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FORECASTING VOLATILITY IN THE PRESENCE OF STRUCTURAL BREAKS: EVIDENCE FROM ISTANBUL STOCK EXCHANGE (ISE) SECTOR INDICES

Efe Çağlar ÇAĞLI

Danışman

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YEMİN METNİ

Tezsiz Yüksek Lisans projesi olarak sunduğum "**Forecasting Volatility in the Presence of Structural Breaks: Evidence from Istanbul Stock Exchange (ISE) Sector Indices**" adlı çalışmanın, tarafımdan, bilimsel ahlak ve geleneklere aykırı düşecek bir yardıma başvurmaksızın yazıldığını ve yararlandığım eserlerin kaynakçada gösterilenlerden oluştuğunu, bunlara atıf yapılarak yararlanılmış olduğunu belirtir ve bunu onurumla doğrularım.

Tarih

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Efe Çağlar ÇAĞLI

ABSTRACT

Master Thesis

Forecasting Volatility in the Presence of Structural Breaks: Evidence from Istanbul Stock Exchange (ISE) Sector Indices

Efe Çağlar ÇAĞLI

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The purpose of this study is to forecast the volatility of the Turkish stock market indices in the presence of structural breaks. The empirical relevance of structural breaks in the volatility of the Istanbul Stock Exchange (ISE) sector indices are examined by conducting GARCH family models in both in-sample and out-of-sample tests.

Empirical results indicate the existence of significant structural breaks in the unconditional variance for all the ISE indices, and GARCH parameter estimates differ across subsamples defined by the modified Iterative Cumulative Sum of Squares (ICSS) algorithm indicating instable GARCH processes governing volatility for all of them. In out-of-sample analysis, two different statistical loss functions over forecast horizons of 1, 5, 10, 15, 20, 60, and 120 days are used to compare forecasts of daily stock market index return volatility produced by the econometric models that assume stable GARCH processes to the forecasts generated by the GARCH type of models that accommodate sudden volatility shifts due to the structural breaks in the unconditional variance of daily stock market index returns. It is evidenced that structural breaks are relevant features for the ISE indices and allowing for instabilities in the data leads to forecasting gains. Moreover, empirical findings reveal that

decision makers should consider structural breaks as well as sectoral differences in modeling and forecasting stock market volatility in both short-term and long-term. Thus, one should be aware of those facts to reach more accurate conclusions in terms of Value-at-Risk (VaR) calculation, risk management, derivative pricing, and hedging and portfolio allocation.

Keywords: Volatility, Structural Breaks, Forecasting, GARCH model, Estimation Window, ISE

ÖZET

Tezli Yüksek Lisans Projesi

Yapısal Kırılmalar Altında Oynaklık Öngörümlemesi: İstanbul Menkul Kıymetler Borsası Sektör Endeksleri Örneği

Efe Çağlar ÇAĞLI

Dokuz Eylül Üniversitesi
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İngilizce İşletme Anabilim Dalı
İngilizce Finansman Programı

Bu çalışmanın amacı yapısal kırılmalar altında Türk Hisse Senedi endekslerinin oynaklığını öngörümlemektir. İstanbul Menkul Kıymetler Borsası (İMKB) sektör endekslerinde yapısal kırılmaların deneye dayalı anlamlılığı GARCH modeli yardımıyla örneklem içi ve dışı testlerle ortaya koyulmuştur.

Ampirik bulgular, tüm İMKB sektör endeks getirilerinin uzun dönem varyanslarında anlamlı yapısal kırılmaların varlığına işaret etmektedir ve yinelenen birikimli kareler toplamı (ICSS) algoritması yardımıyla belirlenen alt örneklemler için elde edilen GARCH parametre tahminlerinin birbirlerinden farklılık göstermeleri tüm endeksler için oynaklığın durağan olmayan bir GARCH süreci izlediğini ortaya koymaktadır. Örneklem dışı analizde, durağan GARCH süreci izleyen ekonometrik modellerden elde edilen oynaklık öngörümlemeleriyle yapısal kırılmalardan kaynaklanan ani şoklarını dikkate alan GARCH modellerinden elde edilen oynaklık öngörümlemeleri 1, 5, 10, 15, 20, 60, ve 120 gün öngörü aralığı için iki farklı istatistiki kayıp fonksiyonuyla karşılaştırılmıştır. Yapısal kırılmaların İMKB sektör endeksleri üzerine yapılan analizler için dikkate alınması gerekliliği sonucuna varılmış ve yapısal kırılmaları dikkate almanın oynaklık öngörümlemesi analizi açısından daha faydalı ortaya koyulmuştur. Bununla birlikte, piyasalarda karar alıcı birimlere kısa ve uzun vadeli oynaklık modellemesi ve/veya öngörümlemesi yaparlarken

yapısal kırılmaları dikkate almalarının yanında sektörel farklılıkları da göz önünde bulundurmaları önerisi sunulmuştur. Bu yüzden, riske maruz değer hesaplaması, risk yönetimi, türev ürün fiyatlaması ve portföy yönetimi vb. finansal konularda daha doğru sonuçlara ulaşmak için yukarıda ortaya konulan olgulara dikkat edilmesi tavsiye edilmiştir.

Anahtar Kelimeler: Oynaklık, Yapısal Kırılmalar, Öngörümleme, GARCH modeli, Tahminleme Penceresi, İMKB

TABLE OF CONTENTS

FORECASTING VOLATILITY IN THE PRESENCE OF STRUCTURAL BREAKS: EVIDENCE FROM ISTANBUL STOCK EXCHANGE (ISE) SECTOR INDICES

CHAPTER III

DATA AND EMPIRICAL RESULTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Risk is defined as a bad future event that might happen. It is not possible to avoid all risks completely; however, there are some risks that participants of the financial markets choose to take as the possible benefits exceed the possible costs. Practitioners and academics in financial markets are interested in measuring and predicting the risk and return of any investment and they optimize their behavior, in particular their portfolio, to maximize the return from an investment and minimize the risks associated with the investment.

Finance investigates which risks are worth taking and which risks are not worth taking. There exists a vast literature about this central paradigm of finance; trade-off between risk and return and defining optimal behavior takes the risks that are worthwhile. Markowitz (1952) is one of the first researchers defining the risk of a financial asset, or basically a portfolio, as its variance of returns. Tobin (1958) and Sharpe (1964) also associate risk with the variance in the value of a portfolio. Moreover, Black and Scholes (1972) and Merton (1973) propose an option pricing model by considering the risk as the variance of returns to determine the cost of put options that can be used as insurance policies to hedge the risks associated with the underlying asset. Put another way, their strategy is satisfying the simple and very powerful theory of Capital Asset Pricing Model (CAPM) of Sharpe (1964) which is also based on relating the variances of return to risks. When the practitioners in financial markets and the academics employ these strategies, they need the estimates of variance of returns of financial assets. In particular they require square root of variances, also known as volatility. Since modeling and forecasting volatility have crucial importance in risk management, derivatives pricing, and portfolio construction it is important to estimate volatility accurately. Well-known financial data stylized facts and determinants of volatility should be taken into account in modeling and forecasting volatility.

Friedman (1977) hypothesizes that unpredictability of inflation is the primary cause of business cycles. He also states that it is the uncertainty of futures costs and prices that might decrease the level of investments and lead to a recession. Engle (1982) deals with this issue and proposes Autoregressive Conditional Heteroskedasticity (ARCH) model. ARCH model is a dynamic volatility model which is able to model and forecast time varying volatility more accurately because it embodies several important characteristics of financial data, particularly mean reversion and volatility clustering. ARCH model overcomes the shortcomings of the other type of volatility models, especially, historical volatility models, by using averages of past squared forecast errors, a type of weighted variance, and following a systematic approach to the estimation of optimal weights so that those weights gives more influence to recent information and less to the distant past (Engle, 2004). The most important feature of ARCH model is that it helps to estimate the weights from historical dataset even though the true volatility is not observed.

ARCH family models, especially generalized ARCH (GARCH) model of Bollerslev (1986), are widely used by both practitioners and academics under the assumption that a stable ARCH process governs conditional asset return volatility. In other words, researchers estimate time-varying volatility via econometric models that follow ARCH process by assuming unconditional, long-run, variance is constant. Also, they forecast volatility using expanding, or fixed data window under the assumption of stable ARCH process. However, these estimation techniques for both modeling and forecasting volatility may give biased forecasting results even if we use econometric models that follow ARCH process because international financial markets experience sudden volatility shifts, such as 2001 Turkish banking crisis, and global financial turmoil that was triggered by the mortgage credit delinquencies in the late of 2007. Those volatility shifts may lead to structural breaks in the unconditional variance of asset returns. As Hendry (1986), Lamoureux and Lastrapes (1990), and Mikosh and Starica (2000, 2004) and many others state parameters of GARCH model can be estimated biased and the persistence of volatility can be overestimated when structural breaks in the data are neglected.

In the light of aforementioned issues, the purpose of this study is to examine the empirical relevance of structural breaks in the volatility of the Turkish stock market, one of the important emerging markets by conducting GARCH family models in both in-sample and out-of-sample tests. In our in-sample analysis, the modified version of Inclan and Tiao's (1994) Iterative Cumulative Sum of Squares (ICSS) algorithm proposed by Sanso et al. (2004) is employed to detect potential structural breaks in the unconditional variance of daily Istanbul Stock Exchange (ISE) sectoral indices. Then, parameters of GARCH(1,1) model are estimated across subsamples identified by the modified version of ICSS algorithm to check whether the parameters estimates and the unconditional variance change across subsamples due to the existence of potential structural breaks. In out-of-sample analysis, two different statistical loss functions over forecast horizons of 1, 5, 10, 15, 20, 60, and 120 days are used to compare forecasts of daily stock market index return volatility produced by the econometric models that assume stable GARCH processes to the forecasts generated by the GARCH type of models which makes some type of adjustment to the estimation window, thus accommodating sudden volatility shifts due to the structural breaks in the unconditional variance of daily stock market index returns.

This thesis consists of three chapters. First chapter concentrates on the definition of uncertainty, risk, and volatility, also gives information about types, determinants, and the stylized facts of the financial market volatility. Second chapter presents comprehensive literature review of volatility models, especially deterministic volatility models. Moreover, Theoretical background of the volatility models, in addition empirical studies on ARCH models with structural breaks and forecasting volatility using ARCH models are summarized in second chapter. Finally, empirical analysis and the results are given in the third chapter.

The thesis provides the following contributions to the literature:

This study provides a very comprehensive literature on volatility models, in particular deterministic univariate volatility models.

To the best of our knowledge, this is the first study which takes structural breaks into account in modeling and forecasting volatility of ISE stock market index returns and conducts recent econometric techniques in the empirical analysis. Empirical results which suggest considering sudden large shocks in the unconditional variance due to the structural breaks in both estimating unconditional variance and forecasting stock market volatility lead us to reach a conclusion that the previous studies that do not consider structural breaks in modeling and forecasting volatility of Turkish stock market are invalid.

CHAPTER I

RISK AND VOLATILITY

This chapter gives the distinctions among uncertainty, risk and volatility and provides information about the types of risk and volatility. In addition, it discusses the determinants of volatility by documenting the empirical studies on the factors which might cause volatility especially in the stock markets.

1.1. Uncertainty, Risk and Volatility

According to Knight (1921) 'risk' and 'uncertainty' have different contents and connotations. Knight (1921: 226) argues that "t*o preserve the distinction ... between the measurable uncertainty and an unmeasurable one, we may use the term 'risk' to designate the former and the term 'uncertainty' for the latter*". In this quote, measurement is assigning 'objective probabilities' to the events in real life. Uncertainty reflects a situation in which one cannot assign probabilities to events therefore, it is not possible to gather any computational inferences. On the other hand, risk is defined as the situations in which one can assign 'objective probabilities' to the decisions depending on his particular knowledge. In the same vein, Keynes (1937) defined uncertainty as situations that might be explained by 'subjective' probabilities.

On the other hand, Markowitz (1952) uses 'variance of return' rather than the 'risk'. He states that 'variance of return is undesirable whereas 'expected return' is desirable for an investor.

'Volatility' is defined as the spread of asset returns (Poon, 2005: 1) and it is measured as the variance of asset returns:

$$\sigma^2 = \frac{1}{n}\sum_{t=1}^{n}\left(r_t - \mu\right)^2 \tag{1.1}$$

where r_t is return of an asset at time t, μ is the average return of the asset over the time period, and n represents length of time period. "Volatility" may not be "undesirable" once the volatility and the risk are different concepts. In addition, it cannot be a perfect measure of risk unless the asset returns have a Gaussian distribution with a zero mean and a constant variance (Poon, 2005:2). Mandelbrot (1963) and Fama (1963 and 1965) evidence that the variance (covariance) of stock returns changes through the time period. Their results indicate that the stock prices do not have a normal distribution. Recognizing such 'behavior' of stock prices leads to a critical problem among both practitioners and scholars who find different variances of returns for different time periods (Fama, 1965; Engle, 2004). Since volatility is a key ingredient in economic and investment decisions such as derivative pricing, hedging strategies, portfolio allocation, risk measurement, risk management, and other financial applications, it is important to model and forecast volatility appropriately by applying statistical tools which capture the changes in variances (Bollerslev, Chou, & Kroner, 1992; Bollerslev, Engle, & Nelson, 1995; Poon & Granger, 2003).

1.2. Types of Risk and Volatility

Basically, there are two types of risks associated with the financial assets including 'systematic' and 'unsystematic' risk. 'Systematic risk' arises from the macroeconomic, legal and political factors, which influences all assets in the whole economy, whereas 'unsystematic risk' results from the factors unique to the firm and independent of whole economic and political events which affects a small number of groups of assets. It is possible to eliminate the unsystematic risk by 'diversification' that is providing by adding more securities with different characteristics into a portfolio. Well diversification helps to reduce the variability of rate of return.

According to Bolak (2004: 5) economic, political, and social environment are the main sources of systematic risk and he classifies the systematic risk into three basic groups as 'Interest rate risk', 'Inflation (purchasing power) risk', and 'Market risk'. Changes in interest rate affect the value of the fixed-income securities which have maturities of more than one year. There is a negative relationship between market interest rates and value of the fixed-income securities. Basically, net present value (NPV) approach that requires a specific interest rate in calculation to determine the values of securities might help us to understand the relationship between the two.

$$PV = C \times \left[\frac{1}{r} - \frac{1}{r\left(1+r\right)^{n}} \right] + \frac{FaceValue}{\left(1+r\right)^{n}} \tag{1.2}$$

where PV stands for present value, C denotes the coupon payment of bond. r indicates the yield to maturity. Since an increase in interest rates decreases the value of a security or vice versa, changes in interest rates can be considered as a systematic risk. ‘Purchasing power risk’ is the ‘inflation risk’. The increase in the inflation rate decreases the amount of goods or services that we can purchase, and affects the returns of securities being traded in the market negatively. Civelek and Durukan (2003) define purchasing power risk as a loss of purchasing power with respect to the possibility of increases in price level. ‘Market risk’ is simply subject to economic, political or psychological natures. It arises due to the psychological reasons, or irrational behaviors of investors in the market leading security prices to fluctuate and investors might experience losses from those fluctuations in securities prices even though earnings power does not change.

Unsystematic risk is specific to a firm or an industry. Strikes, managerial errors, advertising strategies, changes in the consumer preferences, legal issues might lead to higher volatility in the returns. ‘Financial’, ‘operational’, ‘managerial’ and ‘industrial’ risks are the main type of unsystematic risk. ‘Financial risk’ refers to the situation that a company could not satisfy its financial obligations due to having inadequate cash flow. This risk might arise because of the usage of more debt besides the equity financing. Breakdowns in internal procedures, people and systems in a company increase the fixed costs. Similar to the high interest expenses increase the financial risk, high fixed costs increase the ‘operational risk’. In addition, high fixed costs increase the break-even point. This leads high volatility in stock returns of the company, especially when the amount of sales is relatively low. The performance of the companies is mostly related to the abilities of the board of directors. Thus, ‘managerial’ risk arises from the performance of management which directly affects the value of company. Moreover, industrial risk arises due to the changes consumer tastes, increases in foreign competition, industrial accuses, and discontinuities in supply chain.

Moreover, Bolak (2004) distinguishes the types of risk as ‘financial’ and ‘non-financial’. It is not easy to measure non-financial risks as they are closely related to company’s own production technology or workforce. For instance, recording losses due to the inefficient production technologies or disagreement between employee and employer increase the non-financial risks. On the other hand, financial risks arise from the financial activities of firms, global economic environment, and/or high volatility in financial markets. Even though those risks are not generally firm-specific, they can be measured easily and there are a number of common techniques to eliminate them. Bolak (2004: 9) and Cuthbertson and Nitzsche (2001: 566) classified financial risks as ‘market risk’, ‘credit risk’, ‘liquidity risk’, and ‘operational risk’.

‘Market risk’ stems from changes in asset prices. Changes in the exchange rate, interest rate, and prices of common stocks and precious metals are the main subgroups of market risk. ‘Credit risk’, also known as ‘default risk’, refers to the situation where the counterparty could not meet his obligations and then defaults. ‘Liquidity risk’ refers to the situation of that an asset cannot be converted into cash in a short time without a substantial loss in value (Civelek and Durukan, 2003: 116). Liquidity risk might be managed by providing cash outflows and inflows to be simultaneous. ‘Operational risk’, as we mentioned before, stems from mishandled origination settlement and clearing of trades.

Investment choices, consumer spending, economic growth are mostly affected from increasing volatility. Since increasing volatility is a sign of increasing risk, it is important to examine the types of volatility as well. We can calculate volatility based on four types, namely ‘historical’, ‘implied’, ‘deterministic’ and ‘stochastic’ volatility.

‘Historical volatility’ is calculated by using past observations. In historical volatility approach, the variance or standard deviation of past observations (historical returns) over the specific time-period is used as a forecast for future volatility or as an input for option pricing models (Brooks, 2008: 383). Because of its simplicity, it is widely used. However, as Engle (2004) argues, in historical volatility method, it is not easy to determine right period that is used for calculating variance of returns. If variance of returns is calculated over a long time horizon, estimated historical volatility would not be so relevant for today; on the other hand calculation of historical volatility through a short time would be very noisy (Engle, 2004). Moreover, historical volatility approach suffers since it assumes constant variance through a time period. Thus, it is evidenced that volatility estimation via more sophisticated models that embodies some characteristics of data and overcome aforementioned shortcomings might be more accurate for option valuation or risk management issues (Brooks, 2008; Akgiray, 1989; Engle, 2004, Chu and Freund, 1996)

'Implied volatility' is a type of volatility over the life of the option implied by the option valuation such as Black-Scholes (1973) options pricing model (Brooks, 2008: 384). To derive the volatility implied by the option, one can apply numerical procedure, such as the method of bisections or Newton—Raphson (Watsham and Parramore, 2004: 274)[1]. One of the important features of that approach is that implied volatility contains expectations of investors because it is the predicted volatility of the underlying asset of an option until the time to maturity (Duarte and Fonseca, 2002).

Duarte and Fonseca (2002) states that 'deterministic volatility' can be calculated using a function of 'known' variables, i.e. through sophisticated econometric models with autoregressive conditional heteroskedasticity (ARCH) processes. ARCH model is proposed by Engle (1982) and it is generalized by Bollerslev (1986). The logic behind the ARCH models is modeling "uncertainty" of a time series by considering its stylized facts, such as "mean-reverting" or "volatility clustering" and this model does not assume constant variance over time[2]. Thus, Engle's (1982) model simply models the uncertainty that is changing over time called *heteroskedasticity* (Engle, 2004). ARCH family models are capable of modeling mean and variance equations simultaneously and since the variance

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[1] op. cit. Brooks, 2008:384

[2] Volatility clustering and mean reversion are the most important characteristics of the financial market volatility. Volatility clustering refers to a situation that "large changes in asset returns (of either sign) tend to be followed by large changes and small changes tend to be followed by small changes (Mandelbrot, 1963). Moreover, it is widely observed that financial market returns reverts to its long run mean, providing some predictability in volatility.

equation does not contain an additional error term, those type of models are generally called deterministic volatility models.

Lastly, ‘stochastic volatility’ models are different from ‘deterministic volatility’ models, (G)ARCH models, because they contain a second error term in the variance equation (Brooks; 2008: 427). Duarte and Fonseca (2002) states that stochastic volatility models assume that volatility follows a random process different from the one that drives asset prices despite the both of them may be correlated. Different than ‘deterministic volatility’ models, this randomness affects pattern of both returns and volatility. ‘Stochastic volatility’ models are based on the financial theories of the option pricing framework of Black-Scholes (1973). As cited in Brooks (2008: 428) Hull and White (1987) suggests that the main advantage of those models is that they can be viewed as discrete time approximations to the continuous time models employed in options pricing frameworks. Beside the theoretical advantages of stochastic volatility models, in practice there exist computational difficulties (Brooks, 2008: 428).

1.3. Determinants of Volatility

Engle (2004) illustrates the importance of volatility with a hypothetic economy with one risky asset. He states that a rise in volatility should lead investors to sell part of the asset because of increasing uncertainty in the whole economy. Thus, the price of that risky asset, all else being constant, should fall significantly just after demand for that risky asset decreases. However, at this lower price, the expected return of the risky asset will be higher due to the high volatile economic environment. Price of that risky asset will reach equilibrium point if the demand for the lower priced high risky asset increases.

As Engle (2004) puts forth, the consequences of volatility can be explained clearly, but cannot be measured easily. Therefore, one should first understand the causes of volatility to determine its possible effects on the economy. This section attempts to explain the sources of volatility such as macroeconomic factors, arbitrage trading, program trading and portfolio insurance within derivatives market trading, insider trading, seasonality, news announcements, and finally spillover effects.

1.3.1. Macroeconomic Factors

Campbell (1987) conducts a study for the US to investigate the time variation in the covariance matrix of bonds, bills and stock returns. He concludes that nominal interest rates significantly have an impact on volatility. Schwert (1989) asks why the stock market volatility varies over time and find mixed results about the relationship between stock market volatility and the volatility of macroeconomic variables. According to his empirical findings volatility of inflation has an impact on the stock volatility for the period 1953 to 1987 and yet, stock volatility does not affect the inflation volatility. He also concludes that there is a bidirectional relationship between stock volatility and money growth for various subsamples and industrial production predicts the return volatility weakly. In general he evidences that causal relationship from stock market to macroeconomic volatility is stronger. Hamilton and Lin (1996) examine the issue by using the Markov switching conditional volatility model and their results denote that there is a significant relationship between stock price volatility and the volatility of aggregate macroeconomic variables. They also state that macroeconomic variables might be used for forecasting stock market volatility. Hassan and Francis (1998) make an attempt to identify the determinants of volatility of the US. Their findings suggest that dividend yield, the term structure, and the default spread have significant impacts on both small and large firm conditional volatilities. Allowing regression coefficients vary over time, Binder and Merges (2001) investigate the issue using S&P500 data covering February 1929 to April 1989 and Engle and Rangel (2005) apply Spline-GARCH model to investigate the effect of macroeconomic conditions on the unconditional stock market volatility. Their findings suggest that there are positive linkages between volatility of several factors including GDP growth, inflation and short term interest rates and the volatility of stock market. Beltrattia and Morana (2006) use S&P500 data spanning from 1970 to 2001 and find bidirectional relationship between stock market volatility and the volatility of macroeconomic variables; however, the causality direction is found to be stronger from macroeconomic to stock market volatility.

Bekaert and Harvey (1996) conduct a study to characterize and explore the determinants of volatility in a number of emerging markets including Turkey using semi parametric ARCH (SPARCH) model and (non)-linear Factor models. Their findings suggest that volatility is strongly influenced by world factors in fully integrated markets, whereas in segmented capital markets, local factors mostly have a significant impact on volatility. Moreover, they evidence that the more open economies or emerging markets which experienced financial liberalization have lower volatilities than the others. Similar to the findings of Hamilton and Lin (1996), Errunza and Hogan (1998) conduct a study for the several European Stock markets of UK, Germany, France, Netherlands, Switzerland, Belgium, and the US for the period 1959 to 1993 and they reveal that stock market volatility tends to increase in recession periods. Patro et al. (2002) study the impact of macroeconomic and financial variables on predictability of sixteen OECD countries' volatilities. They analyze data with a panel approach for the period of 1980 to 1997 and conclude that imports, exports, inflation, market capitalization, dividend yields, and price-to-book ratios have a significant impact on a country's exposure to world market risk. Davis and Kutan (2003) examine the issue in an international setting using GARCH family model on the monthly post World War II data from 13 developed and developing countries. The findings of their study, similar to Schwert's (1983), indicate mixed results, particularly they conclude that the linkage between volatilities of inflation along with output growth and stock market volatility is not perfect. Ahn and Lee (2006) conduct a study using Bivariate GARCH model for five countries, namely USA, Italy, Japan, Canada, and UK to investigate that relationship between stock index returns and real output growth. Their results reveal that interaction between those two variables are found robust at the second order, indicating a bidirectional relationship between volatility in the stock market and volatility in the output sector. Diebold and Yılmaz (2007) evidence a clear link between stock market volatilities and macroeconomic fundamentals covering approximately forty countries. Abugri (2008) applies Vector Autoregressive (VAR) modeling to investigate the relationship between stock market returns volatility and exchange rates, interest rates, industrial production and money supply for four Latin American economies. He concludes that macroeconomic variables of Argentina, Brazil, Chile, and Mexico have a significant impact on stock market returns.

Liljeblom and Stenius (1997) conduct a study on the relationship between stock market volatility and macroeconomic volatility for Finland by using GARCH family models and they find a significant relationship between them however, the explanatory power of macroeconomic variables is found weak. Kearney and Daly (1998) for Australian economy, signify that volatility of macroeconomic variables namely, inflation and interest rates are particularly important in explaining stock market volatility. Döpke et al. (2008) for Germany use data spanning from 1994 to 2005 and suggest that real-time macroeconomic fundamentals can be used to forecast stock market volatility.

Using GARCH models Saryal (2007) conducts a study for Turkish and Canadian markets to examine the impact of inflation on the stock market volatility. Her findings denote that Canadian rate of inflation is an important variable for predicting Canadian stock market volatility, whereas inflation rate does not have a significant effect on the volatility of Turkish stock market. The study of Basci and Ceylan (2005) for Turkey examines the impact of expected inflation and output growth on stock market volatility using data for the period from 2001 to 2004. Similar to the results of Ceylan and Basci (2004), they evidence that inflation expectation and output growth have a significant negative impact on the mean return of ISE-100; in addition to that there is a close linkage between ISE financial index and the expected inflation. Solakoglu et al. (2009) investigate the importance of macroeconomic fundamentals for the Turkish stock market. They use different volatility measures on several macroeconomic variables using monthly data. They evidence that those macroeconomic factors including a variable that accounts for the impact of foreign investor behaviors on volatility explain a significant amount of the variability in stock index returns.

1.3.2. Derivatives Market

In his seminal paper, Ross (1976) discusses that the volatility of prices is directly related to the rate of flow of information to the market and efficiency of incomplete capital markets advances by trading derivative securities which provide various investment opportunities to the decision makers in the market. Derivative securities may lead to increase or decrease in volatility of cash market depending on the information reach to the financial markets (Ross, 1989). Santoni (1987) and Brown-Hruska and Kuserk (1995) report the relationship between futures trading volume and spot market volatility. These studies reveal that there is a negative correlation between the volatility of S&P500 index and futures trading volume of S&P500. Edwards (1988) investigates the relationship between stock market volatility and the introduction of futures trading using the day-to-day price volatility of the stock market between the years beginning from 1972 to May 1987. He uses the variance of close-to-close percentage daily price changes as a proxy for volatility and states that the volatility of S&P 500 is greater than that before the beginning of futures trading; so there is not enough evidence that futures trading have a long-run destabilizing effect on stock market. He also notes that futures trading induce the short run volatility rather than long term volatility. Conrad (1989), Bansal et al. (1989), and Skinner (1989) examine the effect of introduction of options trading in Chicago Board of Options Exchange (CBOE) on the cash market volatilities. They all find that beginning of options trading stabilizes the underlying market. One of the most influential papers in this issue is conducted by Bessembinder and Seguin (1992) who investigate the dynamic relationship between stock market volatility and futures trading volume and open interest in the US market. Using ARIMA model they state that open interest and derivatives trading, which improve both the liquidity and depth of underlying market, reduce the volatility of the US spot market. The most recent paper of Dawson (2009) examines whether initiation of derivatives trading on Volatility Index (VIX) affect the volatility of S&P500 index. He signifies that volatility derivatives trading activities decreases both the volatility of underlying market and the effect of sudden volatility shifts.

Holmes (1996) conducts an analysis on the relationship between futures trading activities and stock market volatility in the UK. Using GARCH model, he evidenced that the futures trading has a beneficial impact on cash market volatility. Gulen and Mayhew (2000) conduct a study using GARCH family models over a large cross section of twenty-five countries to examine whether cash market volatility after the introduction of derivatives securities trading is related to market variables, namely futures market volume and open interest. Their empirical findings indicate that futures trading activity reduces the conditional volatility in all countries except Japan, and the US. Stewart (2000) examined the affects of introduction of derivatives on the underlying market. His overall results are consistent with the literature and advocate that the speculative trading and derivative markets stabilize the underlying market. In addition, he states that derivative trading provides more liquidity and efficiency. Staikouras (2006) investigates the variability of the UK short term interest rates with the introduction of futures trading in 1982 by including twenty-five years of data. His analysis using conditional variance modeling suggests that the onset of futures trading activities decreases the volatility of short term interest rates.

Studies mostly based on GARCH family models such as Bologna and Cavallo (2002) for Italian capital Market, Pilar and Rafael (2002) for Spanish stock and derivatives markets, Darrant et al. (2002) for U.S. capital market through the time period between November 1987 to November 1997, Pilar and Rafael (2002) for the Spanish capital market covering the time period from October 1990 to December 1994, and finally Drimbetas et al. (2007) for Australian stock market evidence that the inception of futures trading activities reduces the underlying market volatility and enhances the market efficiency through the high rate of flow of information. Using high frequency data Illueca and Lafuente (2007) investigate the impacts of the inception of the mini-futures contract in the Spanish stock index futures market. They conclude that mini futures trading activity stabilizes the spot prices and improves the efficiency in derivative market. For Greek capital market, Alexakis (2007) using GJR-GARCH model concludes that futures trading activity has a stabilizing effect in the underlying market, and it decreases the volatility asymmetries. Karathanassis and Sogiakas (2007) conduct a study on the UK, Spanish, and Greek capital markets using regime switching type of ARCH model to research spillover effects on the spot markets due to the inception of futures trading. Their empirical results exert that derivatives trading stabilize the underlying market either in the long-term or in the short-term. Bohl et al. (2010) apply the Markov Switching GARCH methodology of Gray (1996) in Polish market.

Srinivasan and Bhat (2008) investigate the relationship between futures trading and the spot market volatility of selected twenty-one commercial banking stocks of India by using EGARCH model for the period spanning from January 1^{st}, 1996 through May 29^{th}, 2008. Their empirical findings suggest that inception of the futures market stabilizes the volatility of underlying market. Singh and Bhatia (2006), Vipul (2006), Rao and Tripathy (2009), and Debasish (2009) reach the similar results; however those researchers do not have a consensus on the efficiency of the Indian capital market.

In contrast to the aforementioned studies, there are some papers which indicate negative relationship between initiation of derivatives trading and cash market volatility, these studies argue that the introduction of futures or options trading destabilizes the underlying market and increases the cash market volatility. Harris (1989) advocates that the main reason for the higher volatility in cash market due to the futures market trading activities might be the speculative activity. As cited by Harris (1989), French and Roll (1986) report that stock variance to be strongly related to trading session hour shows the possible evidence of speculation that results in increase in stock market volatility.

In one of the early studies by Figlewski (1981) investigates the relationship between futures trading volume and cash market volatility. He reveals that futures trading activities in Government National Mortgage Association (GNMA) have destabilization effects on the cash market volatility. Stein (1987, 1989) finds that leverage effect of derivatives markets might be the main reason for the destabilization effects and imbalances of stock prices. Harris (1989) finds no significant difference between the magnitudes of volatility before and after the initiation of derivative trading. He conducts an analysis on the U.S. stock market to determine whether the volatilities of stock prices indexed in the S&P 500 have changed relative to those which are not indexed in the S&P 500. Cross-sectional analysis of covariance regression model is applied to estimate the mean difference in volatilities for S&P 500 stocks and a comparable set of non-S&P 500 stocks. Differences are estimated for every year between 1975 and 1987 over both short and longer horizons. Harris (1989) concludes that after the introduction of derivatives trading in year 1983 volatilities increased with respect to volatilities of control sample representing the pre-derivatives trading period. He applies a variance regression model to investigate the objective. Stoll and Whaley (1987, 1991) report that volatilities of both S&P 100 and S&P 500 increase much more on the days surrounding futures and options expirations rather than nonexpiration days. They discuss that large increases tend to occur in the last hour of the quarterly expiration days when derivatives securities expire all together. Consistently, other studies for the US capital market such as Damodoran (1990) and Schwert (1990) assert that futures market trading effects the volatilities of the S&P 500 index stock returns negatively, indicating a positive relationship between the initiation of derivatives trading and the increase in volatility. Similarly, Koutmos and Tucker (1996) conduct a study for the period around the 1987 turmoil considering asymmetric effect. They signify that bad news increases volatility more than the good news reaching to the market and find a positive relationship between the futures market trading and the underlying stock market volatility. Lin and Kensinger (2008) confirm the significant increase in both trading volume and return volatility of the stocks added to S&P500 index over the period September 1976 to December 2005, after the inception of the index futures and options contracts.

Using GARCH family of techniques, Antoniou and Holmes (1995) find significant evidence that volatility of FTSE-100 stock index increases due to the inception of the index futures contract in the UK capital market. Butterworth (1998, 2000) studies the futures trading effect on the UK stock market volatility and evidence that the beginning of the futures trading destabilize the cash market and persistence is found higher than post derivatives period. Board et al. (2001) examine the relationship between futures market volume and the cash market volatility using both GARCH and stochastic volatility models. They find significant evidence that futures trading does not lead to destabilization, however, stochastic volatility model suggests that the volatility of underlying market increases. Oliveira et al. (2001) for the Portuguese stock market, Christos Floros et al. (2006) for Greece capital market signify that spot market volatility increases after the introduction of futures trading by using GARCH model.

Following Harris (1989), Chang et al (1999) conduct their study by using control sample methodology on Osaka securities exchange. They conclude that the initiation of the individual share derivatives has destabilization effects on the spot market volatility. Other studies including Asian countries such as Pok et al. (2004) for Malaysia, Ryoo and Smith (2004) for Korea, Rao (2007) for Indian stock market evidence the destabilization impact of derivatives securities trading on cash market volatility. Mallikarjunappa and Afsal (2007) apply GARCH model to analyze the impact of the initiation of derivatives on underlying market volatility. Their findings indicate that derivatives trading activities increase the spot market volatility in India. Wang et al. (2009) examine whether the introduction of Hong Kong Hang Seng Chinese Enterprise Stock Index (H-share Index) result in an increase in the volatility and the volume of the underlying stocks. They conclude that derivative trading has no effect on the liquidity of the stocks in spot market but increases the volatilities of them.

There are a number of studies reporting neutralization results or conflicting effects of the inception of derivatives trading activities on the underlying market volatility. According to Ma and Rao (1988) neutralization results are found because of the different types of investors appear in the market. They state that while hedgers reduce noise in the underlying market, speculative activities might generate noise.

Some studies conducted by Santoni (1987), Aggarwal (1988), Fortune (1989), Becketti and Roberts (1990) and Baldauf and Santoni (1991), and Pericli and Koutomos (1997) by using EGARCH model for the US evidence that the initiation of derivatives trading has no escalating effect on the corresponding underlying market. Moreover, Mayhew and Mihov (2004) reach conflicting results with respect to introduction of derivatives contracts and volatility of cash market by using control sample methodology.

Illueca and Lafuente (2003) investigate the relationship between spot market volatility and trading volume in index futures market by employing a bivariate error correction GARCH model for Spanish Ibex 35 financial index,. They conclude that there is no difference in the volatility of the spot market before and after the introduction of the index futures. Hodgson and Nicholls (1991), Dennis et al. (1999), Dennis and Sim (1999) for Australia report that the futures trading have no significant effect on underlying market activity. McKenzie et al. (2001) using T-GARCH model, state conflicting results on the same issue for Australian capital market. Bacha and Vila (1994) for the Japanese spot market, Kotha and Chiranjit (2003) for Indian capital market, and Spyrou (2005) for Greek spot market reach the similar conclusions.

Lee and Ohk (1992) study the possible effects of inception of stock index futures on the cash market volatility for several countries, namely the US, the UK, Japan, Australia, and Hong Kong and evidence no significant changes in volatility for Australia and Hong Kong. In case of the UK and Japanese stock markets, they conclude that introduction of futures trading increase the cash market volatility. Antoniou et al. (1998) analyze the effect of derivatives trading on six stock markets, namely the US, the UK, Switzerland, Germany, Spain and Japan. They find stabilization effect of derivatives trading on all stock markets except the US. They evidence that the leverage effect becomes lower in the underlying market using GJR-GARCH model. Jochum and Kodres (1998) for Australia, Mexico, Brazil, and Hungary signify no significant impact of futures trading on the underlying market. Applying GARCH modeling Yu (2001) find conflicting results for six major economies. While destabilization effects exist for the US, France, Japan, and Australia, no significant impact is observed for the capital markets, namely the UK and Hong Kong. Chiang and Wang (2002) conduct a study for Taiwan and report conflicting results on two futures indices. They evidence significant effect of TAIEX futures trading on spot market volatility, whereas MSCI futures index has no effect. The most recent study that conducted by Karathanassis and Sogiakas (2010) investigates the issue for the UK, Spain and Greek capital markets by employing regime switching ARCH to model the timing possible spillover effects. Their empirical findings reveal that there exists a stabilization effect; however they state that in some cases short-run destabilization effects are observed.

Literature on the relationship between derivatives securities trading and the underlying market volatility suggest that the effect of futures trading on spot market volatility depends on the country and might change over time. In case of Turkey, Baklaci and Tutek (2006) signify a significant decline in the volatility of Istanbul Stock Exchange (ISE) after the introduction of index futures. Kasman and Kasman (2008) using EGARCH model investigates the impact of the initiation of stock index futures on the cash market volatility for the period spanning from July 2002 to October 2007. Similarly, they observe decrease in the conditional volatility of ISE-30 index during the post index futures trading period.

1.3.3. Program Trading

Effect of program trading on volatility is another important issue which might influence the volatility. Program trading is being done to leap at an arbitrage opportunity in the market. Program trading, especially index arbitrage program, is altering position in the market due to the changes in the market value by trading many securities simultaneously; however, it is evidenced that program trading decreases liquidity and increases intraday volatility in spot market by transmitting excess volatility from derivatives market to the spot market (Harris, Sofiano, and Shapiro, 1994:654). In addition, Harris, Sofiano, and Shapiro (1994) state that correlation between intraday volatility and program trading may be spurious because of bid-ask bounce and non-synchronous trading. Bid-ask bounce is the transition of single stock prices ask from the bid in case of a buy order follows a sell order and vice versa. Put another way, the fluctuation of transaction prices back and forth from the bid side of the market to the ask side as alternating buy and sell orders arrive at the financial market. Nonsynchronous trading refers to a spurious relationship between volatility and program trading since program trade may simultaneously refresh a large number of stale prices so that the index realizes its underlying value; however only realization of earlier volatility is associated with program trading.

Relationship between program trading and volatility is closely related to the interaction between volatility and inception of derivatives market. Many academics who investigate the impact of initiation of derivatives market on cash market volatility note that one of the reasons for destabilization of spot market might arise from the program trading (Duffee, Kupiec, and White, 1990; Harris, 1989a; Kleidon, 1992)

Schwert (1990) examines the effect of program trading on volatility for the period spanning from October 1988 to April 1989. Schwert (1990) signifies that there exists a positive relation between the aggregate market volume triggered by index arbitrage program trading and high frequency stock volatility.

Harris (1989) states that volatility during 1980s increases after the introduction of derivatives market in which futures contracts are involved in program trading. Similarly, Martin and Senchack (1989 and 1991) investigate the impact of inception of derivatives market on cash market volatility. Their findings suggest a significant relationship between spot market volatility and the introduction of derivatives market. Moreover, they advocate that the stocks on the index that they examined are subject to program trading which leads to a higher volatility.

Harris, Sofiano, and Shapiro (1994) conduct a study to investigate the impact of program trading on S&P500 index volatility in the period from 1989 to 1990. Their findings reveal a positive relationship between program trading and intraday price changes arising from the bid-ask bounce and/or non-synchronous trading. In addition, they conclude that a liquidity problem does not exist in short-term due to the program trading.

Using bivariate error correction GARCH model, Hogan, Kroner, and Sultan (1997) conduct a study to investigate the correlation between volatility and program trading for the US capital market. They find significant relationship between non-program trading and market volatility indicating a strong correlation between market volume and volatility.

Contrary to the previous findings on the effect of program trading on volatility, Grossman (1988) suggests no significant relationship between two in the year 1987 spanning from January to October for NYSE. In other words, Grossman's (1988) findings suggest significant positive relationship between non-program trading intensity and volatility. Baldauf and Santoni (1991) examine the same issue by testing existence of ARCH effects in daily stock returns. Their results indicate no significant relationship between program trading and volatility.

Portfolio managers do use program trading to protect their value of portfolios. Hedging strategies like conveying funds to risky assets when prices increase or altering position when prices decrease are closely related to portfolio insurance (Grossman, 1988; Davis, 1987). Donaldson and Uhlig (1993) and Basak (1995 and 2002) evidence a negative relationship between stock market volatility and portfolio insurance activity. Jacklin, Kleidon and Pfleiderer (1992) reach same results; however, they note that the existence of imperfect information might cause big problems in the market.

Hull (1998) states that there might be no effect of portfolio insurance if those kind of hedging strategies have a small proportion of total trades. Pain and Rand (2008) assert that market illiquidity, imperfect information and gap risk[3] are the main factors explaining why portfolio insurance increases the spot market volatility; on the other hand, they reach a conclusion that the portfolio insurance does not have a significant effect on spot market volatility for the late 2007.

1.3.4. Seasonality

A number of studies focus on the effect of anomalies in the asset returns and volatilities due to the periodical movements in the asset returns. Researchers, mainly, investigate Monday/Friday, January, intra-month (the turn-of-the-month), and holiday effects on stock market returns and volatilities (Bildik, 2004) and reveal empirical findings mostly inconsistent with the Efficient Market Hypothesis proposed by Fama (1970).

Seminal studies by Cross (1973), French (1980), Gibbons and Hess (1981), Keim and Stambaugh (1984), Jaffe and Westerfield (1985), Lakonishok and Levi (1982), Rogalski (1984), Lakonishok and Smidt (1988), Flannery and Protopapadakis (1988), Chiang and Tapley (1983), Johnston et. al. (1991), Cornell (1985), Dyl and Maberly (1986), Miller (1988), Phillips-Patrick and Schneeweis (1988), Yadav and Pope (1992) investigate the day-of-the-week effect. Particularly, first three studies examine the issue for the US stock market and evidence that Monday returns is the lowest while Friday returns is the highest. Lakonishok and

[3] "Gap risk" can be described as the risk that the value of a portfolio declines dramatically even if there exist no trading.

Smidt (1988) for a very long time period use high frequency data and evidence negative Monday returns. Aggarwal and Rivoli (1989) investigate the existence of the Monday effect in the US stock market along with four Asian stock markets namely, Hong Kong, Singapore, Malaysia, and the Philippines. Their results show that Monday effect in the US result in a negative Tuesday effect in four Asian markets. Demirer and Karan (2002) and Karan and Uygur (2001) examine day-of-week effect for Turkey and evidence significant Friday effect. Bildik (2004) and Oğuzsoy and Güven (2003) signifies that returns are found higher on Friday and lower in the first part of the week. Taş et al. (2009) examine the day-of-week effect for both Istanbul Stock Exchange and US$/TRY exchange rate. They find negative returns for Monday and positive returns on Tuesday and Thursday.

Roll (1982) signifies that there exists an excess return distribution on January due to the tax loss sellings at the end of the tax year. This phenomenon was, however, first suggested by Wachtel (1942). This theory suggests that stock prices go down due to the fact that investors sell their stocks at the end of the tax year to realize capital losses against their taxable income and then increase in the beginning of the year. Keim (1983) and Roll (1983) also investigate January effect in stock returns. Overall, French and Roll (1986), Rozeff and Kinney (1976), Keim (1982) along with the others state that stock market returns are time varying and there exist a January effect which is that returns in January are relatively larger than the return in the remaining eleven months. Gültekin and Gültekin (1983) conduct a study on major equity markets and conclude that there exists a January effect for all equity markets except the UK market. Similarly, Kato and Schallheim (1985) for Japanese stock market record the anomalies in January and June. In their seminal paper Glosten et al. (1993) also report significant October and January effects in volatility. For Turkish stock market Karan and Uygur (2004) and Bildik (2004) find significant January effect, whereas Taş et al. (2009) conclude August and February anomalies for Istanbul Stock exchange.

Ariel (1987) propounds the turn-of-the-month effects and states that positive rates of returns are only evidenced in the beginning of the month, the rate of return in the first half of the month is found as slightly higher than the remaining part of the month. Jaffe and Westerfield (1989) for Australia, Lakonishok and Smidt (1988) and Pettengill and Jordan (1988) for the US, Perttunen and Ziemba (1994) for various countries, and Arsad and Coutts (1997) for the UK evidence significant turn-of-the-month effects.

Finally, pre-holiday average returns are found as larger than post-holiday returns by Ariel (1987, 1990) and Lakonishok and Smidt (1988). On the other hand, Bildik (2004) states that the results of studies on various countries are mixed. Nevertheless, Agrawal and Tandon (1994) find that pre-Christmas holiday returns are large and significantly positive in the eleven of the eighteen countries.

1.3.5. News Releases

Finance literature also focuses on the impact of news releases and announcements on financial market volatility. Kalotychou and Staikouras (2009) document four competing theories about the relation between information, volume, and stock market volatility as follows:

i. Mixture of distribution hypothesis by Clark (1973), and Harris (1987)
ii. Sequential information hypothesis by Copeland (1976), Jennings et al. (1981), Smirlock and Starks (1988)
iii. Dispersion of beliefs approach by Harris and Raviv (1993)
iv. The information trading volume model by Blume et al. (1994).

Clark (1973) and Harris (1987) put forward mixture of distributions hypothesis which suggests positive and simultaneous correlation between volume and volatility. Sequential information hypothesis by Copeland (1976), Jennings et al. (1981) postulates that relation between stock market volatility and volume (due to news releases and information flow) is sequential indicating that it is a lead-lag relationship. Dispersion of beliefs approach states that if dispersion of beliefs is greater among investors then volatility/volume relative to equilibrium values will be much higher. Put another way, asymmetric information in financial markets causes greater volatility (Shalen, 1993). The information trading volume approach by Blume et al. (1994) posits that trading volume is the key variable for decision makers in the market where information quality matters.

Early empirical literature focuses on the impact of news announcements on returns for micro level. Ball and Brown (1968) Beaver (1969) Fama et al. (1969), Patell and Wolfson (1984) investigate the effect of earnings announcements, dividend payments, and stock splits as cited in Entorf and Steiner (2006). Recently, Darrat et al. (2007) report that public news has a destabilization effect on the volatility of common stocks traded in New York Stock Exchange. They argue that trading volume is significantly higher when there is no information releases. However, we will report effect of macroeconomic news releases on stock market volatility from now on.

Using models that account asymmetry effect, Chen et al. (2003) investigate the impact of the US news on six developed countries, namely Canada, France, Germany, Japan, Switzerland, and the UK. Their findings reveal the existence of asymmetric effect indicating the fact that the negative US news increases the volatility of those financial markets more than the positive news releases.

Nikkinen and Salström (2004) conduct a study on the effect of both domestic and the US related news on the volatility of German and Finnish stock markets. There exists a significant impact of news announcements about the US inflation levels on those markets.

Harju and Hussain (2006) examine the immediate effect of the US macroeconomic announcements on European stock market volatilities. Their findings suggest a significant relationship between the volatility of the European stock markets and news releases which is consistent with the findings of Wongswan (2006).

In their comprehensive study, Nikkinen et al. (2006) examine the impact of the US macroeconomic news announcements on a number of stock markets including G7 countries, the European Countries other than G7 countries, emerging Asian and Latin American countries, and the other countries from transition economies for the period from July 1995 to March 2002. They test the effect of news announcements in a pooled model using conditional variances produced by univariate GARCH models. Their findings suggest that there exists a close relationship between developed financial markets and the US news announcements; however, the US news do not have a significant impact on Latin America and transition economies including Russia, Slovakia.

Hanousek et al. (2008) examine the effect of the US and the euro area macroeconomic news on the intraday volatility of the financial markets, including Czech Republic, Hungary, and Poland during the period between 2003 and 2006. Their findings suggest that local news announcements do not have a significant impact on those financial markets; however, they reveal that Prague, Budapest, and Warsaw stock markets are mainly affected by news announcements from the US and the European Union (EU). Prague stock market is found as affected by the US news; in addition to that there exists an impact of the EU news on Hungarian and Polish stock markets.

Using GARCH model, Büttner et al. (2009) investigate the impact of the EU and the US macroeconomic news on financial markets of Czech Republic, Hungary, and Poland for the period from 1999 to 2006. They reached several conclusions that the foreign macroeconomic news releases have a significant impact on those financial markets and the Euro area related news has gained importance after the process of the European integration. Particularly, they suggest that there are country-specific characteristics such as Czech financial market is more vulnerable to the foreign news due to the Copenhagen Summit than the other countries.

Hayo and Kutan (2005) conduct a study to investigate the response of financial market volatility in six emerging markets, namely Argentina, Brazil, Indonesia, Pakistan, Russia, and South Korea to a set of IMF related news released during the Asian, Russian, and Brazilian crisis of July 1997 to December 1999. They evidence that good IMF related news increases the daily stock returns and vice versa. However, their empirical findings do not suggest a significant impact of a set of IMF events on financial market volatility indicating that both positive and negative returns arising from IMF news are neutralized over time.

Using econometric models following GARCH process, Evrensel and Kutan (2007) conduct a study to examine the impact of IMF news during Asian crisis on the financial sector returns in three Asian countries, namely Indonesia, Korea, and Thailand. Their study measures the effect of both program negotiations and approval on stock returns. IMF related news of program negotiations and approval is found as having positive effect on financial sector returns for Indonesia and Korea. However, for Thailand, only program approval has a significant positive effect on stock returns.

1.3.6. Insider Trading

There are two contrast opinions about the relationship between insider trading and stock market volatility (Du and Wei, 2004: 917). The former states that insider trading decreases the stock market volatility in the long-run through increasing signal-to-noise ratio (see Manne, 1966; Leland, 1992). On the latter suggests that insider trading destabilizes stock market and reduces economic efficiency in the long-run (see Brudney, 1979; Easterbrook, 1981). Insiders' incentive to invest in risky projects or to manipulate the timing and nature of the information release may lead more price volatility than otherwise.

Acharya and Johnson (2005) state that one of the main reasons for the existence of insider trading and asymmetric information in financial markets may be due to the close relationship between financial institutions and investors. In addition to that market players, recently, can easily access price-sensitive information such as revenue projections and divestiture plans.

For the micro level, Meulbroek (1992) conduct a study on the effect of illegal insider trading on stock prices for the period spanning from 1980 to 1989. Her findings reveal that there exists a close relationship between insider trading and rapid price movements and quick price discovery. Cornell and Sirri (1992) investigate the relationship between insider trading and price movements in case of acquisition of Campbell-Taggart by Anheuser-Busch in 1982. They conclude that insider trading has an important impact on the stock price volatility.

Chakravarty and McConnell (1997) conduct a study for the case of the acquisition of Carnation Company by Nestle S.A. in 1984. Similarly, they conclude that insider trading eases price discovery.

In their study, Du and Wei (2004) examine the impact of insider trading on stock market volatility for a number of countries covering the period from 1984 to 1998. Their findings reveal that insider trading results in higher market volatility. Moreover, they signify that insider trading has a significant and more important effect on stock market volatility rather than fundamental factors.

1.3.7. Spillover Effects

As financial integration accelerates all over the world, interdependence between stock markets is become a popular area for both academics and practitioners. Researchers investigate both long-run and short-run relationship between stock markets along with volatility transmission across them (see Hamao et al. 1990; King and Wadhwani, 1990). It is important to assess relationship between the stock markets for diversifying risk, allocating assets, and forecasting risk and return since investors or decision makers take positions in different financial markets across the world. Moreover, if one knows that two or more stock markets are interdependent and/or there exists volatility spillover between them, policy and decision makers will realize that the financial turmoil breaks out in one of the related countries, would have a significant impact on the other ones since the volatility spillover is the transmission of risk across interrelated financial markets. Investigating volatility spillover has gained importance in recent years in which we have experienced several financial crises especially global financial crisis occurred in the late of 2007. Thus, academics and practitioners examine the issue in terms of contagion effects while capitalism generates economic and financial crisis regularly.

Using multivariate GARCH-in-Mean (GARCH-M) model, Theodossiou and Lee (1993) conduct a study to examine the degree of interdependence of stock markets of five major economies, namely the US, the UK, Canada and Germany. They observe significant spillovers from the US to the UK, Canada, and Germany, and from the UK to Canada and also from Germany to Japan. They report existence of strong time-varying conditional volatility in the return series of all stock markets.

Lin, Engle, and Ito (1994) examine the spillover effects in return and volatility between the US and Japanese stock markets. Their results are not consistent with the previous literature and they find significant evidence for lagged returns spillovers from New York daytime to Tokyo daytime and vice versa. Bae and Karolyi (1994) investigate the volatility spillover effects between the S&P 500 stock index and Nikkei stock average over the period spanning from 1988 to 1992. They conduct GARCH framework considering asymmetric effects of bad news and good news to volatility. They suggest a significant evidence of volatility transmission from either New York or Tokyo to the other market if the asymmetry effect is ignored.

Using ARCH type of model that considers leverage effect[4], Susmel and Engle (1994) conduct a study to investigate the timing of mean and volatility spillovers between the US stock market and the UK stock market. They find a little support for the volatility spillovers between New York and London stock exchanges.

Booth et al. (1997) conduct a study on derivatives market of Japan. They investigate the volatility transmission between Nikkei stock index futures contracts which are traded on international exchanges applying econometric techniques based on cointegration theory including variance decomposition, impulse response functions, Granger causality and vector error correction model. They conclude short-run relationship between those contracts and state that stock markets in the last trading order within 24 hours granger-cause the other ones. Using two-step GARCH process, Pan and Hsueh (1998) analyze the futures prices on the S&P500 and Nikkei 225 stock indices. Their findings reveal that there exists a unidirectional return and volatility spillovers from the US to Japan. Moreover, they find that the impact of the US stock market on Japanese stock market is four times larger than that of Japanese on the U.S. market.

Kanas (1998) conducts a study to investigate the issue of volatility spillovers between among three major European Stock markets namely, the UK, Germany, and France. Applying exponential GARCH model to consider the effect of innovations on conditional variance, Kanas (1998) examines the data covering the period from 1984 to 1993 and finds spillovers between the U.K. and France, and between France and Germany, and unidirectional spillovers from the U.K. to Germany. In addition

[4] "Leverage effect" refers to that negative shocks will have a bigger impact on future volatility than positive shocks of the same magnitude.

Kanas (1998) also analyzes the period before and after 1987 crash and concludes that there exists more spillovers during the post-crash period indicating that those three European markets has become more interdependent after the 1987 financial turmoil experienced in the US.

Darvas and Szapary (2000) examine spillover effects from Russia to five small open economies, namely Czech Republic, Greece, Hungary, Israel and Poland during the period of 1997-1999 global financial crises. They find significant evidence of volatility transmission from Russian crisis to other markets. Scheicher (2001) conduct a study to examine the regional and global integration of stock markets of three economies, namely Hungary, Poland and Czech Republic using a VAR-GARCH model. They evidence statistically significant spillovers of shocks both in returns and volatilities.

Baele (2005) conducts a comprehensive study on the time-varying nature of volatility spillovers from aggregate European and the US market to a number of European stock markets. Using regime-switching model, he finds that regime switches through time is both statistically and economically significant. The results of the study reveals that the volatility transmission increases after the period from mid-1980s to first half of 1990 due to the accelerating financial integration. Moreover, Baele (2004) suggest that there exist a contagion effect from the US stock market to the others in the high volatile time periods.

Using intraday data Egert and Kocenda (2007) conduct a study to investigate possible spillover effects for both stock returns and stock volatilities among stock markets in Hungary, Czech Republic, and Poland covering the period from June 2003 to February 2005. Their study examines the interdependence between stock markets of Budapest, Prague and Warsaw and their interactions with the largest three stock markets in Europe, namely Frankfurt, London and Paris. Since their research period is not including any major financial crises, they do not seach for contagion effects among those stock markets.

Bae et al. (2008) examine the volatility spillover between the index and non-index stocks for the Korean securities market after the initiation of index derivatives trading. They evidence significant relationship between the level of market deregulation and the degree of volatility transmission among those stocks. Their results suggest a significant return volatility transmission from non-index to index stocks during the deregulation period. On the other hand, they suggest that the volatility spills over from index stocks to non-index stocks for the post-deregulation period.

Recently, Mulyadi (2009) conducts a study to investigate volatility spillover among Indonesia, the USA, and Japan using GARCH model covering the period from January 2004 to December 2008. His findings reveal that volatility spills over from the USA to Indonesia indicating a unidirectional relationship between these two markets. Moreover, Mulyadi (2009) also evidences that there is a bidirectional volatility spillover between the stock markets of Indonesia and Japan. Sinha and Sinha (2010) investigate the issue for the US, the Japan, and the Indian capital markets. Using GARCH they investigate whether volatility spillovers among those markets are contemporaneous or dynamic. Their results suggest that contemporary conditional volatility of the Japanese capital market has a significant, unidirectional impact on Indian capital market in the pre-recession period. However, they find no significant contemporaneous spillover from the US and Japanese to Indian capital markets. Moreover, their study indicates an evidence of dynamic volatility spillover from Indian to Japanese market and also dynamic volatility spillover from the US to Indian Market.

1.4. The Stylized Facts of Financial Market Volatility

Enders (2010) classifies stylized facts of economic time series. According to him, most of the series, especially financial price series, have a clear trend indicating the fact that they have unit root (Enders, 2010: 121). In other words, they are integrated[5]. Integration order of an economic time series can be detected via both conventional unit root tests which do not consider structural breaks and more recent ones which allow structural breaks in the data. Since the property of integration

[5] Here, we do not prefer to use the term "non-stationary" because Clive W. J. Granger (2003) in his Nobel Lecture notes states that "Many series in economics, particularly in finance and macroeconomics, do not have this property [stationarity] and can be called "integrated" or, sometimes incorrectly, "non-stationary.""

makes the data unsuitable for the analysis, it is not a desirable thing for a researcher who applies standard statistical procedures (see Granger, 2003). That's why researchers are interested in stationary time series for example financial return series which is the relative price between the purchase and sale points (see Engle, 2004)

It is mostly observed that shocks to a series can display high degree of persistence (Enders, 2010: 122). Volatility persistence can be defined as significant autocorrelation over high lags. If the degree of persistence is calculated very high, then one can conclude that it takes longer time for the forecasts to converge the level of unconditional variance, for instance 1-year (Alexander, 2008: 142).

Volatility clustering and mean reversion are the most important characteristics of the financial market volatility. These observed facts led Engle (1982) to develop Autoregressive Conditional Heteroskedasticity (ARCH) model which embodies these two characteristics very well. These two facts also reveal that volatility of many series is time-varying. As Mandelbrot (1963) puts forward volatility clustering refers to a situation that "large changes in asset returns (of either sign) tend to be followed by large changes and small changes tend to be followed by small changes". When we have high volatility, it comes in bunches; that is to say when we have high volatility it stays high for a while and then declines. And, when we have low volatility it stays typically low for a while (Engle, 2009). Thus, volatility clustering is very important in risk measurement, investment choices, derivatives pricing (Alexander, 2008: 131). Moreover, mean reversion and volatility clustering features provide some predictability in volatility, particularly in financial market volatility.

When market goes down it is often a high volatility period. This indicates the existence of asymmetry effect. Asymmetry effect is first defined by Mandelbrot (1963), and Fama (1965), and then modeled via GARCH process by Nelson (1991) and Glosten et al. (1993) who hypothesize that negative returns may increase conditional volatility much more than positive returns.

Finally, volatility shifts are mainly observed in economic time series. Volatility shifts are evidenced mostly in the periods of economic crisis, and/or financial turmoil. Volatility shifts exist because of aforementioned economic events that are also known as structural breaks. It is a common feature and volatility modeling should be done by considering those volatility shifts due to possible structural breaks. Inclan and Tiao (1994) develop an iterative cumulative sum of squares (ICSS) test detecting possible shifts in variance of returns (volatility) under null hypothesis of homoskedasticity. Sanso et al. (2004) overcome some shortcomings of ICSS and modified their methodology to detect volatility shifts in time series data. They all evidence of existence of volatility shifts in major financial markets including the US, and several European stock markets and emphasize the importance of considering detected volatility shifts in modeling volatility.

CHAPTER II

LITERATURE REVIEW ON VOLATILITY MODELS

This chapter presents theoretical background of several volatility models. Since, our main focus is on the deterministic volatility models, we present Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982) and its numerous extensions in more detail. And then, we present other volatility models including historical, implied and stochastic volatility models briefly. In addition, this chapter summarizes the empirical studies on ARCH models with structural breaks and forecasting volatility using ARCH models.

2.1. Theoretical Background of the Volatility Models

2.1.1. Deterministic Volatility Models (ARCH)

Friedman (1977) hypothesizes that unpredictability of inflation is the primary cause of business cycles. He also states that it is the uncertainty of futures costs and prices that might decrease the level of investments and lead to a recession. Engle (1982) deals with this issue and proposes Autoregressive Conditional Heteroskedasticity (ARCH) model. Engle (1982) measures the time-varying uncertainty of UK's inflation by using his ARCH model. However, ARCH class of models are widely used in finance, since trade-off between risk and return is best modeled by using high-frequency data which is readily available to form accurate volatility forecasts.

ARCH model proposed by Engle (1982) is described as follows:

$$y_t \mid F_{t-1} \sim N\left(x_t^{'}\beta, \sigma_t^2\right) \qquad (2.1)$$

where F_{t-1} stands for information set available at time t-1, and the conditional variance,

$$\sigma_t^2 = f\left(\varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-q}; \theta\right),\ \varepsilon_t \equiv y_t - x_t^{'}\beta \qquad (2.2)$$

is an explicit function of the q lagged innovations, ε_t. Conditional variance equation can also be written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2.3}$$

which is also known as ARCH(q) model and it is a convenient parameterization for capturing volatility clustering characteristics along with mean-reverting (Engle, 1982). Maximum Likelihood (ML) procedure is used in estimation of ARCH class of conditional volatility models. ARCH models uses averages of past squared forecast errors, a type of weighted variance and ML procedure is simply a systematic approach to the estimation of optimal weights so that those weights gives more influence to recent information and less to the distant past (Engle, 2004). ML procedure helps to maximize the following log-likelihood function for the ARCH model:

$$LogL\left(y_T, y_{t-1}, ..., y_1; \beta, \theta\right) = -\frac{T}{2}\log\left(2\pi\right) - \frac{1}{2}\sum_{t=1}^{T}\left[\log\left(\sigma_t^2\right) + \left(y_t - x_t^{'}\beta\right)\sigma_t^{-2}\right]. \tag{2.4}$$

McCulloch (1985) develops Adaptive Conditional Heteroskedasticity (ACH) model which allows scale parameter, c_t, in a sequence of Stable Paretian distributions to change over time (Bollerslev, 2010). McCulloch (1985) describes the ACH model by using exponentially weighted moving average form[6]:

$$c_t = \alpha\left|\varepsilon_{t-1}\right| + \left(1-\alpha\right)c_{t-1} \tag{2.5}$$

Bollerslev (1986) proposes the generalized form of ARCH model of Engle (1982) by including p lags of conditional variance in the variance equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-i}^2 \tag{2.6}$$

There exist two constraints on the parameters of variance equation. Non-negativity and stability constraints on parameters of variance equation can be written as follows: $\omega > 0, \alpha \geq 0, \beta \geq 0 \; and \; \alpha + \beta \leq 1.$ GARCH(p,q) model of Bollerslev (1986) usually outperforms the ARCH(q) in most financial applications (Poon and Granger, 2003).

[6] Following McCulloch (1985), Liu and Brorsen (1995) developed the Stable GARCH (SGARCH), as a special case.

Integrated GARCH (IGARCH) model of Engle and Bollerslev (1986) imposes an exact unit root in the corresponding autoregressive polynomial, $\left(1-\alpha\left(L\right)-\beta\left(L\right)\right)=\varphi\left(L\right)\left(1-L\right)$. so that IGARCH can be used in modeling highly persistent volatility. High persistence in volatility refers to the situation that a shock to a system is permanent. IGARCH model is based on following notation:

$$\varphi\left(L\right)\left(1-L\right)\varepsilon_t^2=\omega+\left(1-\beta\left(L\right)\right)\nu_t \tag{2.7}$$

Engle and Bollerslev (1986) states that their model is theoretically important for asset pricing models and it is empirically relevant since high persistence in volatility can easily be observed.

Geweke (1986), Pantula (1986), and Milhoj (1987) develop the logarithmic GARCH (log-GARCH) model independently. It is mainly a logarithmic form of GARCH model of Bollerslev (1986). In this model, the logarithmic conditional variance is parameterized as a function of the lagged logarithmic variances, σ_{t-i}^2, and the lagged logarithmic squared innovations, ε_{t-i}^2:

$$\log\left(\sigma_t^2\right)=\omega+\sum_{i=1}^{q}\alpha_i\log\left(\varepsilon_{t-i}^2\right)+\sum_{j=1}^{p}\beta_i\log\left(\sigma_{t-i}^2\right) \tag{2.8}$$

Motivation behind the log-GARCH model is actually to relax the nonnegativity constraint on the parameters of the variance equation by adopting natural logarithm of σ_t^2.

Taylor-Schwert GARCH (TS-GARCH) is suggested by both Taylor (1986) and Schwert (1989). TS-GARCH(p,q) model simply models conditional standard deviation as the lagged conditional standard deviation and a distributed lag of the absolute innovations. This model is also known as Absolute Value GARCH, and it is a special case of general Power GARCH or Nonlinear GARCH model (Bollerslev, 2010). TS-GARCH model can be formulated as follows:

$$\sigma_t=\omega+\sum_{i=1}^{q}\alpha_i\left|\varepsilon_{t-i}\right|+\sum_{j=1}^{p}\beta_i\sigma_{t-i} \tag{2.9}$$

This model is used to lower the impact of large observations relative to the standard GARCH(p,q) of Bollerslev (1986) by adopting an absolute device into the variance equation.

ARCH-in-Mean (ARCH-M) model is developed by of Engle, Lilien and Robins (1987) to model the trade-off between risk and return by adding conditional variance into the mean equation of ARCH(q) model of Engle (1982) so that the conditional mean depends directly on the conditional variance. Engle et al. (1987) use this model to estimate time-varying risk premium in the term structure. ARCH-M model may be written as follows:

$$y_t = \mu + \delta\sigma_t^2$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \varepsilon_{t-i}^2 \tag{2.10}$$

where δ can be interpreted as risk premium. If δ is estimated greater than zero, then one can conclude that increased risk through increasing in the conditional variance result in a rise in the mean return (Brooks, 2008: 410).

Since it is observed that financial data typically have skewed and leptokurtic conditional distributions, estimating GARCH model under the assumption that returns errors are conditionally distributed as Gaussian is not realistic at all (Alexander, 2008:157). Thus, Bollerslev (1987) suggests estimating GARCH model under the assumption that the errors follow standardized Student-t distribution. Motivation behind that model is to capture the fat-tail distribution of standardized residuals. He adjusts the log-likelihood function for Student-t distribution as follows:

$$LogL(\theta) = \sum_{t=1}^{T} \log\left(\Gamma\left(\frac{\nu+1}{2}\right)\Gamma\left(\frac{\nu}{2}\right)^{-1} \left((\nu-2)\sigma_t^2\right)^{-1/2} \left(1+(\nu-2)^{-1}\sigma_t^{-2}\varepsilon_t^2\right)^{-(\nu+1)/2} \right), \tag{2.11}$$

where ν indicates to shape parameter that is estimated along with the parameters of variance equation. Shape parameter is called degrees of freedom and if ν is not equal to zero, we conclude that the conditional distribution is non-normal. Moreover, if shape parameter, ν is estimated greater than two, than conditional distribution is simply fat-tailed. (See Lambert and Laurent (2001) for more details on skewed Student t distribution.)

In addition to non-normal distributions, such as Student-t of Bollerslev (1987), and Generalized Error Distribution[7] (GED) suggested by Nelson (1991), Bollerslev and Wooldridge (1992) develop Quasi Maximum Likelihood Estimation (QMLE) method. They postulate that if the first two conditional moments of the model (e.g. standard GARCH) are correctly specified[8], then parameter estimates will remain consistent and asymptotically normally distributed. Moreover, Engle and Gonzalez-Rivera (1991) estimate the distribution of standardized innovations through nonparametric density to relax the assumption of normal distribution.

Modified ARCH model (MARCH) of Friedman, Laibson and Minsky (1989) is based on following formulation:

$$\sigma_t^2 = \omega + \alpha F\left(\varepsilon_{t-1}^2\right) + \beta\sigma_{t-1}^2, \tag{2.12}$$

where *F*(.) is a positive valued function. Friedman et al. (1989) parameterizes the conditional variance as a nonlinear function of the lagged squared innovations and they use the following function:

$$F\left(x\right) = \sin\left(\theta x\right)\cdot I\left(\theta x < \pi / 2\right) + 1\cdot I\left(\theta x \geq \pi / 2\right) \tag{2.13}$$

Asymmetric GARCH (AGARCH) model is developed by Engle (1990) to take into account the asymmetric effects of negative and positive innovations. AGARCH model is based on the idea that negative shocks will result in larger increases in future volatility than positive shocks of the same absolute magnitude. The model may be written as:

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[7] GED is sometimes referred as an exponential power distribution (Bollerslev, 2010).

[8] That is to say, $E_{t-1}\left(\varepsilon_t\right) = 0 \;\; and \;\; E_{t-1}\left(\varepsilon_t^2\right) = \sigma_t^2.$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1} + \beta\sigma_{t-1}^2 \tag{2.14}$$

where γ parameter is estimated to measure the asymmetric effect.

Standard Deviation ARCH (Std-dev ARCH) model is introduced by Schwert (1990). Formulation of that model is simply based on the following notation:

$$\sigma_t^2 = \left(\omega + \sum_{i=1}^{q} \alpha_i \left|\varepsilon_{t-i}\right|\right)^2 \tag{2.15}$$

Schwert (1990) extends his simple model to consider some characteristics of financial market volatility e.g. high persistence, volatility clustering, and asymmetry effects. Nonlinear structure of that model, however, makes the construction of forecasts from the model difficult.

Exponential GARCH (EGARCH) model of Nelson (1991) is formulated to model asymmetries in the relationship between return and volatility. EGARCH model is one of the most important modifications of GARCH process. Nelson (1991) simply adopts "natural device" to ensure that conditional variance is nonnegative. EGARCH(1,1) model is based on following equation:

$$\log\left(\sigma_t^2\right) = \omega + \alpha\left(\left|z_{t-1}\right| - E\left(\left|z_{t-1}\right|\right)\right) + \gamma z_{t-1} + \beta\log\left(\sigma_{t-1}^2\right),\ z_t \equiv \varepsilon_t\sigma_{t-1}^2 \tag{2.16}$$

where z_t denotes the standardized innovations. Negative value of γ indicates the existence of "leverage effect". Leverage effect is a well-known phenomenon in finance and it refers to the situation of that negative shocks will have a bigger impact on future volatility than positive shocks of the same magnitude. Motivation behind the EGARCH model is very similar to the AGARCH model of Engle (1990); however, Nelson (1991) parameterizes the logarithmic form of the conditional variance and his model does not impose any restrictions on the parameters of variance equation.

Robinson (1991) develops the linear ARCH model (ARCH(∞)). The model is represented as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{\infty} \alpha_i \varepsilon_{t-1}^2, \tag{2.17}$$

This model is used by Robinson (1991) in the derivation of diagnostic tests to check whether serial correlation or dynamic conditional heteroskedasticity exist.

Augmented ARCH (AARCH) model of Bera, Higgins and Lee (1992) parameterizes the conditional variance depending on cross-products of the lagged innovations (Bollerslev, 2010). Let the q x 1 vector, $e_{t-1} \equiv \{\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}\}$ AARCH(q) model can be written as follows:

$$\sigma_t^2 = \omega + e_{t-1}' A e_{t-1} \tag{2.18}$$

where A stands for a q x q symmetric positive definite matrix, and if A is diagonal, the model reduces to the standard linear ARCH(q) of Engle (1982). Since AARCH model is not symmetric, and depends on the signs of the individual lagged AARCH considers the leverage effect of the EGARCH model by Nelson (1991).

GARCH Exponential AutoRegression (GARCH-EAR) model of LeBaron (1992) simply combines the GARCH model of Bollerslev (1986) and the exponential AR model of Ozaki (1980). LeBaron's (1992) model is able to capture whether magnitude of first-order autocorrelations are different for different periods of volatility.

$$y_t = \varphi_0 + \left[\varphi_1 + \varphi_2 \exp-\left(\sigma_t^2 / \varphi_3\right)\right] y_{t-1} + \varepsilon_t \tag{2.19}$$

In this formulation, if φ_2 >0, and φ_3 >0, then the magnitude of the autocorrelation in the mean is parameterized as a decreasing function of the conditional variance (Bollerslev, 2010).

Higgins and Bera (1992) introduces the Nonlinear GARCH (NGARCH) model which is a modified version of standard GARCH (p,q) model of Bollerslev (1986).

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i \left|\varepsilon_{t-i}\right|^{\delta} + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^{\delta} \tag{2.20}$$

This model is called as nonlinear since conditional standard deviation raised to the power δ is parameterized as a function of lagged absolute innovations and lagged conditional standard deviations raised to same power. If power parameter, δ, is equal to two (2), then NGARCH model is simply reduced to standard GARCH model. NGARCH model is also known as Power (G)ARCH model.

Ding, Engle and Granger (1993) combines several useful GARCH parameterizations, namely AGARCH of Engle (1990) and NGARCH of Higgins and Bera (1992), TSGARCH(p,q) model, and GJR-GARCH model of Glosten et al. (1993) to take into account both leverage effect and the nonlinearity in the data. Their model, Asymmetric Power ARCH (APARCH), may be expressed as:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^{\delta} \tag{2.21}$$

APARCH model is reduced to standard GARCH when δ and γ are equal to two and zero, respectively, TSGARCH model when δ and γ are equal to one and zero, and NGARCH model when only γ is equal to zero.

One of the most important GARCH family models is introduced by Glosten, Jagannathan and Runkle (1993) is GJR-GARCH model. This model is formulated to capture the leverage effect, that is to say, future volatility is affected differently from the past negative and positive innovations. GJR-GARCH is based on following equation:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I\left(\varepsilon_{t-1} < 0\right) + \beta \sigma_{t-1}^2, \tag{2.22}$$

where statistically significant and positive γ denotes the existence of leverage effect.

Engle and Ng (1993) formulates the Nonlinear Asymmetric GARCH (NAGARCH) model. NAGARCH(p,q) model refers to the parameterization,

$$\sigma_t^2 = \omega + \alpha\left(\varepsilon_{t-1}\sigma_{t-1}^{-1} + \gamma\right)^2 + \beta\sigma_{t-1}^2 \qquad (2.23)$$

This model nests two important features, namely asymmetry, and nonlinearity. Engle and Ng (1993) also introduces the Partially NonParametric ARCH (PNP-ARCH) which formulates the conditional variance as a partial linear function of the lagged innovations, ε_{t-1}, and the lagged conditional variance:

$$\sigma_t^2 = \omega + \sum_{i=-m}^{m} \theta_i\left(\varepsilon_{t-1} - i \cdot \sigma\right) + \beta\sigma_{t-1}^2 \qquad (2.24)$$

This model is developed to measure how the conditional variance responds to different sized shocks.

Autoregressive Conditional Density (ARCD) model of Hansen (1994) is proposed to deal with the problem of approximation to the distribution of a time series variable, y_t, conditional on another variable, x_t. Hansen's (1994) model allows for conditional dependencies beyond the mean and variance under the assumption of skewed-t distribution for the standardized innovations. There are several modifications of ARCD models, namely GARCH with Skewness (GARCHS) model of Harvey and Siddique (1999) and GARCH with skewness and kurtosis (GARCHSK) model of Leon, Rubio and Serna (2005). GARCHS(1,1,1) model is expressed as follows:

$$s_t = \gamma_0 + \gamma_1 z_t^3 + \gamma_2 s_{t-1}, \qquad (2.25)$$

where $s_t \equiv E_{t-1}\left(z_t^3\right)$. Leon, Rubio and Serna (2005) parameterize the GARCHSK model as:

$$k_t = \delta_0 + \delta_1 z_t^4 + \delta_2 k_{t-1}, \tag{2.26}$$

where $k_t \equiv E_{t-1}\left(z_t^4\right)$.

Hamilton and Susmel (1994), and Cai (1994) independently develop regime switching ARCH (SWARCH) model. In their seminal paper, they nest the Markov Switching model of Hamilton (1989) and the standard linear ARCH model of Engle (1982). SWARCH model formulates the parameters in the variance equation to depend upon some latent variable, *s(t)*, with transition between different states governed by a Markov chain:

$$h_t^{(i)} = \omega^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2, \quad i = 1, 2, ... \tag{2.27}$$

where h_t represents the conditional variance and i represents the different states, or regimes. In this model, parameters of ARCH process come from one of several different regimes, with transitions between regimes governed by and unobserved Markov Chain under the assumption that the latent innovations follow Normal and Student t distributions (Hamilton and Susmel, 1994). Thus, this extended ARCH model takes possible structural breaks into account and provides more accurate forecasts.

Threshold GARCH (TGARCH) model of Zakoian (1994) is closely related to GJR-GARCH model and parameterizes the conditional standard deviation to depend upon the sign of the lagged innovations. TGARCH(1,1) model is based on following notation:

$$\sigma_t = \omega + \alpha\left|\varepsilon_{t-1}\right| + \gamma\left|\varepsilon_{t-1}\right| I\left(\varepsilon_{t-1} < 0\right) + \beta\sigma_{t-1} \tag{2.28}$$

Sentana (1995) extends the standard linear GARCH(p,q) model of Bollerslev (1986) and formulates the Generalized Quadratic GARCH (GQGARCH(p,q)) model as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + 2\sum_{i=1}^{q} \sum_{j=i+1}^{q} \alpha_{ij} \varepsilon_{t-i} \varepsilon_{t-j} + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \quad (2.29)$$

GQARCH models consider nonlinearity in the data and also take leverage effect into account. This model is closely related to AARCH model since GQARCH nests the AARCH model of Bera and Lee (1990).

Hentschel (1995) introduces the Hentschel GARCH (HGARCH) model which nests several important univariate formulations, such as APARCH, EGARCH, GJR, NGARCH, TGARCH, TS-GARCH. HGARCH models the Box-Cox transform of the conditional standard deviation:

$$\sigma_t^{\delta} = \omega + \alpha \delta \sigma_{t-1}^{\delta} \left(\left| \varepsilon_{t-1} \sigma_{t-1}^{-1} - \kappa \right| - \gamma \left(\varepsilon_{t-1} \sigma_{t-1}^{-1} - \kappa \right) \right)^{\nu} + \beta \sigma_{t-1}^{\delta} \quad (2.30)$$

HGARCH reduces to standard linear GARCH (1,1) model when $\delta=2$, $\nu=2$, $\kappa=0$, and $\gamma=0$.

Baillie, Bollerslev, Mikkelsen (1996) develop the Fractionally Integrated GARCH (FIGARCH) model to better capture long-memory properties relying on ARFIMA representations. This model is closely related to IGARCH model of Engle and Bollerslev (1986) and may be expressed in the ARMA representation as follows:

$$\varphi(L)(1-L)^d \varepsilon_t^2 = \omega + (1-\beta(L))\nu_t, \quad (2.31)$$

where $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$, $0 < d < 1$, and the roots of $\varphi(z) = 0$ and $\beta(z) = 0$ are all outside the unit root circle (Bollerslev, 2010). If the d parameter is estimated in the interval of $0 < d < 0.5$ then it can be concluded that there exist an evidence of long memory property in the GARCH process. Long memory in finance theory is against the Efficient Market Hypothesis of Fama (1970) since long memory, or fractional slowly decaying hyperbolic dependencies in the conditional variance, means that high order of autocorrelation in squared returns. Fractionally Integrated EGARCH (FIEGARCH) model of Bollerslev and Mikkelsen (1996) nests the EGARCH model of Nelson (1991) and the FIGARCH model. The model may be expressed as:

$$\left(1-\beta L\right)\left(1-L\right)^{d}\log\left(\sigma_{t}^{2}\right)=\omega+\alpha\left(\left|z_{t-1}\right|-E\left(\left|z_{t-1}\right|\right)\right)+\gamma z_{t-1} \quad (2.32)$$

Gray (1996) generalizes the SWARCH model of Cai (1994) and Hamilton and Susmel (1994) and proposes the Regime Switching GARCH (RS-GARCH) model. Gray (1996) solves the problem of path dependence[9] by using the conditional expectation of the past variance in the variance equation. Klaassen (2002) follows a different approach to build the RS-GARCH by adopting the conditional expectation of the lagged conditional variance. This specification is referred to as more flexible in capturing the persistence in variance than Gray's (1996) modification. Haas et al. (2004) propose a new approach to Markov-Switching GARCH models. They extend previous RS-GARCH models to a multi regime setting. According to Haas et al. (2004), their model has the advantage of being analytically tractable and allows the researchers to derive stationary conditions. A general form of RS-GARCH (1,1) model can be written as follows:

$$h_{t}^{(i)}=\omega^{(i)}+\alpha_{1}^{(i)}\varepsilon_{t-1}^{2}+\beta_{1}^{(i)}h_{t-1}, \quad i=1,2,... \quad (2.33)$$

where h_{t-1} is a state-independent average of past conditional variances. Mixture GARCH of Zhang, Li, and Yuen (2006) is closely related to those SWARCH and RS-GARCH models.

Periodic GARCH (PGARCH) model of Bollerslev and Ghysels (1996) allows for periodic dependencies in the conditional variance. PGARCH(1,1) is based on the following equation:

$$\sigma_{t}^{2}=\omega_{(s)t}+\alpha_{s(t)}\varepsilon_{t-1}^{2}+\beta_{s(t)}\sigma_{t-1}^{2} \quad (2.34)$$

where *s(t)* stands for the stage of the periodic cycle. This model formulates the parameters in the variance equation to vary across the cycles.

Fornari and Mele (1996) propose the Volatility Switching GARCH (VSGARCH) model which is closely related to GJR-GARCH. The VSGARCH (1,1) may be expressed as follows:

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[9] Path-dependence problem refers to the situation where conditional variance at time *t* depends on the entire sample path.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\left(\varepsilon_{t-1}^2 / \sigma_{t-1}^2\right) I\left(\varepsilon_{t-1} < 0\right) + \beta\sigma_{t-1}^2, \tag{2.35}$$

In this model, as denoted by, $\varepsilon_{t-1}^2 / \sigma_{t-1}^2$, asymmetry effect of squared innovations is standardized by the corresponding conditional variances.

Crouchy and Rockinger (1997) combines the Taylor-Schwert GARCH (1,1) and GJR-GARCH (1,1) to get more accurate results in an asymmetric fashion. Their model is called as Asymmetric Threshold GARCH (ATGARCH) and it is formulated in the following notation:

$$\sigma_t = \omega + \alpha\left|\varepsilon_{t-1}\right| I\left(\varepsilon_{t-1} \geq \gamma\right) + \delta\left|\varepsilon_{t-1}\right| I\left(\varepsilon_{t-1} < \gamma\right) + \beta\sigma_{t-1} \tag{2.36}$$

Augmented GARCH (Aug-GARCH) model of Duan (1997) combines several popular parameterizations, including EGARCH, GJR-GARCH, NGARCH, TS-GARCH and the VGARCH:

$$\begin{aligned} &\sigma_t^2 = \left|\lambda\varphi_t - \lambda + 1\right| I\left(\lambda \neq 0\right) + \exp\left(\varphi_t - 1\right) I\left(\lambda = 0\right) \\ &\textit{where} \\ &\varphi = \omega + \alpha_1\left|z_{t-1} - \kappa\right|^{\delta}\varphi_{t-1} + \alpha_2 \max\left(0, \kappa - z_{t-1}\right)^{\delta}\varphi_{t-1} + \alpha_3\left(\left|z_{t-1} - \kappa\right|^{\delta} - 1\right)/\delta + \\ &\alpha_4\left(\max\left(0, \kappa - z_{t-1}\right)^{\delta} - 1\right)/\delta + \beta\varphi_{t-1} \end{aligned} \tag{2.37}$$

Aug-GARCH model reduces to the EGARCH model when the following conditions are satisfied: $\lambda=0$, $\kappa=0$, $\delta=1$ and $\alpha_1=\alpha_2=0$.

Müller, Dacorogna, Dave, Olsen, Puctet and von Weizsacker (1997) propose the Heterogeneous ARCH (HARCH) model in which the conditional variance is formulated as a function of the square of the sum of lagged returns over different time resolutions. The HARCH(n) may be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{n} \gamma_i \left(\sum_{j=1}^{i} \varepsilon_{t-j}\right)^2 \tag{2.38}$$

The main motivation behind that model is to analyze the dynamics of market components and through the interaction of traders with different investment horizons (Bollerslev, 2010).

Engle and Russell (1998) introduce the Autoregressive Conditional Duration model to better explain the dynamic dependencies in the time interval between randomly occurring events. ACD(1,1) model can be written in the following notation:

$$\psi_i = \omega + \alpha x_{i-1} + \beta \psi_{i-1} \tag{2.39}$$

In this model, times between trades is denoted by x_i, $x_i \equiv t_i - t_{i-1}$, and $\psi_i = E\left(x_i \mid x_{i-1}, x_{i-2}, \ldots\right)$. Bollerslev (2010) states that ACD model is widely used in the analysis of high-frequency data.

Tse (1998) develops Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) model by combining FIGARCH(p,d,q) model of Baillie et al. (1996) and APARCH(p,q) model of Ding et al. (1993). FIAPARCH model formulation may be expressed as follows:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 \left[1 - \beta_1 L - \left(1 - \phi_1 L\right)^d\right]\left(\left|\varepsilon_t\right| - \gamma \varepsilon_t\right)^\delta, \omega > 0 \tag{2.40}$$

where δ is the power parameter and γ measures the asymmetric effect.

Gonzalez-Rivera (1998) introduces Smooth Transition GARCH (STGARCH) model that is closely related to GJR-GARCH and TGARCH models. STGARCH model is based on following formulation:

$$\begin{aligned} &\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \delta \varepsilon_{t-i}^2 F\left(\varepsilon_{t-1}, \gamma\right) + \beta_i \sigma_{t-1}^2 \\ &where \\ &F\left(\varepsilon_{t-1}, \gamma\right) = \left(1 + \exp\left(\gamma \varepsilon_{t-1}\right)\right)^{-1} \end{aligned} \tag{2.41}$$

In this model, the effect of past squared innovations depends upon the both the sign and the magnitude of past innovations through a smooth transition function, *F*.

The Component GARCH (CGARCH) model of Engle and Lee (1999) is developed to better model the long-run volatility dependencies:

$$\left(\sigma_t^2 - \sigma^2\right) = \alpha\left(\varepsilon_{t-1}^2 - \sigma^2\right) + \beta\left(\sigma_{t-1}^2 - \sigma^2\right), \tag{2.42}$$

where σ^2 represents the unconditional variance defined by $\sigma^2 \equiv \omega / \left(1-\alpha-\beta\right)$, $x_i \equiv t_i - t_{i-1}$, and $\psi_i = E\left(x_i \mid x_{i-1}, x_{i-2}, ...\right)$. Then, CGARCH model is formulated as:

$$\left(\sigma_t^2 - \varsigma_t^2\right) = \alpha\left(\varepsilon_{t-1}^2 - \varsigma_{t-1}^2\right) + \beta\left(\sigma_{t-1}^2 - \varsigma_{t-1}^2\right), \tag{2.43}$$

The unconditional variance is parameterized by relaxing the assumption of constant variance through time:

$$\varsigma_t^2 = \omega + \rho\varsigma_{t-1}^2 + \varphi\left(\varepsilon_{t-1}^2 - \varsigma_{t-1}^2\right) \tag{2.44}$$

Nowicka-Zagrajek and Weron (2001) propose the Randomized GARCH (RGARCH(r,p,q)) model which modifies the intercept term (ω), of GARCH(p,q). RGARCH model may be written as follows:

$$\sigma_t^2 = \sum_{i=1}^{r} c_i \eta_{t-i} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2, \; c_i > 0 \tag{2.45}$$

where η_{t-i}, $\left(i = 1, 2, ..., r\right)$ is the sum of r positive i.i.d. stable random variables. By replacing intercept term with a new modified one, c_i, RGARCH model manipulates the estimation of average conditional volatility.

Hamilton and Jorda (2002) develop the Autoregressive Conditional Hazard (ACH) model to describe the dynamic dependencies in the probability for the occurrence of specific events. Their motivation behind proposing this model is based on determining the likelihood of a specific event to be changed tomorrow, given all that is known today. ACH is, therefore, closely related to the ACD model of Engle and Russell (1998).

Asymmetric Nonlinear Smooth Transition GARCH (ANST-GARCH) model of Nam, Pyun and Arize (2002) is a modified version of ST-GARCH model of Gonzalez-Rivera. ANST-GARCH(1,1) model may be expressed as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \left[\kappa + \delta\varepsilon_{t-1}^2 + \rho\sigma_{t-1}^2\right] F\left(\varepsilon_{t-1}, \lambda\right) \tag{2.46}$$

where F(.) indicates the smooth transition function. ANST-GARCH(1,1) reduces to standard GARCH(1,1) model in the case of κ=δ=ρ=0.

Engle and Manganelli (2004) proposes Conditional Autoregressive Value-at-Risk (CAViAR) model to describe the conditional quantile of a time series, for some specified risk level *p*, as an autoregressive process:

$$f_t = \left(\omega + \alpha y_{t-1}^2 + \beta f_{t-1}^2\right)^{1/2} \tag{2.47}$$

f_t denotes the way how the GARCH(1,1) model formulates the conditional quantiles. Engle and Manganelli (2004) suggest using this model in predicting quantiles in financial return distributions, Value-at-Risk.

Maheu and McCurdy (2004) introduce GARJI model which is a modification of GARCH model. GARJI model allows jumps and large moves that follow Poisson distribution. Mean and variance equations of GARJI model are formulated, respectively:

$$\begin{aligned} rt &= \mu + \sqrt{\sigma_t^2} z_t + J_t, \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned} \tag{2.48}$$

where J is the jump component of the disturbance term, ε_t.

Hyperbolic GARCH (HYGARCH) model of Davidson (2004) is closely related to FIGARCH model of Baillie et al. (1996). HYGARCH simply nests the GARCH, IGARCH, and the FIGARCH models. Thus, HYGARCH is able to capture the long memory property in financial returns via ARCH process.

$$\sigma_t^2 = \omega + \sum_{i=1}^{\infty} \alpha_i \varepsilon_{t-i}^2 \equiv \omega + \left[1 - \frac{\delta(L)}{\beta(L)}\left(1 + \alpha\left((1-L)^d - 1\right)\right)\right]\varepsilon_{t-1}^2 \tag{2.49}$$

Standard GARCH model is obtained when d parameter is equal to 1.

Dynamic Asymmetric GARCH (DAGARCH) model of Caporin and McAleer (2006) modifies the GJR-GARCH model by allowing multiple thresholds, making asymmetric effect time dependent. DAGARCH (1,m,d) model may be written as follows:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \sum_{i=1}^{k} I_i\left(\varepsilon_{t-1}\right)\left(\overline{\gamma}_i + \overline{\phi}_i\gamma_{t-2}\right)\left(\varepsilon_{t-1} - \overline{d}_i\right)^2$$
$$+\sum_{i=k+1}^{m}\left[1 - I_i\left(\varepsilon_{t-1}\right)\right]\left(\overline{\gamma}_i + \overline{\phi}_i\gamma_{t-2}\right)\left(\varepsilon_{t-1} - \overline{d}_{i-1}\right)^2 \qquad where\ \ I_i\left(\varepsilon_{t-1}\right) = \begin{cases} 1 & \varepsilon_{t-1} > d_i \\ 0 & otherwise \end{cases} \tag{2.50}$$

DAGARCH model is also closely related to AGARCH model of Engle (1990), ATGARCH model of Crouhy and Rockinger (1997) and TGARCH model of Zakoian (1994).

Brandt and Jones (2006) introduces Range EGARCH (REGARCH) model which is based on EGARCH model of Nelson (1991) considers asymmetry effect. They argue that range is appropriate to be used as true volatility. REGARCH model can be expressed as follows:

$$\ln\sigma_t^2 - \ln\sigma_{t-1}^2 = \kappa\left(\theta - \ln\sigma_{t-1}^2\right) + \phi X_{t-1}^D + \delta R_{t-1} / \sigma_{t-1}^2 \tag{2.51}$$

In this range based model, demeaned and standardized log range is more informative about the logarithmic volatility innovation (Brandt and Jones, 2006). Authors also postulates Fractionally Integrated REGARCH (FIREGARCH) model as:

$$\left(1 - \omega L\right)\left(1 - L\right)^d\left(\ln\sigma_t^2 - \theta\right) = \phi X_{t-1}^D + \delta R_{t-1} / \sigma_{t-1}^2 \tag{2.52}$$

FIREGARCH enables researchers to investigate long memory dependencies.

ARCH Nonstationary Nonlinear Heteroskedasticity (ARCH-NNH) model of Han and Park (2008) is based on the following equation:

$$\sigma_t^2 = \alpha\varepsilon_{t-1}^2 + f\left(x_t\right) \tag{2.53}$$

where *f(.)* is the nonlinear function of a near or exact unit root process. According to Han and Park (2008) ARCH-NNN captures many important characteristics of the financial data and in particular, the model predicts leptokurtosis very well.

GARCH type of deterministic volatility models gives more reliable results when high frequency (daily or intra-daily) data is used in the analysis. Recently, Engle and Rangel (2008) propose Spline-GARCH model to investigate low-frequency volatility components:

$$\sigma_t^2 = (1 - \alpha - \beta)\omega + \alpha\left(\varepsilon_{t-1}^2 / \tau_t\right) + \beta\sigma_{t-1}^2 \quad (2.54)$$

where $\tau_t = c \cdot \exp\left[\omega_0 t + \omega_1\left((t - t_0)_+\right)^2 \omega_2\left((t - t_1)_+\right)^2 + ... + \omega_k\left((t - t_{k-1})_+\right)^2\right]$ for

$(t - t_i)_+ = (t - t_i)$ *for* $t > t_i$ *and* 0 *otherwise*

Moreover, Spline-GARCH model is closely related to CGARCH model of Engle and Lee (1999).

Finally, Flexible Component GARCH (FCGARCH) of Mederios and Veiga (2009) formulates conditional variance as a linear combination of GARCH family models. Those models are then weighted by a set of logistics functions. Particularly, FCGARCH model combines DTARCH, GJR-GARCH, STGARCH, TGARCH, and VSGARCH models. The motivation behind this model is to design a model that captures sign and size asymmetries in financial volatility along with intermittent dynamics and excess of kurtosis:

$$\sigma_t^2 = G(w_t;\psi) = \alpha_0 + \beta_0\sigma_{t-1}^2 + \lambda_0 y_{t-1}^2 + \sum_{i=1}^{H}\left[\alpha_i + \beta_i\sigma_{t-1}^2 + \lambda_i y_{t-1}^2\right] f(s_t;\gamma_i, c_i), \quad (2.55)$$
$$t = 1, ..., T$$

where $G(w_t;\psi)$ is a vector of parameters and *f(.)* denotes the logistics functions.

Overall, all of the modifications of GARCH models are developed to better capture volatility dynamics. Researchers postulate new GARCH type of models to consider stylized facts of volatility. Recently introduced GARCH models are mostly designed to consider regime changes in the volatility along with asymmetric (leverage) effects, long memory properties, nonlinearity and etc.

2.1.2. The Other Volatility Models

2.1.2.1. Historical Volatility Models

It is easy to calculate variance (or standard deviation) of returns over some historical period, so that the simple historical volatility approach can be used widely. There are several types of historical volatility approaches. The simplest one is the Random Walk (RW) model:

$$\hat{\sigma}_t = \sigma_{t-1} \tag{2.56}$$

where past variance of return at time *t-1* is used to forecast the variance of return at time *t*. The other proposed models, somehow, use past observations over a period of time to model the future volatility under the assumption that variance of returns is time invariant.

Historical Average method (HA) is based on following notation:

$$\hat{\sigma}_t = \left(\sigma_{t-1} + \sigma_{t-2} + ... + \sigma_1\right) / \left(t-1\right) \tag{2.57}$$

This method uses all historical standard deviations to forecast the future volatility.

Moving Average (MA) model is a little bit different from the HA method since it does not consider the all older standard deviation estimations. MA model may be expressed as follows:

$$\hat{\sigma}_t = \left(\sigma_{t-1} + \sigma_{t-2} + ... + \sigma_{t-\tau}\right) / \tau \tag{2.58}$$

Exponentially Weighted Moving Average (EWMA) model considers recent observations rather than older observations. Put another way, this EWMA model place greater weights on the more recent volatility estimates:

$$\hat{\sigma}_t = \sum_{i=1}^{\tau} \beta^i \sigma_{t-i} / \sum_{i=1}^{\tau} \beta^i \tag{2.59}$$

James Taylor (2001) proposes the Smooth Transition Exponential Smoothing (STES) model which is closely related to the previous exponential smoothing models. In particular, STES model assigns weights depending on the size as well as the sign of the past observation. The formulation of the model may be expressed as follows:

$$\hat{\sigma}_t = \alpha_{t-1}\varepsilon_{t-1}^2 + \left(1-\alpha_{t-1}\right)\hat{\sigma}_{t-1}^2$$
$$where \qquad (2.60)$$
$$\alpha_{t-1} = \frac{1}{1+\exp\left(\beta + \gamma V_{t-1}\right)}$$

Finally, Simple Regression (SR) models the volatility as a function of its past values. Therefore SR model is an autoregressive model. One may include past values of error terms into the equation of SR to obtain an ARMA type of model. SR model is simply described as follows:

$$\hat{\sigma}_t = \gamma_{1,t-1}\sigma_{t-1} + \gamma_{2,t-1}\sigma_{t-2} + \dots \qquad (2.61)$$

2.1.2.2. Implied Volatility Models

Implied volatility is simply a type of volatility refers to the volatility over the life of the option implied by the option valuation such as Black-Scholes (1973) options pricing model (Brooks, 2008: 384).

2.1.2.3. Stochastic Volatility Models

Stochastic volatility models simply differs from deterministic volatility models, (G)ARCH models, because they contain a second error term in the variance equation (Brooks; 2008: 427). A possible notation for the simplest stochastic volatility model can be written as:

$$y_t = \mu + v_t\sigma_t, \quad v_t \sim N\left(0,1\right)$$
$$\log\left(\sigma_t^2\right) = \alpha_0 + \beta_1 \log\left(\sigma_{t-1}^2\right)\sigma_n\eta_t \qquad (2.62)$$

where η_t is another random variable that may or may not be independent of v_t.

2.2. Empirical Studies on ARCH Models with Structural Breaks

Lamoureux and Lastrapes (1990) conduct a study to examine the persistence of variance in 30 common-stock daily returns and a stock index data. They hypothesize that persistence of variance measured by GARCH model may be overstated due to the volatility shifts in the time period. In other words, they state that time varying GARCH parameters result in misspecification in the model and overestimation in the persistence of variance. Lamoureux and Lastrapes (1990) estimated two type of GARCH(1,1) models: one with shift dummies, and the other one without dummies. Those dummy variables are assigned to take account possible volatility shifts in stock-returns and represent over 14 nonoverlapping subsamples. They conclude that in average, level of persistence falls dramatically, approximately 16%, after considering volatility shifts.

Aggarwal, Inclan and Leal (1999) conduct a study to examine the large volatility shifts in the index return data and the events that are associated with those shifts in the volatility. They apply iterated cumulative sum of squares (ICSS) algorithm to identify the large volatility shifts in the index return data of several countries, including the US, the UK, Japan, Germany as well as the largest emerging markets in Asia and Latin America. Aggarwal et al. (1999) use two GARCH(1,1) model with and without dummy variables indentified by ICSS algorithm. According to the results, considering structural breaks in GARCH process significantly reduces the estimated persistence of variance. Their findings also suggest that local political events result in increase in variance. Volatility shifts are closely related to local events, namely Mexican Peso Crisis, Marcos-Aquino conflict, stock market scandals in India. Moreover, they state that the October 1987 crash have a significant impact on the volatility of several emerging stock markets.

Andreou and Ghysels (2002) examine changes in the dynamics of volatility of a number of equity indices including the Hong Kong, Japan, the UK and the US. They conduct CUSUM type of test by Kokoszka and Leipus. Their empirical analysis on high-frequency data suggest several change points in the volatility dynamics which are associated with the Asian and Russian financial crises for the aforementioned equity indices.

Malik (2003) investigates the time periods of sudden changes in the volatility of several spot exchange rate series, namely Japanese yen, British pound, Canadian dollar, French franc and German mark from January 1990 to September 2000. He also postulates the economic events related to those volatility shifts. Malik (2003) applies standard ICSS algorithm to detect the volatility shifts and then assigns dummy variables corresponding to determined regime shifts. His findings suggest that incorporating regime shifts in the GARCH model may significantly lower volatility persistence.

Smith (2003) states that GARCH model that is widely used in finance literature fails to take structural breaks into account. Thus, Smith (2003) postulates a new test which uses Generalized Method of Moments (GMM) specification and conducts stability tests of Andrews (1993), and Andrews and Ploberger (1994). He nests his model with standard GARCH model of Bollerslev (1986) to take structural breaks into account.

Malik and Hassan (2004) conduct a study to examine what events have a significant impact on the volatility pattern of five major sector indices of Dow Jones, including financial, industrial, consumer, health, and technology which represent a particular type of index fund and index-based investment. They examine data at a weekly frequency over the period spanning from January 1992 to August 2003. Their paper investigates the periods of sudden changes in volatility by using ICSS algorithm. Then, volatility shifts determined endogenously by ICSS algorithm are added to the variance equation of GARCH model to estimate the volatility persistence more accurately. Their findings suggest considering volatility shifts due to several local or global economic events in the estimation of volatility via GARCH process. Moreover, they report that Russian Ruble Crisis has a significant effect on the volatility pattern of the sector indices. However, they report that volatility shifts in those sector indices are not incorporated to Asian Crisis in 1997. They conclude that when those large volatility shifts in variance are taken into account in the GARCH model, the estimated persistence in return volatility is reduced significantly in every sector index series.

Ewing and Malik (2005) investigate the existence of asymmetry in the predictability of the volatilities of small and large companies. They use ICSS algorithm to detect large changes in the unconditional variance of stock returns and incorporate this information in Bivariate GARCH model. According to their results, spillover effects between small and large cap stock returns disappears when endogenously determined volatility shifts are taken into consideration. Moreover, they observe significant decline in the transmission of volatility between those stock returns. Hence, they suggest not ignoring regime changes to estimate degree of volatility transmission more accurately.

Malik, Ewing and Payne (2005) examine Canadian stock exchange data at a weekly frequency for the period spanning from 10 June 1992 to 27 October 1999. They investigate the impact of regime changes on volatility persistence in the Canadian stock market. They conduct ICSS algorithm to detect sudden changes in the volatility and incorporate those shifts into variance equation of GARCH model to avoid overestimating the volatility persistence. They conclude that volatility persistent is reduced after considering sudden volatility changes in stock returns. In this manner, their findings are consistent with the Lamoureux and Lastrapes (1990), Aggarwal, Inclan, and Leal (1999).

Zhang (2005) conducts a study to examine the volatility dynamics in Shanghai Stock Exchange (SSE) Composite Return Index. They investigate the volatility switching problem due to the facts of less regulation by using CUSUM type tests and Markov Switching ARCH model on weekly frequency data. He prefers to use weekly rather than daily data to overcome the shortcoming of day-of-week effect. They identify several volatility shifts in the return series determined by structural break tests. Their findings suggest significant breaks at mid 1997 which closely associated with Asian Currency Crisis that began in July 1997 in Thailand. Zhang (2005) postulates that volatility persistence is significantly reduced after taking sudden large changes into consideration.

Fernandez (2005) conducts ICSS algorithm and Wavelet Analysis (WA) to investigate the existence of structural breaks in the four stock indices and four interest rates series. Dataset consists of Emerging Asia, Europe, Latin America and North

America indices of Morgan Stanley Capital International (MSCI). Fernandez (2005) focuses on the effects of the Asian crisis and the terrorist attacks of September 11, 2001 on the volatility of those stock indices and the interest rate series of the Central Bank of Chile. Empirical findings suggest that ICSS algorithm and WA detects several breakpoints in the data. Fernandez (2005) concludes that we should consider those sudden changes in the unconditional variance of series. Moreover, WA are found to be more robust than ICSS algorithm because unlike ICSS algorithm, WA suggests structural change in the data series during the period of Asian crisis of 1997-1998.

Wang (2006) conducts a study to examine the impact of financial liberalization on the volatility of several stock indices during the period from 1986 to 1998. They use daily returns data at a daily frequency. Wang (2006) applies ICSS algorithm to detect structural breaks due to the announcement of liberalization. According to the empirical findings, there exists several breakpoints in the unconditional variance of the daily returns of South Korea, Malaysia, Philippines, Thailand, Taiwan, Turkey, Argentina, Brazil, Chile, and Mexico for over ten years. According to analytical results the volatility of stock returns increased significantly for the markets of Thailand, Brazil, Chile, and Mexico; whereas unconditional volatility remains unchanged for the rest.

Fernandez and Lucey (2006) investigates the volatility shifts in the indices of the Dow Jones Country Titans, the CBT-municipal bond, spot and futures prices of commodities for the period spanning from 1992 to 2005. They use ICSS algorithm and WA to determine volatility shifts endogenously, and assign a number of dummy variables associated with those sudden shifts to the variance equation of Power GARCH (PGARCH). Their conclusion reveals that it is important to take into account structural breaks to estimate financial risk more accurately. In addition, they suggest forming portfolios consist of commodities as their low or even negative correlation with stock indices.

Cheong (2008) conducts a study on Malaysian Stock Market to examine volatility dynamics and possible volatility shifts associated with the structural breaks. Cheong (2008) uses Kuala Lumpur sector indices data at a daily frequency for the period from 1996 to 2006 to investigate fractionally integrated time-varying volatility model. When endogenously determined sudden shifts in variance are taken into account in the fractionally integrated time-varying volatility model, the estimated persistence in return volatility is declined significantly in return series. Sudden changes are mostly clustered around the Asian financial and currency crises. Their findings suggest that standard FIGARCH model overestimate financial risk; whereas time varying multiple-shift FIGARCH model performs better in the estimation of volatility.

Wang and Thi (2007) conduct a study to examine the contagion effects between Taiwan and the US stocks in an asymmetric fashion. They conduct ICSS procedure to detect sudden changes in unconditional variance and incorporate that information in Exponential GARCH (EGARCH) model. They also use Dynamic Conditional Correlation (DCC) model to investigate the existence of contagion between them.

Fernandez (2007a) investigates the impact of political events in the Middle East on stock markets worldwide. She applied ICSS algorithm and WA to detect the structural breaks in the unconditional variance of several stock markets. The data in the analysis includes Israel, Turkey, Morocco, Egypt, Jordan, Pakistan, and Indonesia, the UK, Germany, Japan, the US, and Spain, and four international indices for the period spanning from April 2000 to March 2005. Fernandez (2007a) concludes that the war in Iraq have a significant impact on the volatility of several Middle East and Emerging Asian countries. Moreover, volatility of stock markets is affected from Middle East conflicts. Thus, she suggests estimating financial risks by considering breakpoints in the volatility.

Fernandez (2007b) examines volatility dynamics of eight US industries from the late 1800's to the 1930s including the Great Depression. The persistence of volatility, volatility shifts, and the degree of co-movement of stock returns are investigated during this period. The empirical results reveal the fact that stock market becomes more volatile just after the Great Depression; however; persistence of volatility is declined in that period. However, it is not say that, trading volume is the main reason for such behavior.

Fernandez and Lucey (2007) conduct a study to investigate the determinants of volatility shifts on ten emerging markets, namely Argentina, Brazil, Chile, India, Indonesia, Mexico, Philippines, Singapore, South Africa, and Turkey. They use three statistical approaches, ICSS algorithm, WA, and Bai-Perron's (2003) test to determine the breakpoints in the both mean level and variance of the time series at a weekly frequency, over the period from January 1996 to April 2006, giving in total 536 observations. ICSS algorithm and WA tend to estimate more breakpoints than Bai-

Perron’s structural breaks test. Fernandez and Lucey (2007) observe that volatility shifts are mostly associated with local political or economic events rather than global events.

Fang et al. (2008) analyze the volatility dynamics in real GDP growth rates for Canada, Germany, Italy, Japan, the UK and the US. They apply ICSS algorithm to detect sudden large changes in the unconditional variance of output growth. Then they incorporate that information about time of breakpoints to the variance equation of GARCH model. They evidence that the time-varying variance declines dramatically in Canada and Japan, and disappears completely in the UK, US, Germany and Italy when endogenously determined sudden shifts are taken into account. They call attention to the importance of modeling financial risk by considering structural breaks in data and they suggest considering nonstationary variance in the GARCH process.

Using semi-parametric fractional autoregressive integrated moving-average (SEMIFARIMA) model, Fernandez (2008) investigates the stock and commodity indices of AMEX Major Market Index, Mexico, Israel, Egypt, Pakistan, the UK, Germany, France, Spain, India, South Korea, Japan, Australia, Indonesia, and two commodities indices: PHLX Gold and Silver and Dow Jones AIG commodity index (DJAIG). She works with daily data covering the period from January 2000 toJune 2006. Empirical evidences indicate that local political coflicts, Iraq War have a significant impact on the volatility of stock markets worldwide.

Marcelo et al. (2008a) uses Spanish stock market data at weekly frequency covering the period between January 3, 1990 and January 5, 2005. They conduct their analysis in two steps: First they apply ICSS algorithm to detect volatility shifts and then secondly they incorporate this information to EGARCH model. Their motivation behind using EGARCH model is to conduct their analysis to better capture the asymmetric behavior. They observe that volatility persistence is significantly reduced when endogenously determined volatility shifts are taken into account. Moreover, their findings reveal that spillover effects are declined after sudden changes are considered.

Marcelo et al. (2008b) conduct a study to examine the impact of sudden shifts in unconditional variance on large and small capitalization portfolios in Spanish stock market. Sudden shifts are detected via ICSS algorithm and incorporated in the Bivariate GARCH framework. By using such a methodology, they examine spillover effects between small and large capitalization portfolios. Empirical analysis reveals that asymmetric effects disappear when sudden shifts are incorporated into Bivariate GARCH process. Moreover, volatility persistence is significantly reduced when endogenously determined structural breaks in the variance are taken into account and volatility and shock transmissions between large and small cap portfolios are declined to their own past volatility and news after the European Monetary Union (EMU), indicating a clear evidence of mean reversion of volatility.

Kang et al. (2009) conduct an analysis to investigate the large changes in the unconditional volatility in four Asian exchange rate return series, namely Singaporean dollar, Korean won, New Taiwan dollar and Thai Baht between the period 1990 and 2008. They use ICSS algorithm to detect breakpoints in variance series of aforementioned exchange rates. They evidence that volatility shifts are mostly associated with Asian Crises and global financial turmoil that began in late 2007. Persistence of volatility is significantly reduced when endogenously determined sudden shifts are incorporated in GARCH process. They also suggest considering structural breaks due to the local or global economic and/or political events for modeling volatility dynamics and for forecasting gains.

Kasman (2009) investigates the volatility shifts in the stock markets of the BRIC countries, Brazil, Russia, India and China. He works with daily data covering the period between 1990 and 2007 to investigate the effects of sudden volatility shifts on persistence of volatility. Kasman (2009) applies ICSS algorithm to detect the time of breakpoints and incorporate this in GARCH model. Empirical findings suggest that persistence of volatility is dramatically declined when sudden changes in volatility are taken into account. Thus, he states that previous literature may overestimate the persistence of volatility because they do not consider structural breaks in the data due to the economic or political events during the time period.

And lastly, Karaoglou (2010) conducts a study on the stock market indices of 27 OECD countries for the period spanning from 1994 to 2006. He hypothesizes that non-normal behavior may arise because of the joint existence of structural breaks and ARCH effects in the time series data. Karaoglou (2010) employs several econometric tests to determine the sudden changes in variance. These tests include ICSS algorithm of Inclan and Tiao (1994), Kappa tests of Sanso et al. (2004) and Kokoszka and Leipus (2000) type of tests refined by Andreou and Ghysels (2002). Daily closing values of the stock market indices are used in the analysis. The paper concludes that when structural breaks are taken into account high persistence of volatility reduced and asymmetric effects and risk aversion arises only temporarily.

2.3. Empirical Studies on Forecasting Volatility with ARCH Models

Akgiray (1989) conduct a study to evaluate forecasting performance of the GARCH, ARCH, EWMA, HIS models using Center for Research in Security Prices (CRSP) Value-Weighted (VW) and Equally-Weighted (EW) indices. Akgiray (1989) uses data at daily frequency covering the period spanning from January 1963 to December 1986. Empirical findings suggest that GARCH(1,1) model fits to data very satisfactorily. Forecast performance of the GARCH (1,1) model outperforms all the other models based on several statistics including Mean Error (ME), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE). GARCH(1,1) process is the least biased and show the best forecast accuracy.

Dimson and Marsh (1990) examine the predictability of the UK equity market volatility. They use daily Financial Times (FT) All share index data for the period between 1955 and 1989. Dimson and Marsh (1990) focus on data-snooping problem and state that sophisticated forecasting models may perform worse than the naïve benchmark models because of this data-snooping problem. They compare forecast performance of exponential smoothing (ES) model, regression model with fixed weights, Historical Average model, and Moving Average (MA) model over one quarter forecast horizon. Empirical findings recommend using Exponential smoothing models based on the information gathered from statistical loss functions, namely Mean Squared Error (MSE), Relative Mean Absolute Error (RMAE), RMSE, MAE.

Engle, Ng and Rothschild (1990) analyze the Treasury bill (T-Bill) returns, Value-Weighted index of New York Stock Exchange (NYSE), and American Stock Exchange (AMSE) stocks between the period August 1964 and November 1985. Using data at monthly frequency, they conduct Factor ARCH and Univariate ARCH-M model to forecast 1 month ahead volatility and risk premium of T-Bills. Factor

ARCH model introduced by Engle (1987) is found to be superior in forecasting volatility. Their findings reveal that an equally weighted bill portfolio is effective in predicting both the volatility and the risk premia of individual maturities. Finally, Engle, Ng and Rothschild (1990) suggest using Factor ARCH model in forecasting the yield curve, derivatives pricing, portfolio management with dynamic properties, predicting asset risk premia and in many standard finance applications.

Pagan and Schwert (1990) conduct a study to forecast volatility of the US stock market using data at monthly frequency covering between 1834 and 1937. They employ EGARCH(1,2), GARCH (1,2), 2-step conditional variance, Regime Switching-AR(m) of Hamilton (1989), Nonparametric Kernel (1 lag), Nonparametric Fourier (up to 2 lags) models and compare their volatility forecasting performance based on R-square statistic. Empirical findings suggest that EGARCH model which takes volatility asymmetry into account outperforms the other models in forecasting one month ahead volatility when squared residual monthly returns are used as proxy for actual volatility. They conclude that sophisticated models are best done in parametric framework rather than nonparametric approach.

Tse (1991) conducts an analysis on Topix Nikkei Stock Exchange during the period from 1986 to 1989. He uses data at daily frequency and compare 25-day ahead forecasting performance of several models including EWMA, Historical volatility consturucted based on past variance (HIS), ARCH, and GARCH models based on the statistics, namely ME, RMSE, MAE, and MAPE. Empirical results reveal that EWMA model is rapid to react abrupt changes in volatility, and gives the best forecasts among all. Tse (1991) reports that allowing non-normality is useful in modelling financial risk; however it does not lead to out-of-sample forecasting gains.

Cao and Tsay (1992) analyze the excess returns for S&P, Value Weighted and Equally Weighted indices for the period spanning from 1928 to 1989. They use monthly data to perform 1 to 30 months ahead volatility forecasts by conducting Threshold Autoregressive (TAR), EGARCH(1,0), ARMA(1,1), and GARCH(1,1) models. Forecasting performance of those econometric volatility models are evaluated by the MSE, and MAE. Empirical findings recommend that TAR model produces the best forecasts for large stocks, and EGARCH is found as the best forecasting model in the long forecast horizon for small stocks.

Tse and Tung (1992) compare the forecast performance of several models including EWMA, HIS, and GARCH models by using RMSE, and MAE loss functions statistics. They analyze Singapore data at daily frequency in the period between March 1975 and October 1988. They estimate 25 days ahead forecasts from rolling 425 observations. Their empirical findings suggest that the GARCH model is not the best forecasting model; whereas EWMA produces the best forecasts.

Cumby, Figlewski and Hasbrouck (1993) conduct an analysis on time variation for both volatilities and correlations among asset returns in the US and Japan. Weekly data of the equities, long-term government bonds, and the dollar/yen exchange rate are used for the period spanning from July 1977 to September 1990. One week ahead forecasting performance of EGARCH and HIS models are compared. Empirical findings suggest that EGARCH performs better than the other in forecasting volatility.

Hamilton and Susmel (1994) use Regime Switching ARCH (SWARCH) model to forecast NYSE VW stock index volatility. They use data at weekly frequency for the period spanning from July 1962 to December 1987. They consider leverage effect in forecasting volatility and estimate 1, 4 and 8 weeks ahead volatility by using squared weekly residual returns to proxy volatility. According to MSE, MAE, MSLE, MALE statistical loss functions, SWARCH model with leverage which allows up to 4 regimes with t distribution produces the best forecasts among the other models, namely GARCH with leverage, and ARCH with leverage.

West and Cho (1995) conduct a study to forecast volatility in exhange rate market. They analyze Canadian dollar, French Franc, Deutche Mark, Japanese Yen, and British Pound against US dollar. They compare out-of-sample forecasting performance of GARCH(1,1), IGARCH(1,1), AR(12) in absolute, AR(12) in squares, Homoskedastic GARCH, nonparametric models (Gaussian Kernel), using data at weekly frequency for the period March 1973 through September 1989. They estimate 1, 12, and 24 weeks ahead forecasts by rolling 432 weeks and squared returns are used to proxy actual volatility. RMSE statistics and regression tests on variance suggest mixed results; however, it is clear that nonparametric volatility forecasting model is the worst model among all.

Brailsford and Faff (1996) analyze the Australian Statex-Actuaries Accumulation Index for top 56 indexes. They work with daily data covering the period between January 1974 and June 1993. Out-of-sample forecasting performance of GJR-GARCH, Regression, HIS, GARCH, Moving Average, EWMA, RW, ES models are compared based on the ME, MAE, RMSE, MAPE statistics, and a collection of asymmetric loss functions. Brailsford and Faff (1996) estimate one month ahead forecasts by using 12-year rolling window. Empirical findings suggest that GJR-GARCH model outperforms the other models; however it is the only model that always underpredict.

Franses and Van Dijk (1996) conduct a study to analyze the forecasting performane of several econometric models. They use weekly stock index data of Germany, Netherlands, Spain, Italy, and Sweden for the period between 1986 and 1994. One week ahead volatility forecasts are estimated using weekly squared deviations to proxy actual volatility. QGARCH, RW, GARCH, and GJR-GARCH models are compared based on the statistical loss function of median squared error (MedSE). Empirical results suggest that forecasting performance of those models changes due to the extreme values in the data. QGARCH model produces the best forecasts when the dataset has not extreme values such as October 87 Crash. On the other hand, RW model is found to be the best when October 87 crash is taken into account. Franses and Van Dijk (1996) state that volatility forecasting performance of GJR-GARCH model is not good at all.

Gray (1996) introduces Regime Switching GARCH (RS-GARCH) model and compare its forecasting performance with the GARCH model and the Constant Variance model. He analyzes weekly US 1-month T-Bill for the period between January 1970 and April 1994. One-week ahead forecasts are estimated and weekly squared deviations are used to proxy volatility. RS-GARCH model clearly outperforms the other models in forecasting volatility. Empirical findings reveal that interest rate rise increases the probability of switching into high volatility regime. On the other hand, interest rate tend to follow random walk and volatility is highly persistent at the low volatility state.

Hamilton and Lin (1996) conduct a study to compare out-of-sample forecasting performance of several models including Bivariate SWARCH, Univariate SWARCH, GARCH with leverage, ARCH with leverage, AR(1) based on the loss function of MAE. They analyze excess stock returns of S&P500 index and industrial production for the period between January 1965 and June 1993. One month ahead forecasts are estimated and squared monthly residual returns are used to proxy volatility. Empirical findings suggest that SWARCH models produce the best forecasts. Moreover, Hamilton and Lin (1996) report that economic recession drives fluctuations in the volatility of stock returns.

Bera and Higgins (1997) examine daily S&P500 stock index data for the period from 1998 to 1993, weekly $/£ between the period 1985 and 1991, and monthly Industrial Production for the period spanning from 1960 and 1993. One-step ahead forecasts are estimated by employing GARCH and Bilinear models and the forecast performane of those models are compared by using Cox Mean Logarithmic Error (MLE), and RMSE. Empirical findings suggest using GARCH model rather than the other one.

Figlewski (1997) analyzes S&P500, 3-month US Treasury Bill (T-bill), 20-year Treasury Bond (T-Bond), and DM/$ exchange rate data at both daily and weekly frequency. Out-of-sample volatility forecasting performances of HIS and GARCH models are compared based on the loss function of RMSE. According to empirical findings, GARCH(1,1) model outperforms the HIS model when daily data is considered. However, HIS model is found to be better than GARCH(1,1) model when monthly data is analyzed. Figlewski (1997) signifies that the forecast of volatility of the longest horizon is the most accurate.

Andersen and Bollerslev (1998) conduct an analysis on forecasting volatility of the DM/$, and ¥/$. They employ GARCH(1,1) model using data at both daily and 5 minutes frequencies covering the period from 1987 to 1993. One-day ahead forecasts are estimated and forecast performance of GARCH(1,1) model depending on the sample frequency is investigated based on R-square evaluation. Their findings reveal the fact that R-square increases dramatically, from 5% for the daily squared returns to 50% for the 5-min square returns.

Brooks (1998) investigates the predictability of the daily stock return volatility of the stocks traded on NYSE for the period between November 1978 and December 1988. The out-of-sample forecasting performance of several models including RW, HIS, MA, ES, EWMA, AR, GARCH, EGARCH, GJR-GARCH, and the Neural Network are evaluated and compared by using statistical loss functions of MSE, and MAE of variance. One-day ahead forecasts are estimated using rolling 2000 observations for estimation. The forecasting performances of all models are found as approximately the same when October 1987 crash is excluded from the data. Moreover, Brooks (1998) augmented those models by adding lagged volume to form more general ex-ante forecasting models. The motivation behind this idea is based on the evidence of bidirectional causality between volatility and volume. However, volume does not improve forecasting performance of any models as expected.

Walsh and Tsou (1998) conduct a study on Australian stock indices, namely VW20, VW50, and VW300 to compare the volatility forecasting performances of several models including EWMA, GARCH, HIS, and Improved extreme-value (IEV) method. They analyze data at 5-minutes frequencies to form hourly, daily and weekly returns covering the period between January 1993 and December 1995. One-hour, one-day, and one-week ahead forecasts are estimated from a 1-year rolling window sample and volatility models are evaluated and compared by using the statistical loss functions of MSE, RMSE, MAE, and MAPE. They report that HIS and the IEV method were outperformed by EWMA and GARCH in every case. However, they signify that GARCH estimations fail to converge for the weekly series due to the few observations.

Andersen, Bollerslev and Lange (1999) employ GARCH(1,1) model using Deutche Mark/US Dollar exchange rate data at 5-minutes, 10-minutes, 1-hour, 8-hours, 1-day, 5-day, 20-day frequencies in the period between December 1986 and November 1996. Their motivation behind research is to investigate whether using high frequency data provide out-of-sample forecasting gains or not. They estimate 1, 5, and 20 day-ahead forecasts using 5-minutes returns to construct actual volatility. Empirical findings indicate that high frequency GARCH(1,1) models improve forecast accuracy according to statistical loss functions, namely RMSE, MAE, Heteroskedasticity-adjusted RMSE (HRMSE), Heteroskedasticity-adjusted MAE (HMAE), and the logarithmic loss function.

Franses and Ghijsels (1999) conduct a study on the European stock markets, namely Germany, Netherlands, Spain, and Italy in the period between 1986 and 1994. They work with the stock market return data at weekly frequency. They employ Additive Outlier GARCH (AO-GARCH), standard symmetric GARCH, and GARCH with t distribution. Using those models, they estimate one-week ahead forecast from previous four years and squared deviations are calculated to proxy actual volatility. Performance of those volatility models are evaluated and compared according to statistical loss functions of MSE and MedSE. Their empirical findings reveal the fact that forecasting performance of AO-GARCH model is the best among all since parameter estimates of AO-GARCH model are not influenced by the extreme values in the dataset.

Ederington and Guan (2000) analyze the dataset consisting of 5 Dow Jones (DJ) stocks, S&P 500 index, 3-month Eurodollar rate, 10-year T-Bond yield, and DM/$ exchange rate covering the period from 1962 to 1997. They estimate 10, 20, 40, 80, and 120 day ahead volatility forecasts from a 1260-day rolling window conducting several models, namely Geometric Weight Mean Absolute Deviation (GW_{MAD}), Geometric Weight Standard Deviation (GW_{STD}), GARCH, EGARCH, AGARCH, HIS_{MAD} , HIS_{STD}, Their forecasting performance are evaluated and compared by calculating RMSE, and MAE. Empirical findings suggest that absolute returns models produce better forecasts than the square returns models.

Loudon, Watt and Yadav (2000) conduct a study to compare the forecasting performance of GARCH type of models using daily FT All Share index data in the period spanning from 1971 to 1997. Forecasting performance of EGARCH, GJR-GARCH, TS-GARCH, TGARCH, NGARCH, VGARCH, GARCH, MGARCH are evaluated based on the evaluation criterion of RMSE, and regression on log volatility. Using GARCH squared residuals as actual volatility, non-linear, asymmetric versions seem to fare better.

McMillan, Speight and Gwilym (2000) investigate the predictability of volatility of FTSE100 and FT All Share indices. They analyze the stock market data at daily, weekly frequencies in the period spanning from 1984 to 1996, and at monthly frequency covering the period between 1969 and 1996. RW, MA, ES, EWMA, GARCH, TGARCH, EGARCH, CGARCH, HIS and simple regression models are conducted to estimate one-day, one-week, and one-month ahead forecasts and their performance are compared. According to several loss functions, namely ME, MAE, RMSE, Mean mixed error statistics which penalize underpredictions (MME(U)), and Mean mixed error statistics which penalize overpredictions (MME(O)), performances of GARCH family models are not found as good as RW, MA, and ES. RW, MA, and ES models perform better at low frequencies.

Taylor JW (2001) compares the volatility forecasting performances of several models, namely smooth transition exponential smoothing (STES), GJR-GARCH, standard GARCH, MA, and RiskMetrics using stock market indices of Deutscher Aktien IndeX (DAX) of Germany, S&P500, Hang Seng, FTSE100 of the UK, Amsterdam EOE, Nikkei, and Singapore All Share. They work with weekly data covering the period between January 1988 and August 1995. One-week ahead forecasts are estimated using a rolling window with 200 weekly returns. Taylor JW (2001) estimates the aforementioned models based on minimizing in-sample forecasts errors rather than using Maximum Likelihood estimation technique. According to empirical findings, STES model produces the best forecasts for 1-step ahead forecasts.

Andersen, Bollerslev, Diebold and Labys (2002) analyze the predictability of high frequency exchange rate data covering the period from December 1986 to June 1999. They employ various volatility models on the ¥/US$, and DM/US$ quotes. Vector Autoregressive with Realized Volatility (VAR-RV), AR with RV, Fractionally Integrated Exponential GARCH model with RV (FIEGARCH-RV), GARCH model with Daily data (GARCH-D), RM with Daily (RM-D), FIEGARCH with Daily (FIEGARCH-D), VAR with Absolute returns (VAR-ABS) models are conducted to estimate one and ten days ahead forecasts and their forecasting performance are evaluated and compared based on the R-square statistic. According to empirical results, high frequency data improves forecasting accuracy; however, forecasting performance of the models are found as quite same.

Klaassen (2002) conducts a study on the forecasting performance of the new Regime Switching GARCH model relative to standard GARCH(1,1) model. He analyzes daily exchange rate data, US$/£, US$/DM, and US$/¥, covering the period between January 1978 and July 1997. One and ten days ahead forecasts are estimated and mean adjusted one and ten-day return squares are used to proxy actual volatility. Forecasting performance of the RS-GARCH, RS-ARCH, and standard GARCH(1,1) models are compared according to MSE of variance and empirical findings suggest that forecasts generated by GARCH(1,1) model are more variable than Regime Switching models. RS models outperform the standard GARCH(1,1) model and provide out-of-sample forecasting gains for only the series of US$/DM.

Vilasuso (2002) compares the volatility forecasting performance of the FIGARCH, GARCH, IGARCH models using daily exchange rate data, C$/US$, ₣/US$, DM/US$, ¥/US$, £/US$, covering the period the period from March 1979 to December 1999. One, five, and ten days ahead forecasts are estimated and daily squared returns are used to proxy actual volatility. FIGARCH performs better than the other models. Forecasts generated by FIGARCH model are the best according to several loss function criterion of MSE, MAE, and Diebold Mariano’s test.

Forte and Manera (2004) conduct an analysis of the predictability of volatility of Asian, and European stock market indices including Hong Kong, Singapore, Japan, the UK, France, Germany, Italy, Belgium, Switzerland, Greece, Portugal, Spain and Netherlands. They compare VS-GARCH, GJR-GARCH, QGARCH, and the standard GARCH(1,1) models. Their empirical findings suggest taking asymmetric effects into account. It is evidenced that nonlinear models gives more accurate forecasting results than the standard symmetric models.

Martens, van Dijk and de Pooter (2004) develop nonlinear ARFIMA model for realized volatility. Their model generally performs better than several volatility models including GARCH, EGARCH and FIGARCH, Riskmetrics' historical volatility with exponentially declining weights, and stochastic volatility models. S&P 500 index-futures and three exchange rates, the DM/$, ¥/$ and ¥/DM intraday data covering the period from January 3, 1994, until December 29, 2000. Forecasting performance of volatility models are compared based on the loss functions of Mean Squared Prediction Error (MSPE), Mean Absolute Error (MAE), Heteroskedasticity-adjusted MSPE (HMSPE).

Hansen and Lunde (2005) conduct a study to examine out-of-sample forecasting performances of 330 ARCH type of models on the Deutche Mark/US$ exchange rate series and IBM stock return covering the period spanning from January 1990 to May 1999. According to several evaluation criterion, GARCH(1,1) model outperforms the other models for the exchange rate series. However, APARCH(2,2) model performs better than the other models on using IBM stock returns.

Awartani and Corradi (2005) investigate the predictability of the volatility of S&P500 index via GARCH models in an asymmetric fashion. Volatility forecasting performance of GARCH, IGARCH, TS-GARCH, EGARCH, TGARCH, GJR-GARCH, AGARCH, QGARCH, and RiskMetrics models are evaluated and compared according to several tests developed by Diebold Mariano (1995), Clark and McCracken (2001), and White (2000). Allowing asymmetry in the model specification leads to out-of-sample forecasting gains. In the multiple comparison case, the GARCH model is beaten when compared against the class of asymmetric GARCH.

Balaban, Bayar and Waff (2006) conduct an analysis to investigate the out-of-sample forecasting performance of several models, including a random walk model, a historical mean model, moving average models, weighted moving average models, exponentially weighted moving average models, an exponential smoothing model, a regression model, an ARCH model, a GARCH model, a GJR-GARCH model, and an EGARCH model for monthly volatility in daily returns of the stock market indices of Belgium, Canada, Denmark, Finland, Germany, HongKong, Italy, Japan, Malaysia, Netherlands, Philippines, Singapore, Thailand, the UK and the US.

The empirical results reveal that when over-predictions of volatility are penalized more heavily, the exponential smoothing model outperforms the other models; whereas ARCH family models are found to be inferior forecasters.

Chuang, Lu and Lee (2007) conduct a study to examine the volatility forecasting performance of the GARCH models with different statistical distributions, namely exponential generalized beta type two (EGB2), mixture of three normals (M3N), mixture of two normals (M2N), logistic (LOG), exponential power (EXP), mixed diffusion jump (MDJ), normal (N), skewed generalized t (SGT), scaled student’s t (SST), student’s t (ST), SU-normal (SUN), Two-piece mixture of normals (TPM). They analyze stock market and exchange rate data covering the period from 2 January 1996 to 23 October 2003. According to statistical loss functions including MAE, RMSE, LE, for both stock markets and foreign exchange markets, the LOG, the SST distributions and the Riskmetrics models produces the most consistent and best volatility forecasts in general, while the EXP and M2N models are generally outperformed by the other models.

Evans and Mcmillan (2007) analyze the 33 economies covering the period from January 1994 to April 2005 to compare and evaluate the forecasting performances of nine GARCH class models, historical mean, random walk, moving average, and exponential smoothing models. GARCH family models outperform the other models in case of 23 countries, while the moving average model produces the best forecasts in 9 countries including Turkey. Exponential smoothing model provides superior forecasting results in Phillippines stock market returns.

Munoz, Marquez and Acosta (2007) compare the volatility forecasting performance of competing models to estimate and forecast the volatility of S&P500 and IBEX-35 indices in an asymmetric fashion. They conduct Self-Exciting Threshold GARCH (SETAR-TGARCH), the SETAR-Threshold Stochastic Volatility (SETAR-THSV), the GARCH model and Stochastic Volatility (SV) models to examine their forecasting ability and comparing them based on the MSE loss function, and Diebold and Mariano’s sign test. Empirical results depict that The SETAR-THSV with t-distribution is the best model for the IBEX35 returns, whereas simplest SV with t-distribution model produces the best forecasts for the S&P500 returns.

Karmakar (2007) investigates the volatility dynamics in the Indian stock market returns in the period between July 1990 and December 2004 using various GARCH models. According to empirical findings, GARCH(1,1) model outperforms the GARCH(2,1). Karmakar (2007) also reports that EGARCH(1,1) model fits the data well and EGARCH(2,1) model provides the best forecasting results indicating a significant evidence of existence of asymmetric effects in the dataset.

Chen, Gerlach and Lin (2008) conduct an analysis on Nikkei 225 Index (Japan), KOSPI Composite Index (South Korea), Taiwan weighted index (Taiwan), HANG SENG Index (Hong Kong), Straits Times Index (Singapore), and All Ordinaries Index (AORD, Australia) using intraday high-low prices covering the period from January 1, 1998 through December 31, 2004. They conduct standard GARCH, GJR-GARCH, range-based threshold conditional autoregressive model (TARR) and conditional autoregressive range model (CARR) models and compare their forecasting abilities calculating MSE, and MAD loss functions as well as Diebold-Mariano sign test. The TARR models outperform the other popular GARCH models. Moreover, it is asserted that sign and size asymmetry is an important factor in explaning why TARR models dominate the other models in forecasting volatility.

Niguez (2008) conduct an analysis to compare the forecasting performance of volatility and VaR of a number of GARCH family models. They employ standard GARCH, asymmetric GARCH (AGARCH), asymmetric power ARCH (APARCH), exponentially weighted moving average (EWMA), FIGARCH and FIAPARCH assuming that the error terms are distributed as normal or student-t. The data analyzed in their paper is daily closing prices of index IBEX-35, from January 07, 1987 to April 26, 2002. Forecasting performances of those models are evaluated and compared according to Mincer and Zarnowitz (1969) regression test and several statistical loss functions, namely MSPE, MAPE, MME(U), MME(O). According to empirical findings, FIAPARCH model fits the data very well and provide the most accurate forecasts.

Lastly the most recent study, Ou and Wang (2010) use Relevance Vector Machine (RVM) tool to predict GARCH, EGARCH and GJR based volatilities of the Hang Seng Index (HSI) for two stage out-of-sample forecasts. Their main aim is to compare the model with an Support Vector Machine (SVM) method and standard GARCH, EGARCH, and GJR-GARCH models. The data period spans from January 4, 1999 to December 29, 2006 and the dataset is divided into two parts: first part is for the in-sample analysis and the second one is for the out-of-sample analysis. Empirical findings suggest that GJR-GARCH model based on RVM estimation tool is the best volatility forecasting model in the first stage, and EGARCH-RVM model fits the data in the second stage and produces the best forecasts in that period.

To the best of our knowledge, there does not exist any study on forecasting volatility of Turkish stock market returns via GARCH type of models which accommodate sudden volatility shifts due to the structural breaks in the dataset.

CHAPTER III

DATA AND EMPIRICAL RESULTS

It is possible to observe 'sudden' volatility shifts in international markets due to the economic or political crises. Volatility as a key ingredient in investment decisions, e.g. risk management, derivative pricing, hedging, and portfolio construction should be modeled by taking account of those potential structural breaks. Managing risk without considering structural breaks in the time period might lead decision makers in the market to wrong decisions and possible financial looses. The purpose of this chapter is to examine the empirical relevance of structural breaks in modeling and forecasting Turkish Stock Market volatility with generalized autoregressive conditional heteroskedasticity (GARCH) models using both in-sample and out-of-sample tests. Firstly, methodology is discussed and then characteristics of the data are analyzed. Sudden volatility shifts are discussed in our in-sample evaluation. In out-of-sample evaluation, forecast performance of standard GARCH models is compared to a number of GARCH models with several estimation techniques accommodating potential structural breaks in the data.

3.1. Methodology

3.1.1. Descriptive Statistics

Log-returns of price series are calculated as follows:

$$r_t = \ln\left(P_t / P_{t-1}\right) \tag{3.1}$$

where r_t is *continuously compounded return* at time t, P_t and P_{t-1} denote prices at time t and time $t-1$ respectively, and *ln* is the natural logarithm.

Arithmetic mean is calculated by summing all observations and then dividing by the count of those observations. Averages of index returns are calculated as follows:

$$\overline{r_t} = \frac{1}{T}\sum_{t=1}^{T} r_t \tag{3.2}$$

where T is the number of observation.

Standard deviation (σ) is the positive square root of *variance* (σ^2) which measures the variability of returns and is also known as the second central moment. The *standard deviation* is a measure of how widely values are dispersed from the average value and that's why it is also used as a measure of volatility. σ is calculated as follows:

$$\sigma = \sqrt{\frac{\sum (r_t - \bar{r})^2}{T-1}} \tag{3.3}$$

The first two moments of a random variable, namely mean and variance are the determinants of *normal distribution*. For other distributions, *skewness* ($S(r_t)$), normalized third moment of a random variable, and *kurtosis* ($K(r_t)$), the fourth moment of a random variable should be considered. Skewness measures the asymmetry of the distribution whereas kurtosis is used to analyze the tail thickness (Tsay, 2005: 9). Skewness and kurtosis are calculated as follows:

$$\hat{S}_{r_t} = \frac{1}{(T-1)\hat{\sigma}_{rt}^3} \sum_{t=1}^{T} (r_t - \bar{r})^3 \tag{3.4}$$

$$\hat{K}_{r_t} = \frac{1}{(T-1)\hat{\sigma}_{rt}^4} \sum_{t=1}^{T} (r_t - \bar{r})^4 \tag{3.5}$$

where $\hat{\sigma}_{rt}^3$ and $\hat{\sigma}_{rt}^4$ denote third and fourth central moments respectively.

J-B (Jarque & Bera, 1987) is a test to check whether series is normally distributed and computed as follows:

$$J - B = \frac{T}{6}\left(\hat{S}_{rt}^2 + \frac{(\hat{K}_{rt} - 3)^2}{4} \right) \tag{3.6}$$

where *S* and *K* indicate skewness and kurtosis respectively. *J-B* test statistic has a χ^2 distribution with 2 degrees of freedom and has a null hypothesis of normal distribution[10].

Ljung-Box (Q) statistic (Ljung and Box, 1978) checks serial dependency. Q statistic with a null hypothesis of no serial correlation has a χ^2 distribution and it is calculated for both the level of returns and squared returns as follows (Brockwell and Davis, 2002):

$$Q_{LB} = T\left(T+2\right)\sum_{i=1}^{h}\frac{\hat{p}_i^2}{T-i} \tag{3.7}$$

where T denotes number of observation, h denotes number of lags and ρ_i^2 stands for the *i-th* autocorrelation. In this thesis, we also employ the modified version of Ljung-Box Q statistics proposed by West and Cho (1995) that are robust to conditional heteroskedasticity.

3.1.2. Unit Root Tests

Unit root tests, namely Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) check whether return series is stationary. ADF test developed by Dickey and Fuller (1979) is based on the following equation:

$$\Delta y_t = \alpha + \beta t + (\rho - 1) y_{t-1} + \sum_{i=1}^{k}\theta\Delta y_{t-i} + u_t \tag{3.8}$$

where Δ=1-*L*, y_t is stock price at time t, *t* is trend variable. Lag order *k* is determined according to model selection criteria, Akaike or Schwarz information criteria and included to overcome serial correlation problem.

PP test proposed by Phillips and Perron (1988) is based on the following equation:

$$y_t = \alpha + \rho y_{t-1} + \beta(t - N/2) + u_t \tag{3.9}$$

where *N* is the number of observations.

[10] Critical value for J-B statistic is 5.99147

ADF and PP tests the same null hypothesis of having unit root, ρ equals to one, indicating that series have unit root.

KPSS proposed by Kwiatkowski et al. (1992) tests the null hypothesis of stationarity against the alternative of unit root which is the opposite of ADF and PP's null hypothesis. KPSS as a complementary test is more powerful than ADF, and PP since they may lose power against near unit, or fractionally integrated processes (Kwiatkowski et al., 1992; DeJong et. al., 1989; Diebold and Rudebusch, 1991). KPSS test is based on following LM test statistic:

$$LM = \sum_{i=1}^{T} S_i^2 / (T^2 S_{\varepsilon_t}^3) \tag{3.10}$$

where $S_{\varepsilon_t}^3$ is the estimator of the variance of error term, and S_t^2 is the partial sum of the residuals obtained from OLS regression of y_t on deterministic trend, white noise, and stationary error term:

$$y_t = \phi t + r_t + u_t$$

$$\text{where } r_t = r_{t-1} + u_t \text{ , and } u_t \sim N(0, \sigma_u^2). \tag{3.11}$$

3.1.3. ARCH LM Test (TR^2)

Autoregressive Conditional Heteroscedasticity (ARCH) Lagrange Multiplier (LM) test is applied to check the existence of ARCH effects[11] in time series (Engle R. F., 1982). ARCH LM test with a χ^2 distribution with degrees of freedom q is computed with an auxiliary test regression:

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \upsilon_t \tag{3.12}$$

[11] ARCH effect means that residuals obtained from regression do not have a constant variance over time, indicating heteroscedasticity. In addition, testing ARCH effect is simply checking for autocorrelation in the squared residuals.

where ε is the residual. TR^2 is calculated from equation (3.12) and tests the null hypothesis of no ARCH effects[12] in the residuals where T is number of observations and R^2 denotes coefficient of determination.

3.1.4. Autoregressive Conditional Heteroscedasticity Models

Generalized autoregressive conditional heteroskedasticity (GARCH) model proposed by Bollerslev (1986) is an econometric model that is the generalization of autoregressive conditional heteroskedasticity (ARCH) model by Engle (1982). It is a more powerful model than conventional autoregressive moving-average (ARMA) models that assume constant variance over time. ARCH model that embodies two characteristics of volatility-clustering and mean reversion, has a regression form on itself, and is able to model (time-varying) conditional volatility (Alexander, 2008), (Engle, 2009).

ARCH(q) model enables users to estimate mean and variance of time series (daily stock returns) simultaneously (Enders, 2010). Mean and variance equations can be written as follows:

$$r_t = \omega + \varepsilon_t = \omega + v_t \sqrt{h_t}, \quad v_t \mid I_{t-1} \sim i.i.d.D(0,1) \tag{3.13}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{3.14}$$

where ω denotes constant term, h_t is conditional variance of errors (ε_t), I_{t-1} is for all available information at time *t-1*. *D* refers statistical distributions; *q* is the order of the moving average ARCH terms. ARCH model posits several constraints on coefficients of variance equation to ensure the positiveness of conditional variance, h_t: $\alpha_0>0$, $\alpha_i>0$. Unconditional[13] (long-run) variance, σ^2 for ARCH(q) process is calculated as follows:

[12] Rejection of null hypothesis basically suggests that using (G)ARCH family models is appropriate for the data.

[13] Difference between conditional and unconditional variance is that conditional variance is time-varying and changes at every point in data set, but unconditional variance is just a single number indicates long-term average of variance over all time period

$$\sigma^2 = \frac{\alpha_0}{\sum_{i=1}^{q} \alpha_i} \tag{3.15}$$

Bollerslev's (1986) model, GARCH(p,q)[14], includes a GARCH term into variance equation is based on following equations:

$$r_t = \omega + \varepsilon_t = \omega + v_t \sqrt{h_t}, \quad v_t \mid I_{t-1} \sim i.i.d.D(0,1) \tag{3.16}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-j}^2 \tag{3.17}$$

where *p* is the order of last period forecast variance, GARCH term, (σ_{t-j}^2). Non-negativity constraints are hold for GARCH(p,q). Since GARCH(p,q) is the generalized form of ARCH(q), when *p* equals to zero GARCH(p,q) model simply takes the form of ARCH(q). Unconditional variance for GARCH model is computed as follows[15]:

$$\sigma^2 = \frac{\alpha_0}{1 - \left(\sum_{i=1}^{q} \alpha_i \right) - \left(\sum_{j=1}^{p} \beta_j \right)} \tag{3.18}$$

Non-negativity and stability constraints are still hold for GARCH model as in ARCH:

$$\omega > 0,\ \alpha, \beta \geq 0,\ \alpha + \beta < 1 \tag{3.19}$$

where the last one is called stability condition, and sum of α, and β is measure of persistence.

Glosten, Jagannathan and Runkle (1993) introduce GJR-GARCH model. This model is formulated to capture the leverage effect, that is to say, future volatility is affected differently from the the past negative and positive innovations. GJR-GARCH is based on following equation:

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[14] GARCH model is simultaneously developed by Taylor (1986) and Bollerslev (1986).

[15] Unconditional variance is constant over time and could be defined if and only if the GARCH process is covariance stationary, satisfying the conditions of sum of α + β < 1 and ω>0.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I\left(\varepsilon_{t-1} < 0\right) + \beta\sigma_{t-1}^2, \tag{3.20}$$

where statistically significant and positive γ denotes the existence of leverage effect.

Baillie, Bollerslev, Mikkelsen (1996) develop the Fractionally Integrated GARCH (FIGARCH) model to better capture long-memory properties relying on ARFIMA representations. This model is closely related to IGARCH model of Engle and Bollerslev (1986) and may be expressed in the ARMA representation as follows:

$$\varphi\left(L\right)\left(1-L\right)^d \varepsilon_t^2 = \omega + \left(1-\beta\left(L\right)\right)\nu_t, \tag{3.21}$$

where $\upsilon_t \equiv \varepsilon_t^2 - \sigma_t^2$, $0 < d < 1$, and the roots of $\varphi\left(z\right) = 0$ and $\beta\left(z\right) = 0$ are all outside the unit root circle (Bollerslev, 2010). If the d parameter is estimated in the interval of $0 < d < 0.5$ then it can be concluded that there exist an evidence of long memory property in the GARCH process. Long memory in finance theory is against the Efficient Market Hypothesis of Fama (1970) since long memory, or fractional slowly decaying hyperbolic dependencies in the conditional variance, means that high order of autocorrelation in squared returns.

Haas et al. (2004) propose a new approach to Markov-Switching GARCH models. They extend previous RS-GARCH models to a multi regime setting. According to Haas et al. (2004), their model has the advantage of being analytically tractable and allows the researchers to derive stationary conditions. A general form of RS-GARCH (1,1) model can be written as follows:

$$h_t^{(i)} = \omega^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta_1^{(i)} h_{t-1}, \quad i = 1,2,... \tag{3.22}$$

where h_{t-1} is a state-independent average of past conditional variances.

3.1.5. GARCH Estimation Techniques in Out-of-Sample Analysis

Stock index return series are divided into in-sample and out-of-sample portions, where the in-sample portion spans the first S observations and the out-of-sample portion the last K observations. The dataset consists of T observations where T is equal to sum of S and K.

3.1.5.1. Benchmark Models

Out-of-sample forecasts are GARCH(1,1)/FIGARCH(1,d,1) model using data from the first observation through S and then estimation window is expanded by one observation to form a forecast for the next period. Particularly, forecast for the period S+1 is generated by estimating GARCH(1,1)/FIGARCH(1,d,1) model from the first observation through S. Moreover, forecast for the period S+2 is generated by estimating GARCH(1,1)/FIGARCH(1,d,1) model from the first observation through S+1 and so on.

3.1.5.2. Competing Models

Five competing models' estimation windows are designed to accommodate structural breaks in the unconditional variance of daily stock index returns.

GARCH(1,1) model with 0.50 rolling window (0.50 Rolling Window) is estimated using a rolling window with size equal to one half of the S observations. First forecast for the period S+1 is generated by estimating 0.50 Rolling Window based on observations 0.5S+1 through S, second one is estimated based on observations 0.5S+2 through S+1, and so forth.

GARCH(1,1) model with 0.25 rolling window (0.25 Rolling Window) is estimated using a rolling window with size equal to one quarter of the S observations. First forecast for the period S+1 is generated by estimating 0.25 Rolling Window based on observations 0.75S+1 through S, second one is calculated based on observations 0.75S+2 through S+1, and so forth.

GARCH(1,1) model with weighted Maximum Likelihood (Weigted ML) procedure assigns declining weights to observations in the more distant past when forming the likelihood function. Particularly, forecast for the first period of S+1 is estimated using a window from first observation through S. In this case, A weight of ρ^{S-t} is attached to observation t (t=1,…,S) in the log-likelihood function where ρ is equal to 0.994. Forecast for the period S+2 is generated by estimating Weigted ML model from the first observation through S+1 where a weight of ρ^{S+1-t} is attached to observation t (t=1,…,S+1) in the log-likelihood function.

Estimation window for GARCH(1,1) with Breaks (With Breaks) model is determined by employing the modified ICSS algorithm. The modified ICSS algorithm is first applied to in-sample data period, to the observations one through S. If the ICSS algorithm detects one or more breakpoints in the data period, then GARCH(1,1) model with expanding window is estimated using observations T_B+1 through S to estimate the first forecast where T_B represents the final breakpoint suggested by the modified ICSS algorithm. If the modified ICSS procedure does not suggest any significant breakpoint in the data we estimate a GARCH(1,1) model using observations one through S to form an estimate of first forecast.

Lastly, Moving Average model is applied to estimate volatility forecasts. This model allows unconditional variance to change over time, thus considers structural breaks in the data. Moving Average model uses average of the squared returns over the previous 250 days to estimate the volatility forecast and often performs better at longer forecast horizons (Starica et al., 2005)

3.1.6. ICSS Algorithm

Iterative Cumulative Sum of Squares (ICSS) algorithm is based on D_k statistics and tests the null hypothesis of constant unconditional variance. D_k statistics is computed as follows:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \qquad k = 1,...,T \text{ with } D_0 = D_t = 0 \qquad (3.23)$$

where $C_k = \sum_{t=1}^{k} \varepsilon_t^2, k = 1,...,T$ [16]. C_k is the cumulative sum of squares of ε_t. Then, the test proposed by Inclan and Tiao (1994) can be written as follows:

$$IT = \sup_k \left| \sqrt{T/2} D_k \right| \qquad (3.24)$$

where $\sqrt{T/2}$ is used to standardize the distribution. One can conclude that k^*, which is the point of k at which $\sup_k |D_k|$ is obtained, is a change of variance when

[16] Note that D_k statistics have value around zero. However, when change in unconditional variance occurs, D_k statistics take value different from zero in either sign, negative or positive.

$IT = \sup_k \left| \sqrt{T/2} D_k \right|$ exceeds the predetermined boundary estimated by the Inclan Tiao (1994). The asymptotic distribution of the test under the assumption that $\varepsilon_t \sim i.i.d.(0,\sigma^2)$ [17] is based on following notation:

$$IT \Rightarrow \sup_r \left| W^*(r) \right| \tag{3.25}$$

where $W^*(r) \equiv W(r) - rW(1)$ is a Brownian Bridge, W(r) is a standard Brownian motion and $\Rightarrow$ denotes weak convergence of the associated probability measures (Sanso et al., 2004).

Since financial data have generally excess kurtosis (greater than three), and inconstant variance over time, there might be some drawbacks using aforementioned ICSS algorithm because it assumes that $\varepsilon_t \sim i.i.d.(0,\sigma^2)$. To overcome these shortcomings, Sanso et al. (2004) proposed two tests, namely Kappa-1, and Kappa-2 which consider the fourth moment properties of the disturbances and the conditional heteroskedasticity.

Kappa-1 test corrects for non-mesokurtosis and it is a generalized form of IT. The asymptotic distribution of the Kappa-1 test under the conditions of $\varepsilon_t \sim i.i.d.(0,\sigma^2)\ and\ E(\varepsilon_t^4) \equiv \eta_4 < \infty$ can be written as follows:

$$IT \Rightarrow \sqrt{\frac{\eta_4 - \sigma^4}{2\sigma^4}} \sup_r \left| W^*(r) \right| \tag{3.26}$$

Thus, the distribution has nuisance parameters and numerous distortions can occur when critical values of maximization of a Brownian Bridge are used. It is possible to experience that null hypothesis of constant variance might be rejected too many times when distribution is heavily tailed, in other words, leptokurtic[18] ($\eta_4 > 3\sigma^4$). However, when distribution is platykurtic (negative excess kurtosis), the test becomes so prudent that there would not be too many conclusions of inconstant variance. Hence Sanso et al. (2004) suggest following correction for the IT test to be

[17] ε_t are a zero mean, normally, identically and independently distributed random variables.

[18] Under normal distribution $\eta_4 = 3\sigma^4$ and $IT \Rightarrow \sup_r \left| W^*(r) \right|$

free of nuisance parameters for identical and independent zero-mean random variables:

$$\kappa_1 = \sup_k \left| \frac{1}{\sqrt{T}} B_k \right| \tag{3.27}$$

where $B_k = \dfrac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}_4}}$ and $\hat{\eta}_4 = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_t^4$ *and* $\hat{\sigma}^2 = \frac{1}{T} C_T$. Asymptotic distribution under the same conditions of equation 8 can be adjusted as follows:

$$\kappa_1 \Rightarrow \sup_r \left| W^*(r) \right|. \tag{3.28}$$

In case of a conditionally heteroskedastic process, IT and Kappa-1 lose power because they have an assumption of independence of the random variables which is not appropriate for the financial data (Bollerslev et al., 1992; 1994). To correct for non-mesokurtosis and persistence in conditional variance some additional assumptions on ε_t are required similarly following Herrndorf (1984) and Phillips and Perron (1988). Sanso et al. (2004) assume that sequence of random variables, $\{\varepsilon_t\}_{t=1}^{\infty}$ is consistent with following conditions:

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

If the second and the third conditions are hold, it is not the case that ε_t in data sequence are distributed as student-t distribution with three degrees of freedom. ω_4 is the long-run variance of the zero mean variable $\xi_t = \varepsilon_t^2 - \sigma^2$. Fourth condition controls for the degree of independence of the data sample and shows a trade-off between serial dependence and the existence of high order moments (Sanso et al., 2004: pp. 5).

In the light of the facts that Kappa-2 test is based on following equation:

$$\kappa_2 = \sup_k \left| \frac{1}{\sqrt{T}} G_k \right| \tag{3.29}$$

where $G_k = \frac{1}{\sqrt{\hat{\omega}^4}} \left(C_k - \frac{k}{T} C_T \right)$ and $\hat{\omega}^4$ is a consistent estimator[19] of ω_4.

Consequently, under four conditions above, IT, Kappa-1, Kappa-2 can be written as follows:

$$IT \Rightarrow \sqrt{\frac{\omega_4}{2\sigma^4}} \sup_r \left| W^*(r) \right| \tag{3.30}$$

$$\kappa_1 \Rightarrow \sqrt{\frac{\omega_4}{\eta_4 - \sigma^4}} \sup_r \left| W^*(r) \right| \tag{3.31}$$

$$\kappa_2 \Rightarrow \sup_r \left| W^*(r) \right| \tag{3.32}$$

3.2. Data

The data analyzed in this thesis are daily returns of Istanbul Stock Exchange (ISE) indices including ISE National-100 (ISE-100), and sector indices namely ISE-Financial (ISE-FIN), ISE-Industrial (ISE-IND), and ISE-Service (ISE-SRV). Continuously compounded daily returns series are calculated by taking difference of natural logarithm of price indices[20]. Data for ISE-100 covers the period from January 4th 1988 to March 4th 2010[21]. ISE-FIN and ISE-IND indices span from January 2nd 1991 to March 4th 2010 and ISE-SRV is analyzed in the period between January 2nd

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[19] Sanso et al. (2004) also suggest to use non-parametric estimator of ω_4:

$$\hat{\omega}_4 = \frac{1}{T} \sum_{t=1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}^2 \right)^2 + \frac{2}{T} \sum_{l=1}^{m} w(l,m) \sum_{t=l+1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}^2 \right) \left(\varepsilon_{t-l}^2 - \hat{\sigma}^2 \right)$$ where *w (l, m)* is a lag window.

It should be added when $\xi_t = \varepsilon_t^2 - \sigma^2$ and then $\hat{\omega}_4 \to E(\xi_t^2) = \eta_4 - \sigma^4$.

[20] Return series is mostly used in financial literature instead of price series because of several appropriate statistical properties, namely stationarity, ergodicity. In addition, return of an asset is a complete and scale-free of the investment, put another way, returns are unit-free (Campbell, Lo, & Mackinlay, 1997, p.9; Tsay, 2005, p.2; Brooks, 2008, p.7).

[21] Although, ISE-100 index is available from January 1986, following (Kasman & Torun, 2007), we analyzed ISE-100 index for this period because of the disorderliness of the data before the year 1988.

1997 and March 4th 2010. Data is obtained from Electronic Data Delivery System of the Central Bank of the Republic of Turkey[22]. In addition to ISE-100 index, sectoral indices are also examined for providing specific information for the investors diversifying their portfolio risks' by investing in various corporations from different sectors (Maliq and Hassan, 2004: 211).

Descriptive statistics for the four daily ISE index returns are presented in Table 1. In Panel A of Table 1 mean, standard deviation, skewness, and excess kurtosis are reported with their heteroskedastic and autocorrelation consistent standard errors following Rapach and Strauss (2008) and West and Cho (1995). All of the means are significantly different from zero. Mean for the return series of all indices except ISE-SRV vary between 0.15% and 0.16%. Standard deviation statistics of all indices are also significant at 1% level. Skewness, symmetry measure of the distribution, is negative for ISE-100, ISE-FIN, and ISE-IND indices, indicating that the distributions of them are all left-skewed, whereas skewness of ISE-SRV index is right skewed since it is found as 0.015%. Structural breaks such as economic and/or political crises occurred in the data period might be one of the reasons of the left skewed distribution of most indices. Figure 4 reveals that, ISE-SRV which dramatically starts to increase after the global financial crisis occurred in the late of 2007 exceeds the higher price levels than before that financial turmoil and exhibits a peak level in the late of 2009. Additionally, time span of ISE-SRV does not go back year 1997. This situation might lead to right skewness for the ISE-SRV. However, none of the indices exhibits significant skewness at 1% level. We found that all of the indices display significant excess kurtosis which is a well-known stylized fact of the stock market data. In Table 1, excess kurtosis denotes that kurtosis statistics for any index is calculated greater than three. It is conspicuous that the ISE-SRV index has the highest excess kurtosis among all with 5.97%, whereas the others' excess kurtosis statistics range between 3.14% and 4.25% revealing the fact that Turkish stock market indices have leptokurtic distribution in that time horizon.

[22] www.tcmb.gov.tr

We compute the modified Ljung-Box (LB) statistics which reveal significant evidence of autocorrelation in stock market indices except ISE-SRV. It is noteworthy that magnitude of modified LB statistic with respect to standard LB statistics (tough not reported here) declines, indicating that there are still strong evidence of serial correlation in the level of returns. Standard LB test statistics, however, indicate the existence of serial dependence in squared returns for all indices. Existence of serial dependence in both the levels and the squared returns imply volatility clustering and dependence between distance observations (Kasman and Torun, 2007). Engle's (1982) ARCH LM test statistics suggest that there exist significant ARCH effects for all indices, providing additional evidence for modeling daily ISE return indices via GARCH models.

Overall, it is clear from the summary statistics that ISE-SRV has a different characteristic among all other sector indices, fortifying our concern of analyzing ISE-100 index along with sub-sector indices to reach more accurate conclusions for the Turkish Stock Market. It is noteworthy that descriptive statistics of ISE-FIN are calculated very close to the statistics of ISE-100, denoting the fact that companies take part of the ISE-100 index, a proxy for the Turkish Stock Market for many studies in the past (e.g. Durukan, 1999; Kasman and Torun 2007) are mostly financial institutions. In other words, Turkish Stock Market might be lead significantly by the financial institutions.

Stationarity tests, namely Augmented Dickey-Fuller (1979) (ADF), Phillips-Perron (1988) (PP), and Kwiatkowski et al. (1992) (KPSS) are reported in Table 2. According to those unit root tests, all series are found as integrated of order zero (0), regardless the trend variables are taken into consideration. Thus, all series are found as stationary which denotes another desirable statistical property of our dataset for the volatility modeling.

Table 1: Summary Statistics, ISE Daily Return Indices

A. Stock Returns				
	ISE-100	**ISE-FIN**	**ISE-IND**	**ISE-SRV**
Mean	0.1614 (0.0403)	0.1639 (0.0453)	0.1502 0.0378)	0.1068 (0.0472)
Standard deviation	2.8459 (0.0496)	3.1326 (0.0515)	2.6088 (0.0473)	2.7047 (0.0667)
Skewness	-0.0462 (0.1219)	-0.0106 (0.1206)	-0.1235 (0.1479)	0.0156 (0.2304)
Excess kurtosis	3.2823 (0.5131)	3.1352 (0.4428)	4.2525 (0.5927)	5.9653 (0.8968)
Minimum	-19.9785	-20.8422	-18.0142	-19.2559
Maximum	17.7736	17.4553	18.0447	17.3327
Modified LB (20)	63.4891 (0.000)	46.0240 (0.000)	41.8419 (0.003)	23.4655 (0.267)
B. Squared Stock Returns				
LB (20)	1927.9952 (0.000)	1377.8920 (0.000)	2139.0230 (0.000)	1057.0326 (0.000)
TR^2 (2)	565.5024 (0.000)	404.4312 (0.000)	717.7519 (0.000)	397.6896 (0.000)
TR^2 (10)	691.5874 (0.000)	517.5397 (0.000)	806.6856 (0.000)	443.3267 (0.000)

Note: Returns are defined as 100 times the log-differences of daily ISE indices. Ljung-Box statistics correspond to a test of the null hypothesis that the first r autocorrelations are zero. Modified Ljung-Box statistics are robust to conditional heteroskedasticity. ARCH Lagrange multiplier statistics correspond to a test of the null hypothesis of no ARCH effects from lag orders 1 through q. P-values are given in brackets; 0.000 indicates less than 0.0005.

Table 2: Unit Root Tests

		ISE-100	ISE-FIN	ISE-IND	ISE-SRV
ADF	η_μ	-21.0801(9)*	-19.3761(10)*	-17.0709(12)*	-15.1099(12)*
	η_τ	-21.1151(9)*	-19.4157(10)*	-17.1206(12)*	-15.1429(12)*
PP	η_μ	-67.1686(16)*	-64.8222(14)*	-64.0858(18)*	-56.8737(6)*
	η_τ	-67.1149(15)*	-64.826(14)*	-64.0820(18)*	-56.8876(6)*
KPSS	η_μ	0.2676(19)	0.2758(16)	0.3346(20)	0.1926(5)
	η_τ	0.0536(19)	0.0605(16)	0.0265(20)	0.0892(6)

Note: η_τ, and η_μ refer to the test statistics with and without trend, respectively. * denotes statistical significance at level of 1%.

3.3. Empirical Findings

In modeling and forecasting volatility of stock markets, (G)ARCH family models have gained attention and used by many finance researchers since they are simple to implement and are able to cover the stock return volatility features such as clustering and mean-reverting. However, estimating and forecasting volatility via GARCH type of models under the assumption of a stable GARCH process governs conditional stock market volatility[23], might lead one to biased results since financial markets are subject to sudden large shocks, such as domestic or global economic crises (Diebold, 1986; Hendry, 1986; Lastrapes, 1989; Lamoureux and Lastrapes, 1990). Financial or economic crises might cause sudden structural breaks in both unconditional variance of stock market returns and estimated parameters of GARCH process. Put another way, GARCH process might not be stable anymore and estimated parameters could change over time due to the sudden breaks in volatility (Mikosch and Stărică, 2004; Rapach and Strauss, 2008). Thus, it is important to take account of these sudden shifts in volatility in modeling volatility and forecasting exercises.

Table 3: Break Dates for Daily ISE Index Returns

Break Number	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
1	January 7, 1997	October 23, 1997	April 15, 2003	March 18, 2003
2	March 24, 2003	March 24, 2003		
3		June 7, 2004		
4		July 17, 2007		

Modified iterative cumulative sum of squares (hereafter ICSS) algorithm is implemented to detect potential structural breaks in the unconditional variance of return series of four ISE indices. The modified ICSS algorithm determines a single structural break for ISE-IND, ISE-SRV; two structural breaks for ISE-100; and four structural breaks for ISE-FIN. One or more variance breaks are selected by the modified ICSS algorithm for all ISE indices, indicating instable GARCH processes governing volatility for all of them. Break dates for daily ISE index returns are reported in Table 3. Sudden changes in unconditional variances identified by the modified ICSS algorithm appear to be associated with significant economic events.

The first structural breaks of ISE-100 and ISE-FIN occurred in the year 1997. The most important economic event in 1997 was Asian currency crisis which had affected several Asian countries namely, Thailand, Indonesia, South Korea, Hong

[23] In this case, it is assumed that unconditional (long-run) variance is constant over time. Distinction between unconditional and conditional volatility is stressed in the Appendix B.

Kong, Malaysia, Singapore, and Philippines since July 1997. However, volatility shifts of ISE-100 and ISE-FIN were mostly related with local factors. In the period spanning from December 1996 to January 1997, Turkish stock market was testing its peak levels due to the privatization arrangements. Nevertheless, investing in stock market was said to be very risky because of the low transaction volumes along with the increases in the index value in this period. Moreover, Turkish stock market had increased steadily from the index value of 2,943 to 3,451 performing a 17.6% increase in the third week of October 1997. During this period value of some common stocks increased for about 70%-80% which is much more than any financial instruments' yield. Inflation targeting programme by the government, privatization arrangements, and also increases in the transaction volume of Turkish stock market to the daily level of $700 million had triggered the increases in the volatility of ISE indices.

The modified ICSS procedure detected a significant increase in volatility in spring 2003 for all sector indices and ISE 100 index. This could be due to the Iraq War which began on March 20, 2003 with the invasion of Iraq. Turkish stock market decreased by 11.29% during the week from March 17-21, 2003. In addition, the second round of the Assembly session including governmental decree to send Turkish troops to Iraq was another source of this volatility increase. The second volatility shift of ISE-100 index on March 24-25, 2003 is due to the concerns that Iraq war could last longer than expected. At this date, ISE-100 index decreased to the lowest level of the last five months and trading volume decreased substantially. Particularly, information flow about the Iraq War is again the main reason for the only structural break for ISE-IND is detected on April 15, 2003. There is a significant increase in volatility of ISE-FIN on June 7, 2004. The closing price of index reached its maximum level on that date. In addition to the positive developments in international markets, decreases on the Turkish Treasury bill rates, the value of the U.S. dollar against Turkish Lira (TL) and the inflation rate of May were the major determinants of this increasing trend in Turkish stock market.

Figure 1: Daily ISE-100 index prices and returns

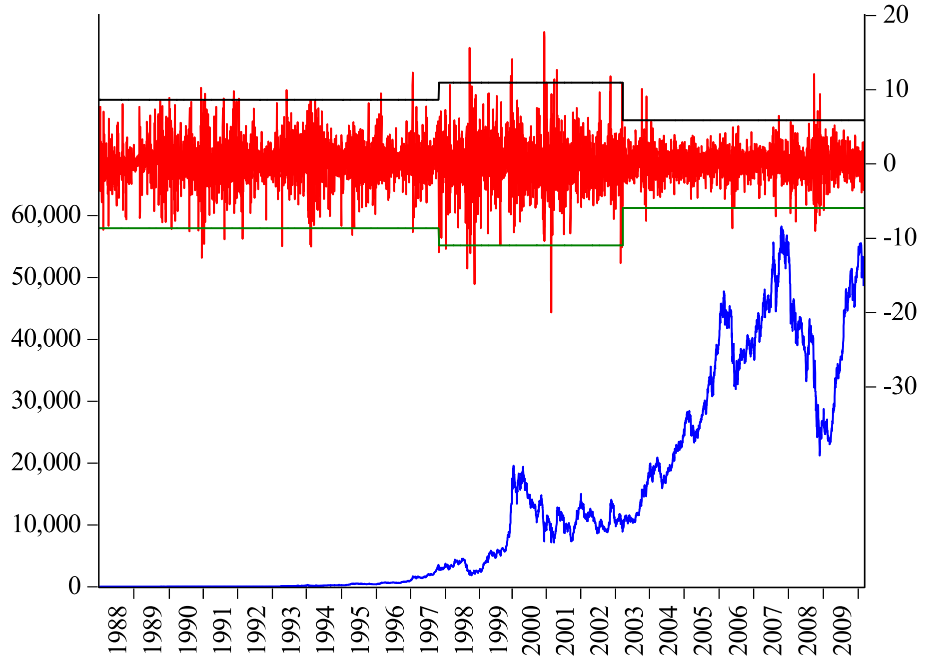


Figure 2: Daily ISE-FIN index prices and returns

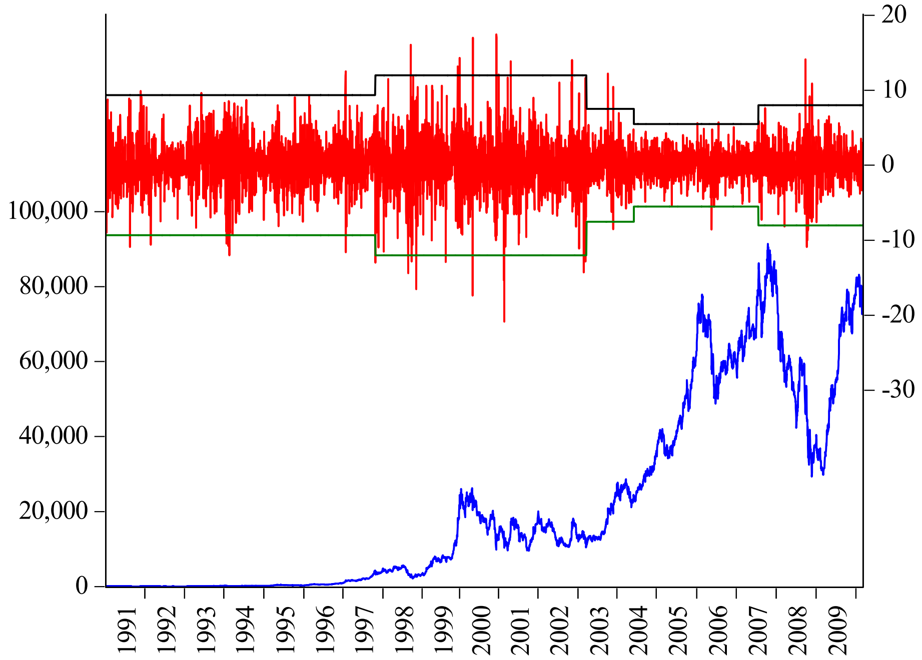


Figure 3: Daily ISE-IND prices and returns

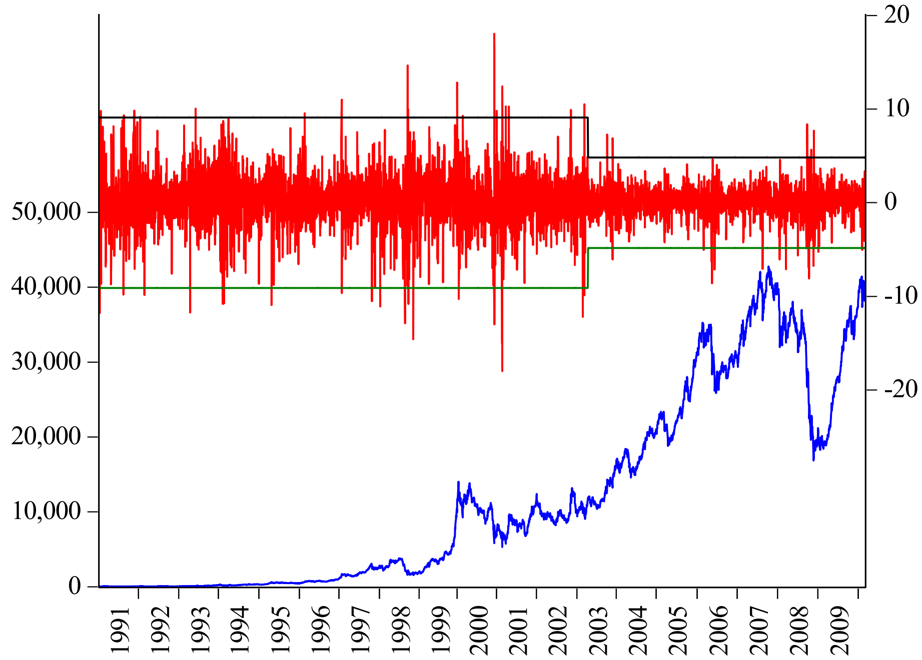
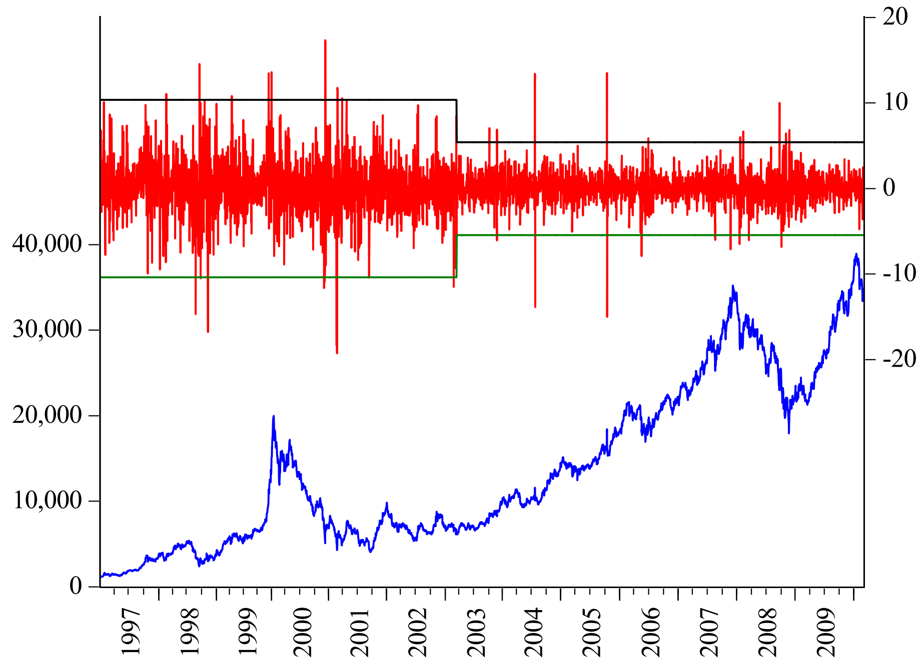


Figure 4: Daily ISE-SRV index prices and returns



The shift in volatility in ISE-FIN index on July 17, 2007 might be the result of the general elections in Turkey. During the third week of July, Turkish stock market increased substantially due to the effect of the optimistic expectations of investors on the grounds that eventually a single party government would again be formed after the elections in Turkey.

The results of the modified ICSS algorithm show that the stock market indices were mostly influenced by domestic factors. One can expect that modified ICSS procedure should be able to detect additional breakpoints for the well-known financial crises such as, 1997 Asian currency crisis, 1998 Russian crisis, 2000-2001 Turkish banking crisis.

However, this algorithm determines only radical regime shifts. If we analyze the changes of the indices on the figures from 1 to 4 which denote the daily prices and returns of ISE indices along with three-standard-deviation bands for each of regimes identified by the structural breaks, we can see these radical shifts clearly. ISE indices exhibit a dramatic increase after 2003 and the index level goes far away from the level of 1998-2003 period rapidly. In addition, it is can be clearly observed that, the speed of increase in index levels during the 2004-2007 period is somewhat higher than that of the 2003-2004 period. On the other hand, the shift during the period 2003 to 2004 is higher than the shifts for the one year periods following. The shift in 2007 can be explained on the grounds that the index was testing its peak level after the period spanning from 2004 to 2007 and then it had begun to fall sharply depending on the effects of the most recent global financial crisis.

3.3.1. In-Sample Estimation Results of GARCH (1,1) Models

Having found that there are one or more sudden volatility shifts in the ISE index returns, we estimate GARCH(1,1) for all ISE indices for the full-sample as well as for each of subsamples defined by the modified ICSS algorithm and report the Quasi Maximum Likelihood Estimation (QMLE) results for GARCH (1,1) models in Table 4[24]. Panel A of Table 4 denotes the GARCH (1,1) full sample estimation results including parameter estimates of the variance equations, unconditional variances and half-life shocks for each indices. Error parameter α indicates the reaction of conditional volatility of each index to market shocks (Alexander, 2008:137). α parameter values range between 0.0975% and 0.1556%. ISE-SRV has the highest α parameter value, indicating that volatility is more sensitive to market conditions than the others. In other words, the effect of a shock to the volatility at time *t* is much more pronounced in period *t+1* for ISE-SRV and ISE-100 suggesting that large α parameter value might be followed by another large α which is the indicator of the volatility clustering in financial series (Tsay, 2005:103; Enders, 2010:148). The GARCH parameter, β, measures the persistence in conditional variance regardless market events are taken into consideration (Alexander, 2008:137). Large values of *c* suggest that the volatility takes a long time to die out and denote conditional volatility exhibits much more autoregressive persistence (Enders, 2010:148). The largest β value is belonging to ISE-FIN index. This situation helps in explaining why ISE-FIN has the utmost volatility shifts among all. Parameter estimates reveal that the sum of α and β, degree of autoregressive decay of the squared residuals, is very close to 1 indicating that the GARCH process of all ISE indices is highly persistent[25] ranging from 98.2% to 99.3% consistent with the findings Aggarwal et al. (1999), Lamoureux and Lastrapes (1990), Malik (2003), Ewing and Malik (2005), Kasman (2009), and Cagli et al. (2010). Another important implication is that if the persistence is calculated very high, then it takes longer time for the forecasts to converge the level of unconditional variance, for instance 1-year (Alexander, 2008:142). Significancy and magnitude of ω, conditional average volatility, is very important in explaining the unconditional (long-term) variance along with the sum of α and β.

[24] Hammoudeh et al. (2009) use QMLE when series are not distributed as standard normal.

[25] Carol Alexander (2008:137) states that the larger the value of α + β, the (relatively) the more flat the term structure of volatility forecast is.

Table 4: Quasi maximum likelihood estimation results for GARCH(1,1) models

	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
A. GARCH (1,1) full sample estimation results				
ω	0.197 (0.037)	0.1679 (0.0362)	0.0917 (0.0185)	0.1900 (0.0352)
α	0.136 (0.012)	0.0975 (0.0105)	0.1231 (0.0117)	0.1556 (0.0183)
β	0.846 (0.014)	0.8882 (0.0121)	0.8702 (0.0117)	0.8293 (0.0178)
Long-RunVar.	11.2280 (2.625)	11.7721 (2.3997)	13.5653 (7.8513)	12.6114 (5.3719)
Half-Life Shock	38.16	48.12	103.11	45.56
B. GARCH (1,1) estimation results for the sub-samples defined by the structural breaks				
Subsample 1	**January 4, 1988- January 7, 1997**	**January 2, 1991 - October 23, 1997**	**January 2, 1991- April 15, 2003**	**January 2, 1997- March 18, 2003**
ω	0.722 (0.137)	0.3751 (0.1293)	0.6874 (0.1442)	0.8534 (0.2791)
α	0.241 (0.029)	0.1215 (0.0231)	0.1589 (0.0198)	0.1381 (0.0261)
β	0.686 (0.035)	0.8404 (0.0320)	0.7677 (0.0309)	0.7944 (0.0422)
Long-RunVar.	9.894 (1.630)	9.8419 (1.6454)	9.3654 (0.8999)	12.6583 (1.6962)
Half-Life Shock	9.14	17.84	9.09	9.92
Subsample 2	**January 8, 1997 March 24, 2003**	**October 24, 1997 - March 24, 2003**	**April 16, 2003 - March 4, 2010**	**March 19, 2003 - March 4, 2010**
ω	1.290 (0.398)	2.2557 (0.6415)	0.1407 (0.0371)	0.6508 (0.1738)
α	0.140 (0.027)	0.1622 (0.0314)	0.1153 (0.0190)	0.2015 (0.0362)
β	0.763 (0.050)	0.6992 (0.0610)	0.8306 (0.0285)	0.6084 (0.0753)
Long-RunVar.	13.325 (1.430)	16.2709 (1.5602)	2.5985 (0.3136)	3.4232 (0.2943)
Half-Life Shock	6.79	4.65	12.46	3.29
Subsample 3	**March 25, 2003 March 4, 2010**	**March 25, 2003 - June 7, 2004**		
ω	0.153 (0.046)	0.3783 (0.4222)		
α	0.091 (0.016)	0.0801 (0.0553)		
β	0.869 (0.024)	0.8626 (0.1110)		
Long-RunVar.	3.862 (0.479)	6.5991 (1.4451)		
Half-Life Shock	16.98	11.75		
Subsample 4		**June 8, 2004 - July 17, 2007**		
ω		0.4009 (0.1758)		
α		0.0828 (0.0285)		
β		0.7992 (0.0685)		
Long-RunVar.		3.3968 (0.3026)		
Half-Life Shock		5.52		
Subsample 5		**July 18, 2007 - March 4, 2010**		
ω		0.1868 (0.0976)		
α		0.0775 (0.0215)		
β		0.8948 (0.0300)		
Long-RunVar.		6.7576 (1.5564)		
Half-Life Shock		24.68		

Unconditional variance for ISE-IND has the highest value among all, since persistence is very high and average conditional volatility is calculated as 0.0917. ISE-100 index in this analysis covers the longest time period of all and it has the lowest unconditional variance along with two sudden volatility shifts. In Table 4, we also report half-life shocks which measure the number of days a shock to conditional variance reduces to half its original size. Half-life shock for ISE-IND through full sample is computed dramatically high, suggesting that a shock to conditional variance reduces to half its original size in about four months. The other indices have relatively lower half-life shocks ranging between 38 and 48 days.

In Panel B of Table 4, GARCH (1,1) estimation results for the sub-samples defined by the structural breaks are summarized. Generally, for all models, degree of persistence declines by significant amounts and estimated half-life shocks decreases dramatically on average. Our findings from models of Panel-B are consistent with the extant literature. That is, degree of persistence of shocks on variance might be overestimated, if volatility shifts (i.e. determined by the modified ICSS algorithm) are not considered. Moreover, changes in the intercept term, ω, should be taken into account through sub-samples because it determines the level of unconditional variance across regimes. Average conditional volatilities are calculated much more higher in sub-samples than in the full-sample estimation. For instance, in the sub-sample 2 for both ISE-100 index and ISE-FIN index, ω is higher than 1, resulting in increase in the unconditional variance although persistence is reduced by at least 10%. This might be due to the serious economic events[26] during the 2000-2001 Turkish banking crisis which cost 31% of GDP in that period (Caprio and Klingebiel, 2003).

3.3.2. Out-of-Sample Volatility Forecasting Results

Turkish stock market volatility forecasts in real time are handled with GARCH type of models with various estimation techniques taking potential structural breaks into account. First two models, namely GARCH(1,1), and fractionally integrated GARCH (1,1), (hereafter FIGARCH (1,1)) are estimated and they serve as natural benchmark models. FIGARCH(1,1) model with expanding window is assessed as a second benchmark model since structural breaks in the unconditional variance of financial asset returns could lead to spurious evidence of long memory in volatility data (Rapach and Strauss, 2008; Mikosh and Starica, 2003;

[26] Figures 1 to 4 depict that there are much more points exceeding the 3-sigma in the period 1997 to 2003 than in the other time horizons.

Perron and Qu, 2009). The other five competing models, 0.50 rolling window, 0.25 rolling window, Weighted ML, With Breaks, Moving Average, are estimated for comparison purposes. Daily stock market return volatility forecasts generated by two benchmark models are compared to the stock market return volatility forecasts generated by five competing models which make some type of adjustment to the estimation window for accommodating potential structural breaks. Loss functions based on mean square forecast error (MSFE), and value-at-risk (MVaR) for 5% quantile are computed for forecast horizons of 1, 5, 10, 15, 20, 60, and 120 days. Bootstrap procedure is conducted to forecast the 5% quantile to calculate the MVaR loss function for all forecast horizons[27]. The last 500 observations for all indices are used for out-of-sample period spanning from March 7th, 2008 to March 4th, 2010.

3.3.2.1. Mean Squared Forecast Error Loss Function

Out-of-sample stock return volatility forecasting results for forecast horizons 1-day to 120-day are represented in the Tables from 5 to 11. The first rows of those tables denote the MSFE loss function values of benchmark GARCH (1,1) expanding window model. The remaining rows report the ratio of the MSFE loss function values for each of other models to the MSFE for the benchmark GARCH (1,1). Thus, mean loss function ratios less than one indicate good performance for forecasting stock market return volatility relative to the benchmark models. P-values corresponding to the White (2000) $\overline{V_l}$ (Hansen, 2005, T_n^{SPA}) statistics are given in brackets (curly brackets) and correspond to a test of the null hypothesis that none of the five competing models has a lower expected loss than the benchmark model[28].

Table 5 indicates the results of out-of-sample stock return volatility forecasting results for 1-day forecast horizon. According to Table 5, GARCH(1,1) with 0.50 rolling window models deliver the lowest mean loss function for ISE-100 along with the two sub-sector indices namely, ISE-FIN and ISE-IND and the other competing models mostly do not perform well in forecasting the volatility of stock

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[27] The logic behind bootstrapping procedure is simply to gather an estimate of the sample distribution without assuming that standardized residuals follow any statistical distributions, such as Gaussian, Student-t etc. (Hamilton, 1994: 337). Hence, bootstrap procedure is used for relaxing the assumption of normal distribution, and allowing leptokurtosis in the standardized residuals since it is a useful technique when sampling distributions are unknown (Liao, 1995).

[28] The lower loss function value for any model indicates better out-of-sample forecasting performance.

market returns. However, 0.25 rolling window model for ISE-100 index ranks the second. GARCH (1,1) model with 0.25 rolling window gives the lowest MSFE loss function for ISE-SRV. However, 0.25 rolling window model for ISE-100 index ranks the second. GARCH (1,1) model with 0.25 rolling window gives the lowest MSFE loss function for ISE-SRV.

Table 5: Out-of-sample stock return volatility forecasting results, s = 1

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	120.43 [0.52] {0.09}	239.02 [0.89] {0.22}	51.5853 [0.68] {0.16}	48.3402 [0.34] {0.17}
FIGARCH(1,d,1)	1.0090 [0.42] {0.13}	1.0173 [0.65] {0.28}	1.0012 [0.85] {0.62}	0.9794 [0.54] {0.47}
0.50 rolling window	**0.9812**	**0.9971**	**0.9919**	0.9934
0.25 rolling window	0.9830	1.0084	1.0058	**0.9709**
Weighted ML	1.0390	1.0534	1.0433	0.9874
With breaks	1.0227	1.0500	1.0299	0.9910
Moving average	1.0726	1.0995	1.1042	1.0072

Note: Entries for the GARCH(1,1) expanding window model give the mean loss for this model. Entries for the other models give the ratio of the mean loss for each model to the mean loss for the GARCH(1,1) expanding window model. Bold entries denote the model with the smallest mean loss among all of the models. P-values for the White (2000) $\overline{V}_l$ (Hansen, 2005, T_n^{SPA}) statistics are given in brackets (curly brackets) and correspond to a test of the null hypothesis that none of the five competing models (two GARCH(1,1) rolling window, GARCH(1,1) weighted ML, GARCH(1,1) with breaks, and moving average models) has a lower expected loss than the benchmark model indicated on the left against the one-sided (upper-tail) alternative hypothesis that at least one of the competing models has a lower expected loss than the benchmark model; 0.00 indicates less than 0.005.

As we concluded in the summary statistics section, it is clear that ISE-SRV has different characteristics among all. Since none of the benchmark models delivers the lowest mean loss function for the 1-day forecast horizon, it is the first evidence that allowing for parameters of GARCH process evolving over time results in out-of-sample forecasting gains. In addition, out-of-sample forecasting results for forecast horizon one are quite consistent with the findings of Rapach and Strauss (2008).

Out-of-sample volatility forecasting results for 5-day (one-week), 10-day (two weeks), 15-day (three weeks), and 20-day (one-month) forecast horizons are summarized in Table 6 through 9. Results for those forecast horizons are very similar for all ISE indices, indicating that one of the rolling window models performs better than the two benchmark models for all indices except ISE-IND index. We observe significant reductions in mean loss functions of competing models by approximately 1-3% for the ISE-FIN index. In addition to that the best competing models for ISE-

100 and ISE-IND realize mean loss reductions of approximately 5-20% relative to the GARCH (1,1) with expanding window. In case of ISE-SRV, we see dramatic reductions in the mean loss function values by approximately 16-49%. FIGARCH (1,1) model with expanding window always produces the lowest mean loss function using MSFE criterion for those forecast horizon for the ISE-IND. However, 0.50 and 0.25 rolling window models exhibit good performance as well as the benchmark FIGARCH (1,1) model for ISE-IND index. For ISE-SRV index, there is strong evidence of allowing instabilities in GARCH process leads to out-of-sample forecasting gains for the time horizon up to 20 days since five competing models produce lower mean loss functions compared to the first benchmark model.

Table 6: Out-of-sample stock return volatility forecasting results, s = 5

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	712.07 [0.70]	1260.86 [0.89]	373.658 [0.63]	352.222 [0.11]
	{0.24}	{0.51}	{0.06}	{0.01}
FIGARCH(1,d,1)	0.9717 [0.89]	1.0315 [0.87]	**0.9398** [0.98]	0.8538 [0.65]
	{0.57}	{0.65}	{1.00}	{0.58}
0.50 rolling window	0.9511	**0.9963**	0.9582	0.9223
0.25 rolling window	**0.9419**	1.0418	0.9892	**0.8433**
Weighted ML	1.1378	1.1925	1.1095	0.8839
With breaks	1.0923	1.2610	1.1259	0.9042
Moving average	1.3802	1.5548	1.3244	0.9901

Table 7: Out-of-sample stock return volatility forecasting results, s = 10

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	1981.55 [0.58]	3432.32 [0.80]	1061.64 [0.56]	1003.5 [0.02]
	{0.08}	{0.60}	{0.02}	{0.01}
FIGARCH(1,d,1)	0.9265 [0.88]	1.0309 [0.88]	**0.8876** [0.96]	0.7066 [0.64]
	{0.54}	{0.75}	{1.00}	{0.51}
0.50 rolling window	0.9279	**0.9912**	0.9100	0.8284
0.25 rolling window	**0.8876**	1.0644	0.9678	**0.6914**
Weighted ML	1.1773	1.2783	1.1414	0.7240
With breaks	1.1029	1.4306	1.1479	0.8003
Moving average	1.5035	1.7793	1.3758	0.9462

Table 8: Out-of-sample stock return volatility forecasting results, s = 15

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	4057.84 [0.55]	7024.61 [0.73]	2093.57 [0.48]	2289.48 [0.01]
	{0.09}	{0.53}	{0.02}	{0.01}
FIGARCH(1,d,1)	0.8855 [0.86]	1.0188 [0.89]	**0.8246** [0.96]	0.6052 [0.60]
	{0.60}	{0.80}	{1.00}	{0.58}
0.50 rolling window	0.9171	**0.9825**	0.8594	0.7267
0.25 rolling window	**0.8406**	1.0712	0.9199	**0.5845**
Weighted ML	1.1940	1.3310	1.1036	0.6159
With breaks	1.1556	1.5129	1.1411	0.6958
Moving average	1.4907	1.7937	1.3816	0.8197

Table 9: Out-of-sample stock return volatility forecasting results, s = 20

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	7451.56 [0.46] {0.14}	12802 [0.73] {0.50}	3975.41 [0.43] {0.01}	4354.16 [0.01] {0.01}
FIGARCH(1,d,1)	0.8482 [0.83] {0.64}	0.9995 [0.91] {0.84}	**0.7747** [0.97] {1.00}	0.5305 [0.57] {0.51}
0.50 rolling window	0.9046	**0.9750**	0.8271	0.6384
0.25 rolling window	**0.7972**	1.0606	0.8689	**0.5026**
Weighted ML	1.2098	1.3839	1.0780	0.5322
With breaks	1.1843	1.5264	1.0917	0.6069
Moving average	1.3796	1.6846	1.2409	0.7137

Table 10 and 11 report the out-of-sample forecasting results for longer forecast horizons, namely 60-day, and 120-day respectively. As the forecast horizon enlarges differences between the values of mean loss functions of good forecasting models and bad forecasting models increases. In other words, competing models which perform better at short forecast horizons continue to perform better and better in longer forecast horizons. Starica (2005) and Rapach and Strauss (2008) advocate that GARCH(1,1) expanding window model that does not allow structural breaks might fail in modeling and forecasting volatility as the forecast horizon increases. Particularly, according to Table 10, five competing models perform better than GARCH (1,1) expanding window in case of ISE-IND and ISE-SRV indices. 0.25 rolling window models deliver the minimum mean loss function for the ISE-100 and ISE-SRV, whereas benchmark FIGARCH(1,1) expanding window model is the best for ISE-FIN and ISE-IND. Moreover, all competing models perform better relative to the GARCH (1,1) expanding window model for the ISE-IND and ISE-SRV indicating the importance of forecasting volatility by considering structural breaks in the longer forecast horizons.

Table 10: Out-of-sample stock return volatility forecasting results, s = 60

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	90448.4 [0.32] {0.19}	130736 [0.71] {0.39}	56112.5 [0.06] {0.01}	87209.1 [0.01] {0.01}
FIGARCH(1,d,1)	0.6625 [0.69] {0.57}	**0.9072** [0.95] {1.00}	**0.4921** [0.98] {1.00}	0.2607 [0.32] {0.38}
0.50 rolling window	0.8385	0.9189	0.5729	0.2414
0.25 rolling window	**0.5794**	0.9765	0.5195	**0.2157**
Weighted ML	1.3427	1.9374	0.7640	0.2489
With breaks	1.1402	1.8495	0.7805	0.2291
Moving average	0.8879	1.2753	0.6858	0.2799

Table 11: Out-of-sample stock return volatility forecasting results, s = 120

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1)	439729 [0.26] {0.17}	508416 [0.62] {0.38}	372214 [0.01] {0.01}	618689 [0.01] {0.01}
FIGARCH(1,d,1)	0.5264 [0.61] {0.62}	0.8645 [0.93] {0.82}	0.2831 [0.90] {0.81}	0.1541 [0.11] {0.08}
0.50 rolling window	0.8314	**0.8589**	0.3758	**0.0963**
0.25 rolling window	**0.4288**	0.9274	**0.2714**	0.1002
Weighted ML	1.7592	3.1102	0.5437	0.1538
With breaks	1.0963	2.2087	0.5108	0.0995
Moving average	0.6345	1.1482	0.3659	0.1415

According to Table 11, GARCH(1,1) with 0.25 rolling window model have the best performance in forecasting volatility for the ISE-100 and ISE-IND and GARCH(1,1) with 0.50 rolling window model deliver the lowest mean loss function for the other ISE indices.

Overall, GARCH(1,1) models with rolling window estimation adjustments mostly deliver the lowest mean loss function based on criterion MSFE for the ISE-100 and ISE-FIN. For only the 60-day forecast horizon, FIGARCH (1,1) model with expanding window is best model for forecasting volatility. Results are a little bit mixed in case of ISE-IND. Beside FIGARCH(1,1) benchmark model produces the lowest mean loss function for the most forecast horizons, GARCH (1,1) rolling window models outperform benchmark GARCH(1,1) expanding model as well[29]. Moreover, it is important to realize that the other competing models namely, GARCH(1,1) with breaks, Weighted ML, and Moving Average starts to deliver lower mean loss function values than GARCH (1,1) expanding window model in longer forecast horizons, 60-day and 120-day, indicating that forecasting performance of the first benchmark model relative to the other models begins to suffer for ISE-IND index. All competing models, including GARCH(1,1) with breaks, Weighted ML, and Moving Average, produce lower mean losses than the benchmark GARCH(1,1) with expanding window in case of ISE-SRV. In sum, out-of-sample volatility forecasting results based on MSFE criterion for the forecast horizon from 1-day to 6-month reveal that GARCH (1,1) models with rolling

[29] Because persistence of ISE-IND for the full-sample is calculated very high, 0.993, returns volatility seems to have long memory and this might be the main reason why FIGARCH(1,1) is the best among all for the most cases (Engle and Patton, 2007)

window estimation techniques do outperform benchmark GARCH (1,1) model with expanding window. In addition to that since results for the ISE-100 index and the other sub-sector indices are not exactly same. Decision makers should consider structural breaks as well as sectoral differences in modeling and forecasting stock market volatility in both short-term (e.g. up to one month) and long-term (up to 6 months).

3.3.2.2. Value-at-Risk Loss Function

Forecasting stock market volatility is essential to measure Value-at-Risk (VaR) which is very important for risk management as VaR denotes the extreme losses with respect to a given probability (e.g. 5%) for a specified time horizon (Gonzalez et al., 2004: 630). That is to say, VaR is calculated to see how much money would be lost when undesirable events occur in a given period. Moreover, Basel Committee defines VaR as a short term forecast (Poon, 2005: 132). In this part, we compare our two benchmark models with four of our competing models based on the goodness-of-fit of a VaR calculation. The VaR loss function (MVaR) proposed by Gonzalez et al. (2004) is considered. It is a sophisticated VaR-based loss function reflecting a relatively high cost associated with extreme losses, put another way, we are able to signify the opportunity cost of the capital held to cover the potential losses (Rapach and Strauss, 2008: 72).

Table 12 reflects out-of-sample forecasting results based on the MVaR loss function criterion at horizon of 1, 5, 10, 15, 20, 60, and 120 days.MVaR is calculated using bootstrapping procedure to relax Gaussian distribution assumption as suggested by Rapach and Straus (2008). GARCH (1,1) models with rolling window estimation mostly outperform the benchmark models. Particularly, GARCH(1,1) 0.50 rolling window model gives the lowest MVaR loss function for the forecast horizon from 1-day to 60-day for the ISE-100 and ISE-FIN indices. Note that, forecasting performances of GARCH(1,1) with 0.25 rolling window and GARCH with breaks models in the 5-day forecast horizon are better than two benchmark models for ISE-100.

Table 12: MVaR Loss Function Results

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
s=1				
GARCH(1,1) expanding window	0.2354	0.2780	0.2157	0.1846
FIGARCH(1,d,1) expanding window	1.0084	1.0132	1.0202	**0.9973**
GARCH(1,1) 0.50 rolling window	**0.9929**	**0.9903**	**0.9995**	1.0360
GARCH(1,1) 0.25 rolling window	1.0053	1.0152	1.0072	1.0115
GARCH(1,1) with breaks	1.0084	1.0279	1.0341	1.0271
Moving average	1.1707	1.1771	1.1464	1.0895
s=5				
GARCH(1,1) expanding window	0.6293	0.7286	**0.5962**	0.4783
FIGARCH(1,d,1) expanding window	1.0078	1.0219	1.0296	1.0226
GARCH(1,1) 0.50 rolling window	**0.9933**	**0.9921**	1.0071	1.0757
GARCH(1,1) 0.25 rolling window	0.9973	1.0058	1.0390	**0.9989**
GARCH(1,1) with breaks	0.9811	1.0169	1.0366	1.0707
Moving average	1.1354	1.1507	1.1370	1.0769
s=10				
GARCH(1,1) expanding window	0.8063	0.9685	0.7904	**0.5683**
FIGARCH(1,d,1) expanding window	1.0224	1.0083	1.0541	1.0254
GARCH(1,1) 0.50 rolling window	**0.9731**	**0.9982**	**0.9931**	1.1050
GARCH(1,1) 0.25 rolling window	1.0066	1.0250	1.0804	1.0024
GARCH(1,1) with breaks	1.0255	1.0331	1.0657	1.1022
Moving average	1.2761	1.2742	1.2637	1.1401
s=15				
GARCH(1,1) expanding window	0.9855	1.1979	1.0338	**0.6565**
FIGARCH(1,d,1) expanding window	1.0407	1.0373	1.0671	1.0323
GARCH(1,1) 0.50 rolling window	**0.9968**	**0.9993**	**0.9873**	1.0893
GARCH(1,1) 0.25 rolling window	1.0166	1.0189	1.1058	1.0173
GARCH(1,1) with breaks	1.0484	1.0608	1.0831	1.0765
Moving average	1.2503	1.2209	1.2481	1.1207
s=20				
GARCH(1,1) expanding window	1.2596	1.4754	1.4143	**0.8728**
FIGARCH(1,d,1) expanding window	1.0420	1.0449	1.0502	1.0311
GARCH(1,1) 0.50 rolling window	**0.9854**	**0.9913**	**0.9923**	1.0787
GARCH(1,1) 0.25 rolling window	1.0265	1.0366	1.0863	1.0059
GARCH(1,1) with breaks	1.0635	1.0660	1.0798	1.0633
Moving average	1.1855	1.1798	1.1659	1.0537
s=60				
GARCH(1,1) expanding window	3.4900	3.6946	4.6081	1.8061
FIGARCH(1,d,1) expanding window	1.0075	1.0055	1.0383	1.0236
GARCH(1,1) 0.50 rolling window	**0.9690**	**0.9845**	**0.9886**	1.0284
GARCH(1,1) 0.25 rolling window	1.0035	1.0234	1.0681	1.0136
GARCH(1,1) with breaks	1.0368	1.0500	1.0666	1.0231
Moving average	1.0150	1.0172	1.0529	**0.9534**
s=120				
GARCH(1,1) expanding window	5.2536	5.1905	9.3966	2.3921
FIGARCH(1,d,1) expanding window	0.9790	0.9722	1.0285	1.0095
GARCH(1,1) 0.50 rolling window	0.9880	0.9793	**0.9906**	0.9768
GARCH(1,1) 0.25 rolling window	1.0362	1.0471	1.0589	0.9861
GARCH(1,1) with breaks	1.0774	1.0730	1.0628	0.9764
Moving average	**0.9291**	**0.9409**	0.9940	**0.9699**

Notes: Entries for the GARCH(1,1) expanding window model give the mean loss for this model. Entries for the other models give the ratio of the mean loss for each model to the mean loss for the GARCH(1,1) expanding window model. Bold entries denote the model with the smallest mean loss among all of the models.

In the long-run, for the 120-day forecast horizon, GARCH(1,1) 0.50 rolling window models again outperform the benchmark GARCH(1,1) expanding window model for the same ISE indices; however, moving average model produces the lowest mean loss function based on MVaR criterion. Because there exists a long memory evidence in the squared residuals due to the high persistence in the volatility, one of the benchmark models, FIGARCH(1,1) with expanding window, also beats the GARCH(1,1) expanding window model at the 120-day forecast horizon. For ISE-IND index, GARCH(1,1) with 0.50 rolling window delivers the lowest mean loss function for all the forecast horizons except 5-day ahead. The benchmark model, GARCH(1,1) expanding window is not outperformed by any competing models as well as FIGARCH(1,1) expanding window model for the forecast horizon of 5-day; however, mean loss ratio of GARCH(1,1) with 0.50 rolling window model is so close to one, indicating that performance of that model in forecasting volatility for 5-day period is not very bad relative to the benchmark model. In the long forecast horizon of 120-day, moving average model again gives slightly better mean loss function value than benchmark model for ISE-IND. Mean loss function ratios based on MVaR criterion for different forecast horizon windows suggest mixed results for ISE-SRV. The benchmark models have mostly better performance than four competing models for the forecast horizon up to 1-month. Particularly, FIGARCH(1,d,1) expanding window and one of the competing models, GARCH(1,1) with 0.25 rolling window, deliver the lowest mean loss functions for 1-day and 5-day forecast horizons respectively. Moreover, the benchmark GARCH(1,1) expanding model outperforms all competing models for both 15-day and 20-day forecast horizon. As the forecast horizon increases, moving average model again gives the lowest mean loss function. In 60-day forecast horizon, moving average model outperforms the others, reducing the MVaR by approximately 5% relative to the GARCH(1,1) expanding window. In addition, all of the competing models beat the benchmark models, particularly, GARCH (1,1) with breaks ranks the second, and GARCH(1,1) with rolling window is the third one.

Although moving average model for all indices performs the worst for the forecast horizon up to 1-month, the mean loss of that model approaches to one in the 60-day forecast horizon and becomes the best forecasting model in the longest horizon, 120-day, for all the ISE indices except ISE-IND. This is consistent with the findings of Starica et al. (2005) for the stock return volatility. Results of mean loss function based on MVaR criterion again indicate the importance of considering structural breaks for the most ISE indices, especially ISE-100 and ISE-FIN for forecasting gains as GARCH (1,1) rolling window models in the short-run and Moving average models in the long-run perform well. As we concluded in forecasting results based on MSFE loss function, results of ISE indices are not found as exactly same, indicating the importance of considering sectoral differences in risk management. Thus, one should be aware of those facts to reach more accurate conclusions in terms of VaR calculation, risk management, derivative pricing and hedging and portfolio allocation.

3.3.2.3. Empirical Coverage Frequencies

Empirical coverage frequencies are reported in Table 13 and Table 14. Christoffersen's (1998) likelihood ratio (LR) statistic is implemented to test the null hypothesis of unconditional coverage[30]. Put another way, Christoffersen's (1998) test examines whether the failure rate of a model is statistically equal to the expected one. Hence, this LR statistic helps us to ensure that the decision makers will not mis-allocate their investments (Huang et al. 2009). The empirical coverage frequencies for 1-day ahead 5% VaR forecasts for all ISE indices are found near 5% and null hypothesis cannot be rejected for any cases. However, empirical coverage frequencies for 5% VaR for all the stock indices except ISE-SRV are calculated higher in the 120-day forecast horizon. Those frequencies are likely to change as forecast horizon increases due to the decreasing number of out-of-sample observations and the evidence of ARCH effects.

[30] This test, however, might suffer in the presence of ARCH effects (Clements and Taylor, 2003).

Table 13: Empirical Coverage Frequencies: 5% VaR

Model	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
A. s=1				
GARCH(1,1) expanding window	0.0420 [0.40]	0.0500 [0.99]	0.0500 [0.99]	0.0360 [0.13]
FIGARCH(1,d,1) expanding window	0.0480 [0.84]	0.0520 [0.84]	0.0540 [0.69]	0.0420 [0.40]
GARCH(1,1) 0.50 rolling window	0.0460 [0.68]	0.0520 [0.84]	0.0520 [0.84]	0.0520 [0.84]
GARCH(1,1) 0.25 rolling window	0.0500 [0.99]	0.0600 [0.32]	0.0600 [0.32]	0.0500 [0.99]
GARCH(1,1) weighted ML	0.0500 [0.99]	0.0480 [0.84]	0.0560 [0.55]	0.0480 [0.84]
GARCH(1,1) with breaks	0.0480 [0.84]	0.0500 [0.99]	0.0540 [0.69]	0.0560 [0.55]
Moving average	0.0480 [0.84]	0.0420 [0.40]	0.0600 [0.32]	0.0400 [0.29]
B. s=5				
GARCH(1,1) expanding window	0.0544	0.0585	0.0605	0.0423
FIGARCH(1,d,1) expanding window	0.0706	0.0665	0.0907	0.0565
GARCH(1,1) 0.50 rolling window	0.0625	0.0585	0.0645	0.0544
GARCH(1,1) 0.25 rolling window	0.0746	0.0746	0.0766	0.0565
GARCH(1,1) weighted ML	0.0665	0.0625	0.0645	0.0605
GARCH(1,1) with breaks	0.0665	0.0645	0.0746	0.0544
Moving average	0.0706	0.0665	0.0907	0.0565
C. s=10				
GARCH(1,1) expanding window	0.0407	0.0428	0.0631	0.0204
FIGARCH(1,d,1) expanding window	0.0631	0.0631	0.0733	0.0448
GARCH(1,1) 0.50 rolling window	0.0448	0.0509	0.0692	0.0367
GARCH(1,1) 0.25 rolling window	0.0652	0.0652	0.0876	0.0326
GARCH(1,1) weighted ML	0.0468	0.0468	0.0774	0.0387
GARCH(1,1) with breaks	0.0550	0.0591	0.0794	0.0367
Moving average	0.0631	0.0631	0.0733	0.0448
D. s=15				
GARCH(1,1) expanding window	0.0329	0.0453	0.0576	0.0082
FIGARCH(1,d,1) expanding window	0.0514	0.0494	0.0782	0.0391
GARCH(1,1) 0.50 rolling window	0.0453	0.0494	0.0679	0.0288
GARCH(1,1) 0.25 rolling window	0.0597	0.0617	0.0844	0.0206
GARCH(1,1) weighted ML	0.0453	0.0473	0.0720	0.0288
GARCH(1,1) with breaks	0.0576	0.0597	0.0802	0.0288
Moving average	0.0514	0.0494	0.0782	0.0391
E. s=20				
GARCH(1,1) expanding window	0.0457	0.0499	0.0790	0.0104
FIGARCH(1,d,1) expanding window	0.0665	0.0582	0.1019	0.0541
GARCH(1,1) 0.50 rolling window	0.0561	0.0561	0.0873	0.0478
GARCH(1,1) 0.25 rolling window	0.0644	0.0728	0.0998	0.0520
GARCH(1,1) weighted ML	0.0644	0.0582	0.0956	0.0541
GARCH(1,1) with breaks	0.0624	0.0686	0.0998	0.0499
Moving average	0.0665	0.0582	0.1019	0.0541

Notes: The table reports the proportion of actual stock index returns that are below the 5% VaR forecast. *P*-values for the Christoffersen (1998) likelihood-ratio statistic corresponding to a test of the null hypothesis of correction unconditional coverage are given in brackets.

Table 14: Empirical Coverage Frequencies: 5% VaR (Cont'd)

F. s=60	ISE-100	ISE-FIN	ISE-IND	ISE-SRV
GARCH(1,1) expanding window	0.0816	0.0794	0.1111	0.0091
FIGARCH(1,d,1) expanding window	0.1066	0.0998	0.1429	0.0544
GARCH(1,1) 0.50 rolling window	0.0907	0.0839	0.1338	0.0544
GARCH(1,1) 0.25 rolling window	0.0930	0.0975	0.1429	0.0703
GARCH(1,1) weighted ML	0.0907	0.0907	0.1406	0.0612
GARCH(1,1) with breaks	0.0952	0.0930	0.1429	0.0612
Moving average	0.1066	0.0998	0.1429	0.0544
G. s=120				
GARCH(1,1) expanding window	0.0682	0.0840	0.2625	0.0010
FIGARCH(1,d,1) expanding window	0.2231	0.1759	0.3150	0.0446
GARCH(1,1) 0.50 rolling window	0.1444	0.0971	0.2756	0.0236
GARCH(1,1) 0.25 rolling window	0.2388	0.2178	0.3150	0.0446
GARCH(1,1) weighted ML	0.2283	0.1759	0.3018	0.0420
GARCH(1,1) with breaks	0.2388	0.2021	0.3150	0.0499
Moving average	0.2231	0.1759	0.3150	0.0446

Notes: The table reports the proportion of actual stock index returns that are below the 5% VaR forecast. *P*-values for the Christoffersen (1998) likelihood-ratio statistic corresponding to a test of the null hypothesis of correction unconditional coverage are given in brackets.

Consequently, results are supporting our findings for the out-of-sample forecasting results based on MVaR criterion.

One can conclude that results for empirical coverage frequencies for 5% VaR indicate an important fact that using estimation techniques such as bootstrap procedure that we implement in the previous part, value-at-risk loss function, to relax the normality assumption leads to more accurate results, and out-of-sample forecasting gains[31].

3.3.2.4. Results for the GJR-GARCH(1,1) and MS-GARCH(1,1)

Asymmetric effect of news, often called leverage effect is a fact that there exists a significant negative correlation between the current return and future volatility (Enders, 2010:155). In other words, bad news has much more certain impact on volatility than good news does, revealing the fact that when bad news arrive at the market, returns decline and then volatility tends to rise. In light of this information, we consider the GJR-GARCH(1,1) model with an expanding window that takes asymmetry effect into account. Moreover, we estimated Markov Switching GARCH (MS-GARCH) model with an expanding window in our analysis. In our analysis, MS-GARCH is a model that uses two-state (two regimes) Markov Chain

[31] Our results for the empirical coverage frequencies for 5% VaR for 120-day forecast horizon are inconsistent with the calculations of Rapach and Strauss (2008).

process which simply allows parameters of GARCH process to switch within a number of regimes (here two) determined endogenously. GJR-GARCH(1,1) model of Glosten et al. (1993) and MS-GARCH specification of Haas et al. (2004) are estimated with an expanding window for all cases to compare their out-of-sample forecasting performances with the benchmark GARCH(1,1) model with expanding window[32]. Out-of-sample forecasting results are reported in Table 15.

Table 15: Forecasting results for the GJR-GARCH(1,1) and MS-GARCH(1,1) expanding window models (MSFE)

Model	ISE-100	ISE-FIN	ISE-IND
s=1			
GJR-GARCH(1,1)	1.1230	1.1904	1.1499
MS-GARCH(1,1)	**0.9985**	1.0246	1.0198
s=5			
GJR-GARCH(1,1)	1.8790	1.1904	1.7687
MS-GARCH(1,1)	**0.9477**	1.0246	**0.9784**
s=10			
GJR-GARCH(1,1)	2.3309	2.9323	2.0873
MS-GARCH(1,1)	**0.9682**	1.1203	1.0511
s=15			
GJR-GARCH(1,1)	2.4222	3.0711	2.2019
MS-GARCH(1,1)	1.0303	1.2064	1.2453
s=20			
GJR-GARCH(1,1)	2.2848	2.9263	2.0058
MS-GARCH(1,1)	1.1189	1.3051	1.5697
s=60			
GJR-GARCH(1,1)	1.5455	2.3416	1.1408
MS-GARCH(1,1)	5.6742	7.6594	39.3005
s=120			
GJR-GARCH(1,1)	1.2444	2.3251	**0.6516**
MS-GARCH(1,1)	124.4366	4.2602×10^3	10.077×10^3

Note: Each of the models is estimated using an expanding window. Entries give the ratio of the mean loss for the model indicated on the left to the mean loss for the benchmark GARCH(1,1) expanding window model.

According to Table 15, MS-GARCH(1,1) outperforms the benchmark GARCH(1,1) model for ISE-100 index at shorter horizons up to 10 days. This is consistent with the findings of Marcucci (2005) who reports that MS-GARCH models outperform various uni-regime GARCH models at horizons of 1 and 5 days. In case of ISE-IND, we evidence that MS-GARCH model again delivers lower mean loss than the benchmark model for 5-day forecast horizon. Surprisingly, GJR-

[32] Using those models we couldn't generate out-of-sample forecast for ISE-SRV index due to the technical difficulties arising from the statistical procedures embedded in GAUSS software. Number of observation might not be enough for the MS-GARCH (1,1) model.

GARCH(1,1) model at the horizon of 120-day gives mean loss ratio of 0.6516 indicating forecasting gains relative to GARCH(1,1) expanding window model. Both GJR-GARCH(1,1) model and MS-GARCH(1,1) models have a loss that are always much higher than the benchmark model for the ISE-FIN index. Results, in general, suggest that MS-GARCH model at short forecast horizons provide more accurate results than GARCH(1,1) with expanding window. However, GJR-GARCH(1,1) model have relatively worse performance in our out-of-sample forecasting analysis based on the MSFE mean loss function. Since, those two models, GJR-GARCH and MS-GARCH do not consistently outperform the benchmark model of GARCH(1,1) expanding window, we do not estimate out-of-sample forecasts generated by the mean loss function of MVaR.

3.3.2.5. Summary Statistics for the Mean Loss Ratios

Table 16 indicates the summary statistics for the mean loss ratios based on both MSFE and MVaR criterion. We report the number of times both benchmark and competing models have the lowest mean loss, denoted by "#Best", at the forecast horizon of 1, 5, 10, 15, 20, 60, 120 days. According to the Table 16, performance of rolling window models stands out. Although GARCH(1,1) 0.25 rolling window model has the lowest MSFE in 13 cases, it has higher standard deviation than that of GARCH(1,1) 0.50 rolling window model which has the lowest MSFE in 9 cases. Moreover, FIGARCH(1,1) expanding window model ranks third and it has the lowest mean value with a standard deviation of 25%. For the MSFE loss function, among competing models rolling window models with standard deviation ranging between 23-27% outperform the benchmark model of GARCH(1,1) expanding window consistently.

Panel B of Table 16 records the summary statistics for the mean loss ratios based on MVaR criterion estimated by bootstrap procedure.

Table 16: Summary Statistics for the Mean Loss Ratios

Model	#Best	Mean	Median	S.D.	Minimum	Maximum
A. MSFE						
GARCH(1,1) expanding window	0					
FIGARCH(1,d,1) expanding	6	0.7855	0.8750	0.2537	0.1541	1.0315
GARCH(1,1) 0.50 rolling window	9	0.8219	0.9136	0.2343	0.0963	0.9971
GARCH(1,1) 0.25 rolling window	13	0.7879	0.9038	0.2788	0.1002	1.0712
GARCH(1,1) weighted ML	0	1.1099	1.1066	0.5527	0.1538	3.1102
GARCH(1,1) with breaks	0	1.0639	1.0943	0.4315	0.0995	2.2087
Moving average	0	1.1093	1.1262	0.4327	0.1415	1.7937
B MVaR						
GARCH(1,1) expanding window	4					
FIGARCH(1,d,1) expanding	1	1.0285	1.0231	0.0212	0.9722	1.0285
GARCH(1,1) 0.50 rolling window	18	0.9906	0.9926	0.0365	0.9690	0.9906
GARCH(1,1) 0.25 rolling window	1	1.0589	1.0170	0.0295	0.9861	1.0589
GARCH(1,1) with breaks	0	1.0628	1.0554	0.0302	0.9764	1.0628
Moving average	4	0.9940	1.1386	0.1052	0.9291	0.9940

It is clear from the results that performance of GARCH(1,1) 0.50 rolling window at all the forecast horizons is the best among all. GARCH(1,1) 0.50 rolling window model has the lowest MVaR in 18 cases with the lowest values of mean, median, and maximum, indicating the fact that this model performs very well. Among competing models Moving Average model delivers the lowest MVaR in 4 cases which are mostly associated with the 120-day forecast horizon.

We sometimes observe that benchmark models that do not accommodate structural breaks outperform the competing models which have internal estimation techniques considering structural breaks in the data. The failure of those forecasting models can be explained by bias-efficiency trade-off described by Clark and McCracken (2004) and Pesaran and Timmermann (2007). Bias-efficiency tradeoff is about selecting optimal estimation window size in the presence of structural breaks. Summary statistics for the mean loss ratios reveal that allowing for instabilities in GARCH process leads to out-of-sample forecasting gains based on the mean loss function criterion of MSFE and MVaR.

CONCLUSION

This thesis examines the stock return volatility forecasting in the presence of structural breaks. The empirical relevance of structural breaks in the volatility of the Istanbul Stock Exchange (ISE) sector indices, namely ISE National – 100, ISE National – Financial, ISE National – Industrial, ISE National – Service are examined by conducting GARCH family models in both in-sample and out-of-sample tests.

Empirical results indicate the existence of significant structural breaks in the unconditional variance for all the ISE indices, and GARCH parameter estimates differ across subsamples defined by the modified Inclan and Tiao’s (1994) Iterative Cumulative Sum of Squares (ICSS) algorithm proposed by Sanso et al. (2004) indicating instable GARCH processes governing volatility for all of them. The modified ICSS algorithm determines a single structural break for ISE-IND, ISE-SRV; two structural breaks for ISE-100; and four structural breaks for ISE-FIN. One or more variance breaks are selected by the modified ICSS algorithm for all ISE indices, indicating instable GARCH processes governing volatility for all of them. Sudden changes in unconditional variances identified by the modified ICSS algorithm appear to be associated with significant economic events and mostly related with the domestic factors. Having found that there are one or more sudden volatility shifts in the ISE index returns, we estimate GARCH(1,1) for all ISE indices for the full-sample as well as for each of subsamples defined by the modified ICSS algorithm and report the Quasi Maximum Likelihood Estimation (QMLE) results for GARCH (1,1) models. Generally, for all models, degree of persistence declines by significant amounts and estimated half-life shocks decreases dramatically on average when structural breaks are taken into account.

In out-of-sample analysis, two different statistical loss functions, namely mean square forecast error (MSFE) and value-at-risk (VaR) over forecast horizons of 1, 5, 10, 15, 20, 60, and 120 days are used to compare forecasts of daily stock market index return volatility produced by the econometric models that assume stable GARCH processes to the forecasts generated by the GARCH type of models that accommodate sudden volatility shifts due to the structural breaks in the unconditional variance of daily stock market index returns. Particularly, two models, namely

GARCH(1,1), and fractionally integrated GARCH (1,1), (FIGARCH (1,1)) are served as natural benchmark models. The other five competing models which makes some type of adjustment to the estimation window, thus accommodating sudden volatility shifts due to the structural breaks in the unconditional variance of daily stock market index returns, 0.50 rolling window, 0.25 rolling window, Weighted ML, With Breaks, Moving Average, are estimated for comparison purposes.

Out-of-sample volatility forecasting results based on MSFE criterion for the forecast horizon from 1-day to 6-month reveal that GARCH (1,1) models with rolling window estimation techniques do outperform benchmark GARCH (1,1) model with expanding window. In addition to that since results for the ISE-100 index and the other sub-sector indices are not exactly same. Decision makers should consider structural breaks as well as sectoral differences in modeling and forecasting stock market volatility in both short-term (e.g. up to one month) and long-term (up to 6 months). Results of mean loss function based on MVaR criterion again indicate the importance of considering structural breaks for the most ISE indices, especially ISE-100 and ISE-FIN for forecasting gains as GARCH (1,1) rolling window models in the short-run and Moving average models in the long-run perform well. Additional empirical analysis on comparison of GARCH(1,1) expanding window model with two other GARCH models, namely GJR-GARCH and MS-GARCH suggest that MS-GARCH model at short forecast horizons provide more accurate results than GARCH(1,1) with expanding window. However, GJR-GARCH(1,1) model have relatively worse performance in our out-of-sample forecasting analysis based on the MSFE mean loss function. Since, those two models, GJR-GARCH and MS-GARCH do not consistently outperform the benchmark model of GARCH(1,1) expanding window, we do not estimate out-of-sample forecasts generated by the mean loss function of MVaR.

It is evidenced that structural breaks are relevant features for the ISE indices and allowing for instabilities in the data leads to forecasting gains. Moreover, empirical findings reveal that decision makers should consider structural breaks as well as sectoral differences in modeling and forecasting stock market volatility in both short-term and long-term. Thus, one should be aware of those facts to reach more accurate conclusions in terms of Value-at-Risk (VaR) calculation, risk management, derivative pricing, and hedging and portfolio allocation. Empirical results which suggest considering sudden large shocks in the unconditional variance due to the structural breaks in both estimating unconditional variance and forecasting stock market volatility also lead us to reach a conclusion that the previous studies that do not consider structural breaks in modeling and forecasting volatility of Turkish stock market are invalid.

For further research, modeling and forecasting volatility of Turkish stock market may be investigated via high frequency data, such as 1-minute or 5-minute interval data. Furthermore, the analysis may be conducted on the single stock returns, or on the exchange rate series of Turkish Lira against the U.S. dollar or on the Euro/Dollar parity.

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