.242
		9	0.004	0.005	5.5122	0.357
		10	0.054	0.054	14.318	0.026
		11	0.002	0.002	14.327	0.046
		12	0.004	0.005	14.387	0.072
		13	0.026	0.023	16.368	0.060
		14	-0.007	-0.006	16.496	0.086
		15	0.009	0.007	16.736	0.116
		16	-0.011	-0.010	17.088	0.146
		17	-0.015	-0.014	17.764	0.167
		18	0.005	0.003	17.854	0.214
		19	0.000	0.001	17.854	0.270
		20	-0.009	-0.012	18.096	0.318
		21	-0.020	-0.020	19.298	0.312
		22	-0.017	-0.018	20.208	0.321
		23	-0.046	-0.049	26.431	0.119
		24	0.003	0.004	26.451	0.151
		25	0.019	0.018	27.504	0.155
		26	0.018	0.021	28.464	0.161
		27	-0.015	-0.014	29.102	0.177
		28	0.000	0.001	29.102	0.216
		29	-0.002	-0.004	29.118	0.259
		30	-0.034	-0.032	32.477	0.178
		31	-0.010	-0.006	32.757	0.205
		32	-0.021	-0.018	34.098	0.198
		33	-0.029	-0.023	36.593	0.157
		34	0.018	0.019	37.587	0.161
		35	0.021	0.022	38.917	0.155
		36	-0.003	-0.003	38.941	0.186

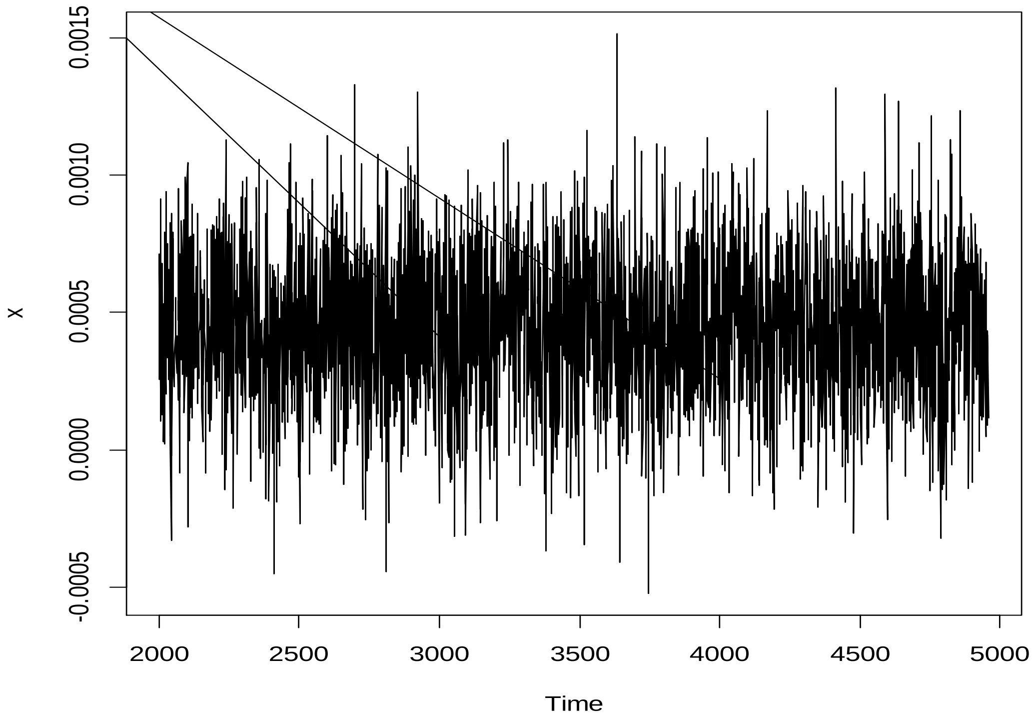
APPENDIX 7: Autocorrelation and Partial Autocorrelation Functions of Standardized Residual Series of model ARMA(2,2)-APARCH(1,1) of Series SR

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.038	0.038	4.2457	
		2	0.014	0.012	4.8181	
		3	0.014	0.013	5.3740	
		4	0.010	0.009	5.6562	
		5	0.026	0.025	7.5983	0.006
		6	-0.020	-0.022	8.7945	0.012
		7	0.005	0.006	8.8828	0.031
		8	-0.009	-0.010	9.1205	0.058
		9	0.026	0.026	11.060	0.050
		10	0.051	0.049	18.861	0.004
		11	-0.008	-0.011	19.030	0.008
		12	0.002	0.000	19.043	0.015
		13	0.029	0.028	21.512	0.011
		14	-0.011	-0.015	21.850	0.016
		15	0.009	0.008	22.101	0.024
		16	0.007	0.008	22.234	0.035
		17	0.018	0.017	23.199	0.039
		18	0.017	0.015	24.063	0.045
		19	0.014	0.011	24.648	0.055
		20	-0.021	-0.026	25.947	0.055
		21	-0.014	-0.011	26.504	0.066
		22	-0.002	-0.003	26.514	0.089
		23	-0.013	-0.014	27.021	0.104
		24	-0.032	-0.029	30.050	0.069
		25	0.014	0.017	30.627	0.080
		26	0.007	0.005	30.786	0.101
		27	-0.053	-0.055	39.118	0.019
		28	-0.028	-0.026	41.400	0.015
		29	0.015	0.018	42.045	0.018
		30	-0.030	-0.029	44.693	0.013
		31	-0.000	0.004	44.693	0.018
		32	0.018	0.021	45.667	0.019
		33	-0.029	-0.027	48.193	0.014
		34	-0.004	-0.001	48.230	0.019
		35	0.007	0.006	48.357	0.024
		36	0.002	0.003	48.374	0.032

APPENDIX 8: Autocorrelation and Partial Autocorrelation Functions of Standardized Residual Series of model ARMA(2,3)-GARCH(1,1) of Series ST

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0086	
		2	0.009	0.009	0.2340	
		3	-0.008	-0.008	0.4207	
		4	0.014	0.014	1.0336	
		5	0.003	0.003	1.0609	
		6	0.014	0.014	1.6593	0.198
		7	-0.008	-0.008	1.8478	0.397
		8	-0.016	-0.016	2.6139	0.455
		9	0.004	0.005	2.6686	0.615
		10	0.033	0.033	5.9334	0.313
		11	0.010	0.010	6.2321	0.398
		12	0.011	0.011	6.5861	0.473
		13	0.011	0.012	6.9634	0.541
		14	-0.006	-0.007	7.0879	0.628
		15	0.014	0.013	7.6974	0.658
		16	0.008	0.007	7.8879	0.723
		17	0.018	0.018	8.8968	0.712
		18	0.005	0.006	8.9595	0.776
		19	0.030	0.030	11.729	0.628
		20	0.005	0.005	11.807	0.694
		21	0.011	0.009	12.149	0.734
		22	0.002	0.001	12.165	0.790
		23	0.011	0.009	12.500	0.820
		24	0.003	0.004	12.531	0.862
		25	0.024	0.022	14.209	0.820
		26	0.010	0.010	14.515	0.846
		27	-0.014	-0.015	15.092	0.858
		28	-0.034	-0.035	18.475	0.731
		29	-0.001	-0.004	18.480	0.779
		30	0.002	0.001	18.496	0.821
		31	0.017	0.015	19.358	0.821
		32	0.015	0.015	20.040	0.829
		33	-0.027	-0.026	22.150	0.774
		34	-0.014	-0.015	22.697	0.790
		35	0.012	0.009	23.125	0.810
		36	0.014	0.010	23.745	0.821

APPENDIX 9: Mean and Conditional Variance Graph of Series SP

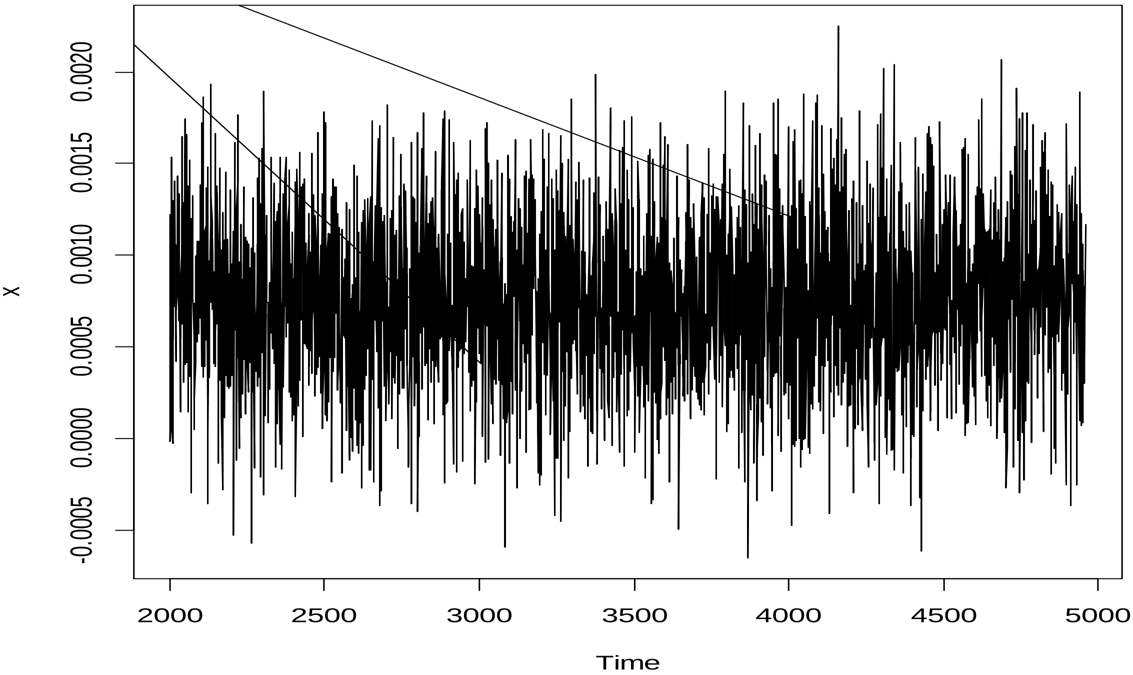


Shapiro-Wilk normality test

data: x

W = 0.9994, p-value = 0.4569

APPENDIX 10: Mean and Conditional Variance Graph of Series SR



Shapiro-Wilk normality test

data: SR

W = 0.9994, p-value = 0.4779